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 **Tomas Bata University in Zlín**
Faculty of Management and Economics

Conference Proceedings
DOKBAT 2025
21st International Bata Conference
for Ph.D. Students and Young Researchers



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EFFECTIVENESS OF EMOTIONAL AND RATIONAL APPEALS IN SOCIAL MEDIA ADVERTISING: A SYSTEMATIC REVIEW

Anshu Anshu

Abstract

This systematic review explores how emotional and rational appeals work in advertising on social media platforms. As brands increasingly turn to digital spaces to connect with their audiences, it's becoming more important to understand which strategies resonate best. Emotional appeals like those using fear, humor, guilt, or happiness and rational appeals focused on product features, benefits, or logical reasoning can have very different impacts depending on how and where they're used. Following the PRISMA 2020 guidelines, the review analyzed 1,007 studies from databases like Scopus and Web of Science, ultimately narrowing them down to 25 that met the inclusion criteria. The results show that the effectiveness of emotional versus rational appeals varies based on platforms (such as Instagram, Facebook, or YouTube), how users engage, and the format of the content. Emotional appeals often lead to more engagement and sharing, especially when they match the interactive and visual nature of social media. On the other hand, rational appeals tend to work better in situations where people are looking for detailed information or comparing options. Overall, the findings highlight the need for advertisers to adapt their approach to fit both the platform and the audience. Blending emotional impact with logical reasoning could offer the most effective strategy.

Keywords: *Emotional appeals, Rational appeals, Advertising effectiveness, social media advertising, Digital marketing*

1 INTRODUCTION

In today's increasingly digital and saturated media environment, marketers are confronted with the challenge of designing advertising strategies that not only capture attention but also resonate with diverse consumer segments. Traditional rational appeals those emphasizing information, logic, or utility are no longer sufficient to drive engagement and conversion in isolation. As advertising ecosystems shift toward personalized, platform-specific, and emotionally intelligent communication, there is a growing recognition that emotional, psychological, and contextual variables play an integral role in shaping consumer responses (Bandyopadhyay et al., 2022) (Jiang et al., 2025). Recent years have witnessed a surge in empirical research exploring how factors such as emotional appeal, message framing, platform affordances, gift-giving reciprocity, green ethics, and influencer authenticity affect advertising effectiveness. These studies span diverse contexts from green marketing and luxury branding to social media influencer posts, crisis communication, and neurophysiological advertising testing yet remain fragmented in how they address these dimensions collectively (Kim et al., 2022) (Madadi et al., 2024b) (Bou Saada et al., 2023)

Moreover, advertising researchers increasingly call for integrated perspectives that consider how media affordances, consumer psychology, and message strategies interact (Gross & von Wangenheim, 2022) (Kim et al., 2022). Despite these advancements, there remains a lack of comprehensive synthesis that brings together the wide-ranging constructs and experimental findings to inform unified theories and practice.

This systematic literature review (SLR) addresses this gap by synthesizing insights from 25 peer-reviewed studies published between 2021 and 2025. Specifically, it aims to answer the following guiding question:

How do emotional and rational appeals moderate by contextual variables such as platform, consumer traits, and product category influence advertising effectiveness in digital and social media contexts?

To address this, the review is thematically organized into categories such as emotional appeal, influencer marketing, green and ethical advertising, gift-giving reciprocity, consumer reviews, health and crisis communication, and neuroscientific approaches. Through this synthesis, the review identifies key theoretical patterns, practical implications, and research gaps that pave the way for future advertising scholarships.

2 METHODOLOGY

A systematic review of empirical studies was undertaken to explore how emotional and rational appeals in digital advertising influence consumer behavior across diverse digital platforms. This review followed the reporting framework outlined by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Liberati et al., 2009). The objective was to synthesize findings from a wide range of studies that examined advertising effectiveness as influenced by message appeal, platform type, consumer psychological traits, and advertising context. Specifically, the review focused on themes such as emotional appeal, influencer marketing, green advertising, gift-giving, ethical messaging, health communication, and neuroscience-informed ad strategies. To this end, a comprehensive search strategy was developed and implemented, targeting major academic databases including Scopus, Web of Science, ScienceDirect, SpringerLink, Emerald Insight, ProQuest, and Google Scholar. The search aimed to capture all relevant studies published up to March 2025, without restrictions on methodological design or country of origin, but limited to empirical articles written in English and published in peer-reviewed journals.

A review protocol was developed in advance to guide the inclusion and screening process. Search terms included combinations of *"emotional appeal"*, *"rational appeal"*, *"advertising effectiveness"*, *"digital advertising"*, *"green marketing"*, *"influencer marketing"*, *"consumer behavior"*, *"social media advertising"*, *"purchase intention"*, *"brand attitude"*, *"gift-giving"*, *"ethical advertising"*, and *"health communication."* These terms were searched in article titles, abstracts, and keywords. No publication date restrictions were applied, and both quantitative and qualitative studies were considered eligible if they reported primary data and explicitly addressed advertising appeals and their behavioral or attitudinal outcomes. Conceptual, theoretical, editorial, and non-advertising-focused studies (e.g., on political messaging or emotional product design) were excluded.

All search results were exported into a Microsoft Excel spreadsheet, where duplicates were removed. An independent reviewer screened the titles and abstracts of the remaining records to assess eligibility based on predefined inclusion and exclusion criteria. Discrepancies were resolved through discussion, and a review was consulted if needed. Studies that met the inclusion criteria at this stage were retrieved in full and subjected to a full-text eligibility review.

Studies were included if they:

- Focused on emotional or rational advertising appeals,

- Investigated consumer psychological or behavioral outcomes (e.g., engagement, recall, purchase intention),
- Were situated within digital advertising environments (e.g., social media, influencer platforms, video or mobile ads),
- And reported empirical findings with clearly described methodology

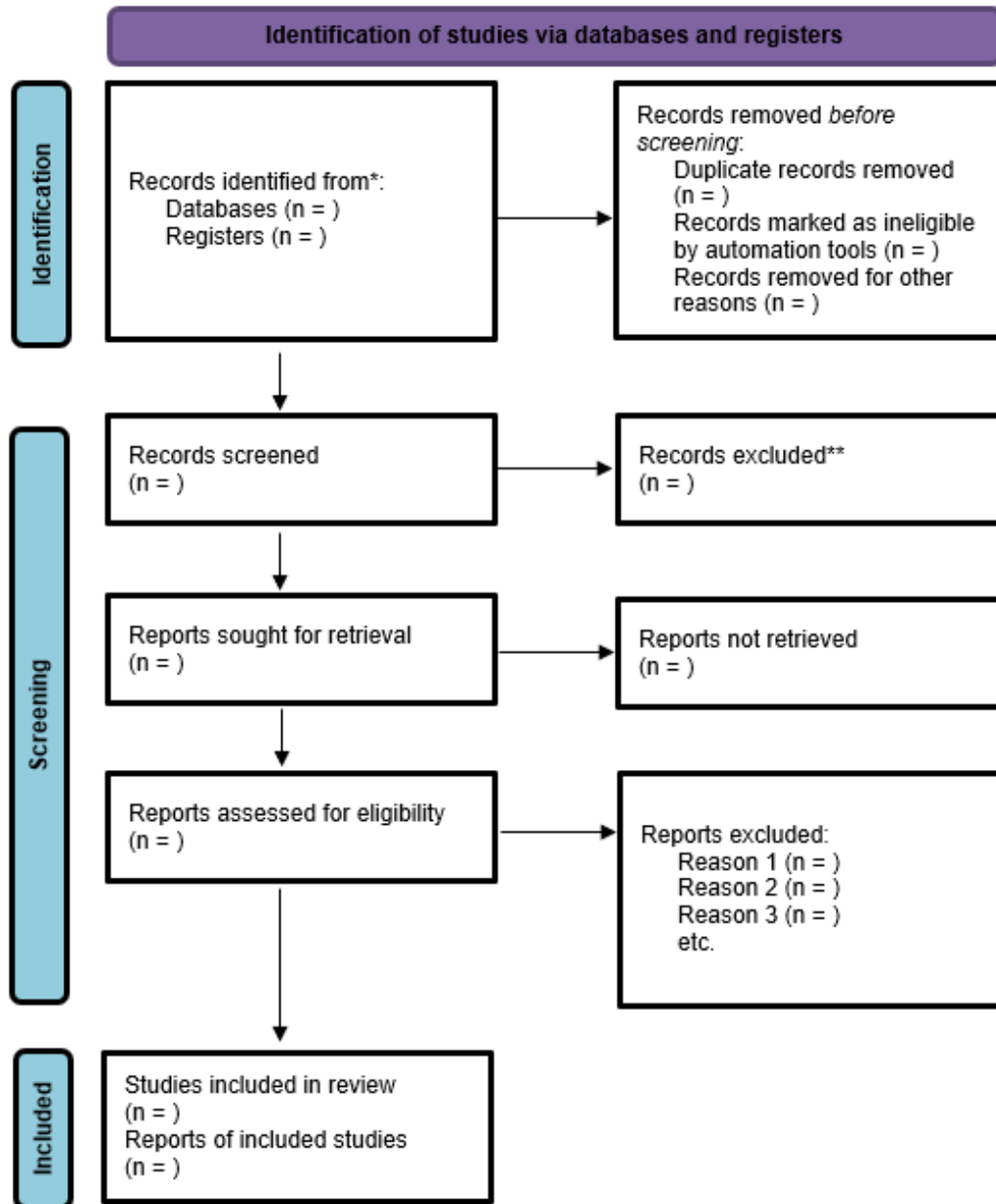


Fig. 1. The PRISMA flow diagram. Source: own research

Following the final selection process, 25 studies were retained. A total of 1,007 records had been initially identified. A PRISMA flow diagram was used to document the number of records identified, screened, excluded, and included at each stage.

The Excel database was further adapted to extract and catalog bibliographic details, advertising appeal type (emotional, rational, mixed), platform or media context (e.g., Instagram, Snapchat, online reviews), theoretical frameworks (e.g., ELM, Dual Process Theory, Narrative Transportation), sample traits (age, culture, psychological variables), outcome measures (e.g., attitude toward ad, purchase intent, sharing intention), and key findings. Studies were also categorized thematically into nine major groups: Emotional Appeal, Influencer Marketing, Green Advertising, Gift-Giving & Reciprocity, Health & Ethical Messaging, Neuroscience of Advertising, Social Media Ad Mechanics, Consumer Reviews, and Luxury Branding.

To evaluate the methodological quality and risk of bias, studies were assessed using simplified appraisal tools derived from the Critical Appraisal Skills Programme (CASP) for qualitative studies and a modified checklist based on the Cochrane Risk of Bias Tool for quantitative designs. Each study was independently assessed by the author. Any disagreements were resolved by consensus. Due to the diversity of study designs, variables, and analytical methods, meta-analysis was not feasible. Instead, a thematic qualitative synthesis was conducted using an inductive coding strategy to group findings into meaningful clusters across the identified themes. This approach enabled the identification of key advertising mechanisms, emotional triggers, and contextual moderators affecting consumer responses to advertising in varied digital formats.

3 RESULTS

The current study reviewed 25 empirical papers. The study selection process has been summarized in Fig. 2. An initial search across selected databases and search engines yielded 1007 records. After screening the titles and abstracts, 963 records were excluded because they did not meet the inclusion criteria or were found irrelevant based on the scope. The full texts of the remaining 44 articles were then carefully assessed for eligibility. During this stage, 19 articles were excluded due to reasons such as insufficient methodological rigor, lack of focus on advertising appeals, or failure to report empirical findings. Ultimately, 25 studies were retained for the final qualitative synthesis through thematic analysis. These included papers drawn from journals across different quality tiers: six from Q1 journals, fourteen from Q2 journals, and five from Q3 journals.

Table 2 reports the names of journals and years of publication for the 25 studies included in the review. The results indicate that most selected articles were published recently, with a notable growth in publications during 2024, accounting for 40% of the total sample. Publications in 2022 and 2025 contributed 42.85% and 14.28% respectively, while only a few papers were published before 2022. This trend suggests that research focusing on advertising appeals, emotional marketing, social media environments, and ethical communication has gained significant scholarly attention in recent years. Moreover, the distribution of journals by quality tier shows a clear association between journal ranking and the publication of advertising-related studies. Out of the 25 papers, six articles (24%) were published in Q1-ranked journals such as the *European Journal of Marketing*, *Information and Management*, *Journal of Advertising*, *Journal of Advertising Research*, and *Psychology and Marketing*. Q2 journals hosted the largest share of papers, with 14 articles (56%) distributed across reputable outlets such as the *Asia Pacific Journal of Marketing and Logistics*, *International Journal of Market Research*, *Journal of Marketing Communications*, and *Journal of Interactive Advertising*. Meanwhile, five articles (20%) were published in Q3 journals, including the *International Journal of Internet Marketing and Advertising* and the *Journal of Global Marketing*.

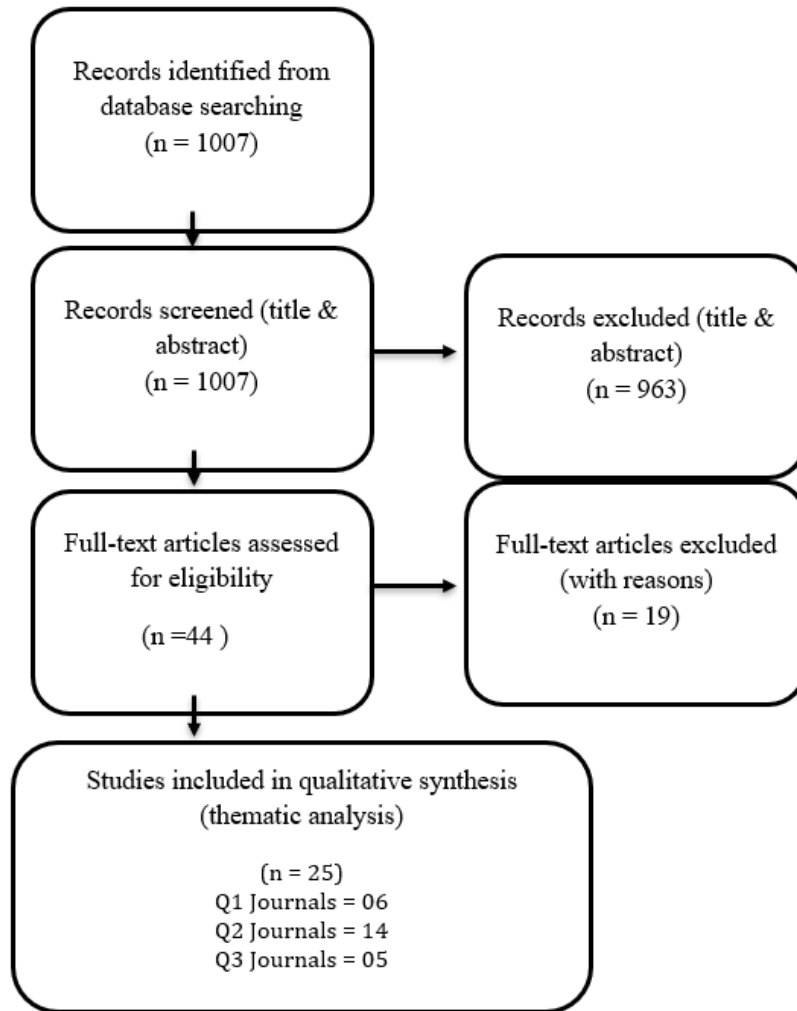


Fig. 2 - PRISMA Flow Diagram Summary. Source: own research

3.1 Title, Abstract and Introduction

The results revealed that out of the screened articles, 18 studies (72%) explicitly focused on advertising appeals, including emotional, rational, or mixed strategies. Around 80% ($n = 20$) of the papers concentrated on consumer behavioral outcomes such as purchase intention, brand attitude, or engagement. Approximately 60% of the papers ($n = 15$) addressed social media advertising, reflecting the growing role of digital environments in consumer research. A smaller proportion, 24% ($n = 6$), focused specifically on influenced marketing strategies. Furthermore, about 28% of the studies ($n = 7$) examined trust and privacy concerns related to advertising effectiveness, while 20% ($n = 5$) explored ethical advertising themes, including green marketing and Halal advertising. Articles that lacked original empirical data or did not directly investigate these thematic areas were excluded during this stage.

3.2 Method

To systematically analyze the diverse findings across the included studies, thematic synthesis was chosen as the primary method of evidence integration. According to Thomas and Harden (2008), thematic synthesis is particularly suitable when synthesizing findings from empirical studies that differ in focus, methods, or outcomes but share conceptual relevance. Although the majority of the 25 studies in this review were quantitative (n = 22) and only a few employed mixed-methods designs (n = 3), thematic synthesis was applied at the level of reported study findings rather than at the raw data level, following the approach recommended for mixed evidence reviews (Dixon-Woods et al., 2005).

The synthesis process involved several stages. First, findings were extracted from all 25 studies, focusing on advertising appeals (n = 18), consumer behavioral outcomes (n = 20), social media advertising dynamics (n = 15), influencer marketing (n = 6), trust and privacy concerns (n = 7), and ethical advertising themes (n = 5). In the second step, open coding was conducted across these extracted findings, identifying recurring concepts such as emotional appeal effects, rational appeal effectiveness, credibility and trust factors, and platform-specific advertising strategies. Third, the codes were systematically organized into Level 2 themes, grouping conceptually similar findings for example, emotional-cognitive pathways and discrete emotional impacts were merged under the broader theme of emotional and rational processing. Finally, five overarching Super-Themes were developed: Emotional and Rational Processing in Advertising, Social Media Environment Effects, Consumer Trust and Ethical Messaging, Personal and Psychological Moderators, and Neuroscientific Insights in Advertising. A thematic map was generated to visually represent the interconnections between these synthesized findings.

Using thematic synthesis allowed for a transparent, systematic, and conceptually coherent integration of insights across a wide range of empirical studies, addressing the complexity of advertising appeals and consumer behavior in digital contexts (Thomas & Harden, 2008)

Tab. 1 – A summary of names of the journals and year of publication of the included review. Source: own research

Note – Journals without any included systematic review were not listed in this table

Name of Journals	SJR Quartile	ABS Rank	2021	2022	2023	2024	2025	Total
European Journal of Marketing	Q1	3	-	1	-	-	-	1
Information and Management	Q1	3	-	-	-	1	-	1
Journal of Advertising	Q1	3	-	-	-	1	-	1
Journal of Advertising Research	Q1	2	-	-	1	1	-	2
Psychology and Marketing	Q1	3	-	-	-	1	-	1
All Q1 Journals			0 (0.00%)	1 (16.6%)	1 (16.6%)	4 (66.6%)	0 (0.00%)	6 (100.00%)
Asia Pacific Journal of Marketing and Logistics	Q2	1	-	2	1	-	-	3
Australasian Marketing Journal	Q2	1	-	1	-	-	-	1
International Journal of Market Research	Q2	2	-	-	-	1	-	1
Journal of Consumer Behaviour	Q2	2	-	-	-	-	1	1
Journal of Interactive Advertising	Q2	1	-	1	-	-	-	1
Journal of Marketing Communications	Q2	1	-	2	-	-	-	2

Journal of Marketing Theory and Practice	Q2	2	-	-	-	1	1	2
Journal of Research in Interactive Marketing	Q2	1	-	-	-	1	-	1
Journal of Travel and Tourism Marketing	Q2	1	-	-	-	1	-	1
Marketing Intelligence and Planning	Q2	1	-	-	-	1	-	1
All Q2 Journals			0 (0.00%)	6 (42.85%)	1 (7.14%)	5 (35.71%)	2 (14.28%)	14 (100.00%)
International Journal of Internet Marketing and Advertising	Q3	1	-	-	-	1	-	1
Journal of Global Marketing	Q3	1	-	2	-	-	-	2
Journal of Marketing Analytics	Q3	1	-	-	-	1	-	1
Review of Marketing Science	Q3	1	-	-	-	-	1	1
All Q3 Journals			0 (0.00%)	2 (0.00%)	0 (0.00%)	2 (40.00%)	1 (20.00%)	5 (100.00%)
				2 (40.00%)				
Total			0 (0.00%)	9 (36.00%)	2 (8.00%)	11 (44.00%)	3 (12.00%)	25 (100.00%)

3.3 Synthesis of Key Themes and Sub-Theme

To systematically organize the findings from the reviewed studies, a thematic synthesis approach was employed. At the first stage (Table 2), Super-Themes (Level 1) were developed by clustering studies according to broad conceptual domains that repeatedly emerged across literature. Each Super-Theme represents a major research focus or psychological process addressed in the context of social media advertising. Within each Super-Theme, more specific and nuanced subtopics were identified, forming the Theme (Level 2) categories. These finer-grained themes capture the detailed mechanisms, pathways, or outcomes explored by the studies.

The first and most central theme, Emotional and Rational Processing, captures the comparative performance of emotional versus rational appeals. Numerous studies have found that emotional appeals are more effective in driving engagement and behavioral outcomes, particularly when advertising experiential products or services. Platforms like Instagram that emphasize aesthetics and storytelling tend to amplify the effectiveness of emotionally rich content (Agarwal & Mitra, 2025; Jiang et al., 2025; Donadapati, 2025; Choi & Choi, 2024). In contrast, rational appeals were more successful for material goods, especially when promoted on cognitively oriented platforms like Snapchat (Wen-Kuo et al., 2023; D. H. Kim et al., 2022). Several studies further revealed that emotional appeals work through mediating constructs such as empathy, pride, and narrative transportation (Bandyopadhyay et al., 2022; Tan et al., 2024), and that discrete emotions like anger, fear, or joy uniquely shape consumer responses and memory outcomes (Madadi et al., 2024a). These findings underscore the necessity of emotional-cognitive alignment in advertising strategy.

The second theme, Social Media Environment Effects, reflects how platform-specific features known as media affordances shape consumer reactions to advertising appeals. Instagram's high visibility, persistence, and editability make it well-suited for emotional and experiential appeals, while Snapchat's ephemeral and intimate nature favors rational messaging and material gifts

(Agarwal & Mitra, 2025; Donadapati, 2025; Bahriarзад et al., 2024; D. H. Kim et al., 2022). Additionally, user-generated content and real-time emotional expressions (e.g., Danmu overlays) can intensify ad processing and persuasion by increasing affective involvement (Guo et al., 2024). Influencer characteristics also interact with platform effects micro-influencers using emotionally resonant content were shown to elicit stronger engagement than macro-influencers with generic content (Jiang et al., 2025; Donadapati, 2025; Gross & von Wangenheim, 2022). These findings demonstrate how the technological and social affordances of platforms condition the success of both emotional and rational appeals.

The third theme, Consumer Trust and Ethical Messaging, centers on the role of credibility, perceived authenticity, and alignment with consumer values. Several studies noted that trust, privacy, and corporate reputation moderate the relationship between ad appeal and consumer response (J. Zhang et al., 2024; Shi & Jiang, 2023; Rana & Arora, 2022). Notably, trust did not significantly influence outcomes in contexts of high ad clutter or privacy concerns (Rana & Arora, 2022), highlighting the fragility of credibility in digital environments. In ethical and environmental marketing contexts, such as green or Halal advertising, ads that aligned with consumers' values and ethical beliefs either emotionally or rationally framed were far more effective (Shi & Jiang, 2023; Taufique, 2022; Al-Kwifі et al., 2022). These results support the importance of congruence between message framing and ethical orientation in shaping persuasion.

The fourth theme, Personal and Psychological Moderators, reflects how individual traits influence the effectiveness of advertising appeals. Regulatory focus (promotion vs. prevention), interdependent self-construal, social comparison orientation (SCO), and mindfulness were all found to shape perception and processing depth (Madadi et al., 2024a; Srivastava et al., 2024). For example, FOMO-based appeals worked better for younger consumers high in SCO, while JOMO-based appeals resonated more with older individuals (Jiang et al., 2025). Similarly, green and ethical advertising outcomes varied depending on consumers' power distance beliefs (PDB), with high PDB favoring rational, competence-based messaging ((Shi & Jiang, 2023). These moderators explain observed variation in ad effectiveness and emphasize the importance of segmentation and personalization.

Finally, the fifth theme, Neuroscientific Insights in Advertising, introduces a biologically grounded dimension to ad evaluation. Studies using EEG and fMRI demonstrated that emotionally rich, metaphorical, and ethically aligned ads activate brain regions associated with memory, emotion, and decision-making, such as the hippocampus and ventromedial prefrontal cortex (vmPFC) (Wu & Chen, 2024; Al-Kwifі et al., 2022). For example, fMRI scans showed stronger vmPFC activation in Muslim consumers when viewing Halal versus non-Halal food ads, confirming cognitive engagement rooted in ethical alignment (Al-Kwifі et al., 2022). Another study found that emotional appeals elicited olfactory and gustatory imagery on EEG, further validating the use of multisensory stimuli in enhancing ad effectiveness (Wu & Chen, 2024). These findings support the cognitive and emotional underpinnings of persuasion, adding a neuroscientific foundation to message design strategy.

Tab. 2 - Categorizing themes. Source: own research

Super-Theme (Level 1)	Theme (Level 2)	Example Studies
Emotional and Rational Processing	Emotional Appeals in Ads	(Agarwal & Mitra, 2025) (Jiang et al., 2025) (Dondapati, 2025) (Choi & Choi, 2024) (Kim et al., 2022)

	Rational Appeals in Ads	(Wen-Kuo et al., 2023) (Kim et al., 2022)
	Emotional-Cognitive Pathways	(Bandyopadhyay et al., 2022) (Tan et al., 2024)
	Discrete Emotions and Specific Outcomes	(Madadi et al., 2024a)
Social Media Environment Effects	Instagram better for emotional/experiential, Snapchat for rational/material	(Agarwal & Mitra, 2025) (Dondapati, 2025) (Bahrainizad et al., 2024) (Kim et al., 2022)
	User-generated content enhances processing through emotional intensity	(Guo et al., 2024)
	Micro-influencers and emotional tone drive engagement	(Jiang et al., 2025) (Dondapati, 2025) (Gross & von Wangenheim, 2022)
Consumer Trust and Ethical Messaging	Trust, Privacy, Credibility	(J. Zhang et al., 2024) (Shi & Jiang, 2023) (Rana & Arora, 2022)
	Environmental and Ethical Messaging	(Shi & Jiang, 2023) (Taufique, 2022) (Al-Kwif et al., 2022)
Personal and Psychological Moderators	Mindfulness, Regulatory Focus, PDB	(Madadi et al., 2024a) (Srivastava et al., 2024)
Neuroscientific Insights in Advertising	Sensory Imagery, Ethical Cognition	(Wu & Chen, 2024) (Al-Kwif et al., 2022)

3.4 Rational View

Emotional and Rational Processing

Across numerous studies, emotional and rational appeals were found to function differently based on context, platform, and product type. Emotional appeals consistently outperformed rational ones in terms of engagement and purchase intent, particularly when paired with experiential goods and platforms that encourage affective expression, such as Instagram (Agarwal & Mitra, 2025) (Jiang et al., 2025) (Dondapati, 2025) (Choi & Choi, 2024) (Kim et al., 2022). For example, emotional appeals were more effective for green or luxury products when they invoked mixed emotions (Bandyopadhyay et al., 2022) or aligned with narrative storytelling (Beard et al., 2024). In contrast, rational appeals demonstrated strength in promoting material or utilitarian gifts, especially on platforms like Snapchat that favor cognitive processing (Wen-Kuo et al., 2023) (Kim et al., 2022).

Affective mediators such as empathy (Agarwal & Mitra, 2025), pride and gratitude (Tan et al., 2024), and attitude toward the ad (Choi & Choi, 2024) (Tsotsos et al., 2023) played key roles in bridging emotional responses to behavioral outcomes. Emotional cues, including emojis and facial expressions, also enhanced or detracted from message fluency depending on ad context (Madadi et al., 2024a) (K. Zhang et al., 2023). Thematic consistency between ad type and product nature (e.g., emotional appeal for experiential gifts) was essential for maximizing persuasive impact (Northcott et al., 2024) (Kim et al., 2022).

Social Media Environment Effects

The affordances and psychological implications of various social media platforms strongly shaped advertising outcomes. Instagram, characterized by high visibility, persistence, and self-presentation, was found to be more effective for emotional and experiential campaigns (Agarwal & Mitra, 2025) (Dondapati, 2025) (Kim et al., 2022). Snapchat, with its ephemeral and personal nature, aligned better with rational appeal and material goods (Bahrainizad et al., 2024) (Kim et al., 2022). These platform-specific affordances activated different cognitive or affective processing routes in consumers (Kim et al., 2022). User-generated content and real-time interactions (e.g., Danmu comments) were found to enhance central or peripheral processing depending on their emotional intensity and relevance (Guo et al., 2024). Similarly, the type of influencer and the emotional tone of their content influenced consumer engagement, with micro-influencers generating higher trust and interaction rates (Jiang et al., 2025) (Dondapati, 2025) (Gross & von Wangenheim, 2022). Thus, the platform's technological and social features mediated the ad's reception, contributing to differential message processing.

Consumer Trust and Ethical Messaging

Trust, ethical alignment, and perceived authenticity emerged as critical dimensions in shaping ad effectiveness, especially in CSR, green, and Halal marketing contexts. Ads that aligned with consumers' ethical frameworks, such as environmental values or Islamic food ethics, led to stronger cognitive engagement and intention to purchase (Shi & Jiang, 2023) (Taufique, 2022) (Al-Kwafi et al., 2022). Interestingly, trustworthiness did not always play a significant role in driving ad attitudes in cluttered or privacy-sensitive environments (Rana & Arora, 2022). However, perceived CSR associations, brand warmth or competence, and corporate reputation moderated ad receptivity and trust (J. Zhang et al., 2024) (Shi & Jiang, 2023) (Rana & Arora, 2022). For Muslim consumers, ethical decision-making was shown to be primarily cognitive and internalized, as confirmed by fMRI scans (Al-Kwafi et al., 2022).

Personal and Psychological Moderators

Several individual-level traits significantly moderated advertising responses. Traits like interdependent self-construal (J. Zhang et al., 2024), health consciousness (Madadi et al., 2024a), social comparison orientation (Tan et al., 2024), and regulatory focus (Choi & Choi, 2024) (Paper 10) affected how consumers processed ad messages. For instance, younger consumers with high social comparison orientation responded more favorably to FOMO appeals, while older individuals aligned better with JOMO and gratitude-based messaging (Tan et al., 2024). Segmentations based on involvement (emotional vs. rational), age, or religious identity further explained ad effectiveness in hashtag use, influencer campaigns, and green advertising (Madadi et al., 2024a) (Srivastava et al., 2024). Psychological alignment between message appeal and user traits emerged as a robust determinant of both engagement and purchase behavior.

Neuroscientific Insights in Advertising

A select group of studies applied neuroscientific tools to unveil deeper cognitive mechanisms in advertising. Metaphorical and emotional ads activated memory-related brain regions, leading to better recall and brand association (Beard et al., 2024). EEG and fMRI studies demonstrated how sensory cues (smell, taste) and religious ethics activated specific brain areas (Wu & Chen, 2024) (Al-Kwafi et al., 2022). For example, rational ads stimulated olfactory imagery, while emotional ads activated both olfactory and gustatory imagery in EEG measures (Wu & Chen, 2024).

4 DISCUSSION

This review of 25 studies paints a rich and nuanced picture of how emotional and rational appeals function in the ever-evolving landscape of social media advertising. Rather than declaring a winner between the two, the findings emphasize the importance of context who the audience is, what they care about, where they encounter the message, and how it's framed.

Emotional appeals often shine brightest when they are in the right setting targeting users on platforms like Instagram that prioritize visual storytelling and emotional resonance. Whether it's empathy in social causes, gratitude in gift-giving, or pride in identity-based appeals, emotional messages can powerfully connect with people when the product being marketed is experiential, symbolic, or hedonic in nature. However, that doesn't mean rational appeals to take a back seat. Especially for utilitarian or information-heavy products, rational ads grounded in facts, features, and function play a crucial role in persuading more deliberative, goal-oriented users, particularly on platforms like Snapchat, where quick decisions and direct messaging prevail.

Ads are most effective when the type of message matches the nature of the product and the digital environment in which they appear. This alignment, referred to as appeal-message-product congruence, helps reduce friction in processing and increases message impact. It's not just about what you say, but how and where you say it.

The review also brings attention to the rising need for personalization. A person's age, psychological traits, cultural background, and even how they compare themselves to others all play a role in shaping how they respond to different types of messages. Emotional appeals may work better for some, while others may respond more favorably to rational logic or clear facts. These insights argue strongly against a one-size-fits-all approach to advertising. In today's digital space, success lies in tailored communication that speaks directly to individual needs and mindsets. Moreover, ethical alignment and trust are not to be overlooked. It's not enough for an ad to be emotional, it must feel genuine and reflect the audience's values. In religious or environmentally conscious markets, ads fail to align with consumers' ethical standards even if emotionally rich risk falling flat. This makes a strong case for thoughtful, culturally attuned messaging.

What makes this review particularly compelling is the inclusion of neuroscientific findings. Studies using EEG and fMRI scans reveal that emotionally charged ads, especially those using metaphors or multisensory triggers, are not just persuasive, they're memorable. They activate deeper brain regions responsible for memory and sensory recall, offering scientific backing for why such messages work.

Lastly, the review underscores how social media platforms themselves are active participants in the communication process. Instagram and Snapchat aren't just venues for ads, they influence how users interpret messages. Understanding the affordances of each platform how content is created, consumed, and shared helps advertisers better craft and position their messages.

In sum, emotional and rational appeals are both effective tools, but their success hinges on thoughtful integration with platform design, audience psychology, and value alignment. Advertisers should embrace a more nuanced strategy, combining behavioral science with creative storytelling and technological awareness. Future studies should further investigate how these elements evolve over time, especially in light of personalization technologies and multi-platform marketing campaigns.

5 CONCLUSION

This systematic review synthesized evidence from 25 empirical studies to understand how emotional and rational advertising appeals, social media affordances, consumer trust factors, individual psychological traits, and neuroscientific mechanisms interact to shape advertising effectiveness in digital environments. The findings underscore that advertising success is not determined by message content alone, but by a complex interplay of platform characteristics, consumer traits, emotional-cognitive pathways, and broader ethical and trust considerations.

Importantly, this review reveals that emotional appeals tend to be more persuasive for experiential products and hedonic consumption, while rational appeals are more effective for functional and utilitarian products. Furthermore, the alignment between advertising message type and social media platform affordances significantly enhances consumer engagement. The critical roles of trust, corporate reputation, and privacy concerns in moderating advertising outcomes were also highlighted, emphasizing the growing importance of ethical communication practices in the digital era. Finally, emerging neuroscientific evidence supports the existence of distinct cognitive processing routes activated by advertising stimuli, offering new directions for theory and practice.

Overall, the findings provide a comprehensive framework for designing more effective, context-sensitive advertising strategies and offer a roadmap for future research integrating behavioral, cultural, and biological perspectives in advertising science.

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THE COMPETENCE DIVIDEND: A CONCEPTUAL FRAMEWORK FOR TESTING THE ECONOMIC IMPACT OF INTERNATIONAL STUDY ON GRADUATE EMPLOYABILITY IN THE CZECH REPUBLIC

František Brázdilík, Zuzana Tučková

Abstract

The internationalization of higher education (IoHE) is increasingly justified by its potential to enhance graduate employability, a key driver of national and sectoral competitiveness. This is particularly true for the tourism sector, a growing industry defined by its intercultural nature, which is currently facing significant skills shortages. This paper addresses this need by proposing a comprehensive conceptual framework to test the economic impact of international study experiences (ISE) on graduate employability. It builds explicitly the theoretical foundation for investigating a causal pathway where ISE fosters cross-cultural adaptation and develops key human capital, including Intercultural Competence (ICC), Cultural Intelligence (CQ), and Global Mindset (GM), which in turn lead to superior employability outcomes that enhance competitiveness the broader tourism economy. We propose testable hypotheses concerning these outcomes, including higher starting salaries (H1) and the positive predictive power of CQ/GM on career success (H2). The paper presents a focused case study of the Czech Republic, a nation with high inbound student mobility and a tourism sector with a documented skills gap, to ground this framework. By triangulating data on international student outcomes and industry needs, we argue that internationally educated graduates represent a vital talent pool capable of enhancing the competitiveness of the Czech tourism industry. This paper provides a robust theoretical model for future empirical research.

Keywords: *Internationalization of Higher Education, International Study Experience, Intercultural Competence, Cultural Intelligence, Global Mindset, Employability*

1 INTRODUCTION

In an era of intensified global competition, nations and industries increasingly depend on a highly skilled, global competent workforce to maintain their competitive edge. The internationalization of higher education (IoHE) is now globally a central pillar of university strategy, driven by the imperative to prepare graduates for a globalized labour market (Helms et al., 2015). As argued by scholars like de Wit et al. (2017), the core assumption is that international study experiences (ISE) cultivates unique form of human capital which includes intercultural skills, adaptability, and a global mindset, that translates into superior career outcomes. However, while this link is often claimed, Leask (2001) and Teichler (2017) note that the precise causal mechanisms connecting mobility to market value demand more rigorous investigation. Much of the existing research establishes a correlation but fails to adequately explain the process of competence development that creates the economic dividend.

This paper develops a conceptual framework to facilitate such an investigation, aiming to move beyond mere correlation and test a specific causal pathway. Focusing primarily on the Czech

Republic as a case study, it establishes the theoretical foundation for evaluating two central hypotheses vital to understanding the economic returns of IoHE:

- H1: Graduates with significant international study experience will report on average, higher starting salaries than their counterparts without such expertise, controlling for relevant covariates.
- H2: Enhanced Cultural Intelligence (CQ) and Global Mindset (GM) developed during international study will positively predict favourable employability outcomes (e.g., career progression, job satisfaction).

To develop the case for testing these propositions, this paper proceeds as follows. Firstly, it synthesizes the existing literature on IoHE, human capital development (focusing on constructs such as Intercultural Competence (ICC), CQ and GM, and employability. Secondly, it presents a detailed methodology and introduces the “Competence Dividend” model, which operationalizes the causal pathway: *ISE* → *Cross-Cultural Adaptation* → *Human Capital Development* → *Enhanced Employability Outcomes*. Finally, the model is applied to the Czech tourism sector to ground the research in a real-world context.

Tourism provides an ideal "laboratory" for this study. Specifically, it is an industry where intercultural and adaptive skills developed through international research are not merely advantageous but are representing the essential professional competencies (Brookes, 2011). In previous years Czech Republic's popularity amongst international visitors considerably rose and as the studies of CzechTourism (2025) confirmed, this trend of growing popularity of the Czech Republic amongst tourists from all major visiting countries persist also in the future as overwhelming majority of respondents portrayed interest to visit the Czech Republic in the next 3 years. As the number of international tourists grows, the need for internationally educated graduates advanced Intercultural Competences, Cultural Intelligence and Global Mindset rises as well. And subsequently with given rate of international student enrolment and a tourism sector with a documented skills gap, the country offers a valuable context for examining the economic benefits of this specialized human capital (MSMT, 2021a). This paper thus lays the necessary theoretical groundwork for a rigorous empirical investigation and contributes to the broader discourse on how strategic investment in IoHE can directly enhance the international competitiveness of key economic sectors.

2 LITERATURE REVIEW

The argument that internationalization boosts employability rests on synthesizing three interconnected research bodies. The first traces the evolution of student mobility from a peripheral activity to a central economic imperative for higher education institutions. The second examines the specific global competencies that such experiences are theorized to develop. The third ground of this discussion is the practical skill requirements of a key global industry, tourism. Together, these streams of literature establish the theoretical foundation for this paper's central hypotheses.

A foundational premise of modern IoHE is that student mobility provides a direct pathway to enhanced career prospects. Reasons for this premise has shifted in time from primarily political and cultural aims towards a strong economic focus, with the preparation of students for a globalized workforce (Fakunle, 2023). Considerable amount of empirical works supports this view, as it consistently shows that mobile graduates face lower unemployment rates and often

experience faster career progression than their non-mobile peers (King et al., 2016). But this relationship is not always straightforward. The literature highlights two critical factors. Firstly, a well-documented self-selection bias suggests that students, who choose to go abroad may already possess traits (e.g., higher motivation, greater openness to experience) that are independently correlated with career success, making it difficult to isolate the causal effect of the mobility experience itself. Secondly, a persistent "disconnect" has been observed between universities, students, and employers, wherein the valuable but often tacit skills gained abroad - the so-called "hidden competences" like resilience and adaptability - are not effectively articulated by graduates or recognized by employers (Coelen, 2019).

Addressing this disconnect requires a deeper understanding of the specific human capital that mobilities intend to foster. For an international experience to create economic value, it must cultivate a measurable set of skills (Black, 2004). The literature identifies a set of related concepts - ICC, CQ, and GM - as the primary outcomes of successful cross-cultural adaptation. For this framework, we adopt a multidimensional definition of ICC that encompasses these constructs, viewing it as a combination of cognitive (knowledge and cultural awareness), affective (motivation, confidence, and sensitivity), and behavioural (the ability to act appropriately and effectively in diverse settings) components. Cseh, Crocco, Engel, and Follman (2024) demonstrates that well-designed international programs, particularly those of longer duration and incorporating guided reflection, can produce significant gains in these competencies. This development, however, is not an automatic outcome of simply being abroad; it is the result of intentional pedagogical design that encourages students to process and learn from their experiences actively.

While these global competencies are valuable across many fields, the tourism industry provides a uniquely powerful context for observing their economic impact. As an industry built on the movement of people and the delivery of services across cultural boundaries, tourism demands a workforce with exceptional intercultural skills (Grobela, 2015). Employers in the sector consistently prioritize soft skills such as communication, cultural sensitivity, foreign language proficiency, adaptability, and problem-solving over purely technical knowledge.

This near-perfect alignment between the documented learning outcomes of IoHE and the explicit skill demands of the tourism industry makes it an ideal sector to test the "Competence Dividend" model and investigate the tangible economic returns of a global education.

3 METHODOLOGY

This paper employs a conceptual-qualitative methodology, ideal for a foundational conference paper seeking to establish a robust theoretical framework. The argument is built upon a comprehensive synthesis of the academic and policy literature concerning IoHE, intercultural competence, and graduate employability (Brandenburg, 2014). This theoretical framework is then applied to a focused case study of the Czech Republic. The case study uses a triangulation approach to construct a rich, contextualized argument, analysing and synthesizing data from a wide range of publicly available sources. These include national and EU-level statistics on student mobility and graduate employment from bodies such as Eurostat and the Czech Statistical Office; detailed research reports from the Czech National Agency for International Education and Research (DZS) on the motivations and career outcomes of International experienced alumni; and various academic and industry studies that identify the specific skills required by, and often lacking in, the Czech

tourism labour market. This method of triangulating official statistics, dedicated research reports, and industry analysis allows for constructing a compelling case that establishes the rationale and urgency for the primary empirical research.

To formalize the causal pathway and provide a testable framework, we propose the “Competence Dividend” model (Fig. 1). This model illustrates how an ISE is converted into measurable economic value. The model posits a three-stage causal chain:

- **ISE:** This is the primary intervention or independent variable. It encompasses various forms of internationalization, from short-term mobility and full-degree programs to international internships.
- **Human Capital Development:** This is the crucial mediating stage. The model theorizes that the ISE is a catalyst for developing specific human capital, most notably Intercultural Competence (ICC/CQ/GM) and a suite of related transferable skills like adaptability, problem-solving, and resilience. This development process is synonymous with successful cross-cultural adaptation.
- **Enhanced Employability Outcomes:** The final dependent variable represents the economic “dividend”. The model hypothesizes that the human capital developed in the second stage translates into tangible career benefits.

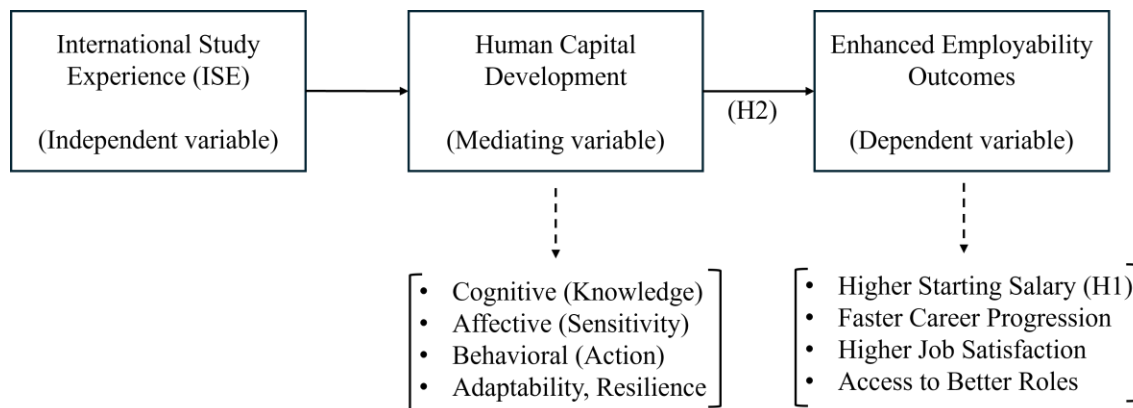


Fig. 1 – The Competence Dividend Conceptual Model. Source: own research

In the diagram, arrows represent the hypothesized positive relationships. The pathway from ISE to Human Capital Development is the first step. The subsequent path from Human Capital Development to Employability Outcomes forms the core of Hypothesis 2 (H2), which states that improved competencies such as CQ and GM will positively predict favourable career outcomes. The item “Higher Starting Salary” in the outcomes box exemplifies Hypothesis 1 (H1), positing a direct economic benefit for mobile graduates.

4 CASE STUDY

The case of the Czech Republic is not unique but it is a powerful exemplar of a broader international trend. Many non-Anglophone countries across Europe and Asia similarly leverage international education to attract talent and address domestic skill shortages. The challenges and opportunities observed in the Czech tourism sector mirror those in developed economies globally,

where service industries grapple with the need for a more culturally agile and adaptable workforce. Therefore, while this analysis is grounded in the Czech context, its implications are relevant for any nation seeking to leverage international student mobility as a strategic asset for economic competitiveness.

To demonstrate the real-world applicability of the “Competence Dividend” model, we present a detailed case study of the Czech Republic. This context is ideal due to two converging trends: a significant and growing population of internationally mobile students who often remain in the country to work, and a vital tourism sector with clearly identified human capital needs.

4.1 The Landscape of International Education and Alumni Employment in Czechia

The Czech Republic has become a central European hub for international students. The international student population has surged from just 11,000 in 2002 to over 55,000 today, meaning approximately one in five students at Czech universities is international. This large cohort is not merely transient; research from the Czech National Agency for International Education and Research (DZS) shows that 45% of international graduates choose to stay in Czechia to work, becoming part of the domestic labour market (DZS, 2022). The vast majority (90%) perceive their Czech education as a direct benefit to their career. Tab. 1 summarizes the key statistics that define this landscape.

Crucially, the DZS survey provides detailed insights into their work experiences. A clear majority of full-degree alums have work experience in the country. Overall, 79% of alumni found it “easy” or “very easy” to find a job or start a business, indicating a strong demand for their skills (MSMT, 2021b). However, the experience is not uniform. The data reveals a nuanced picture: while 37% of full-degree alums describe their work experience positively, others cite challenges such as low salaries (3%) or difficulties finding a job (7%). Indeed, “unsatisfactory wage or work conditions” was a reason for leaving the country for 15% of alumni who departed. This suggests that while jobs may be plentiful, the quality and remuneration of those jobs are critical variables. This tension makes the Czech Republic an ideal context to test H1, which posits that despite these challenges, a wage premium for mobile graduates does exist when controlling for other factors.

Tab. 1 – Key statistics on International Students in the Czech Republic. Source: DZS, 2022

Metric	Statistic
Total International Students	~52,000 – 55,000
Share of Total Student Body	~17-20%
Post-Graduation Stay Rate	45% of full-degree graduates stay to work
Perceived Career Benefit	90% of alumni report their studies improved their career
Ease of Finding Employment	79% of alumni rate finding a job as easy/ very easy.

Furthermore, qualitative comments from the survey suggest a pathway to better career outcomes, directly informing H2. One alumnus noted, “It’s difficult to find a job in local companies. It’s easier to get into a multinational company” (MSMT, 2021b). This aligns with the theory that international

firms particularly value the intercultural competencies (CQ/GM) fostered by an ISE. These graduates are better equipped to work in diverse environments, making them prime candidates for such roles. Testing whether higher CQ/GM predicts employment in these more desirable, internationally oriented roles is a core component of verifying H2.

4.2 Human Capital Needs of the Czech Tourism Sector

Tourism is a significant contributor to the Czech economy, accounting for approximately 4% of total employment before the pandemic (CzechTourism, 2022). However, like many regional service industries, it faces a documented skills gap. Studies of Czech tourism employers consistently highlight a pronounced need for stronger soft skills among the workforce, including leadership, time management, communication, and problem-solving abilities (Maráková et al., 2025). More specifically, recent research has identified a critical mismatch in the digital domain, with high demand for skills in tourism information systems (e.g., GDS, PMS) and online marketing (SEO/SEM) (Strietska-Ilina, 2005).

4.3 Bridging the Gap: The Competence Dividend in Action

The “Competence Dividend” model argues that the human capital developed through an ISE directly addresses the needs of a globalized workforce. When we map the identified needs of the Czech tourism sector against the documented outcomes of international mobility, a powerful alignment emerges, as demonstrated in Tab. 2. This table illustrates the core of our argument: the pool of internationally educated graduates who remain in the Czech Republic represents a valuable source of talent, uniquely equipped with the intercultural, adaptive, and often digital skills needed to fill identified gaps in the country's vital tourism sector. The DZS finding that 79% of these alumni find it easy to secure employment provides strong real-world evidence of this successful match between their skills and the labour market demands.

Tab. 2 – Mapping the Competence Dividend in Czech Tourism. Source: Freillon, 2023

Key Competencies Demanded by Czech Tourism Sector	How ISE Fills the Gap
Digitals & Technical Skills (e.g., GDS, SEO)	Fosters digital literacy, students often gain exposure to new technologies and system abroad.
Foreign Language Proficiency	The most direct and obvious outcome of living and studying in a new linguistic environment.
Intercultural Communication & Teamwork	Develops skills through daily interaction in multicultural academic and social settings.
Adaptability & Problem Solving	The act of navigating a new country is a rigorous, real-world test of these skills.
Confidence & Resilience	Successfully overcoming the challenges of living abroad builds self-efficacy and resilience.

5 DISCUSSION

The evidence presented in the case study provides a strong rationale for testing this study's core hypotheses and offers a preview of the complex dynamics at play. The discussion of H1, that graduates with profound International Study Experiences earn higher starting salaries, is set against

a nuanced backdrop. On one hand, the clear skills gap in the Czech tourism sector and the high demand for internationally competent graduates suggest that employers would be willing to offer a wage premium to attract this talent. On the other hand, the DZS survey reveals that “low wages” is a significant concern and a key reason for some international alumni to leave the country. This tension makes H1 a critical and non-obvious hypothesis to test. The research must investigate whether a wage premium exists despite general wage dissatisfaction, and whether this premium is concentrated in specific sub-sectors, such as multinational hotel chains or international travel companies, where the value of global competencies is most explicitly recognized.

The case study also strongly supports the case for H2, that enhanced CQ and GM predict favourable employability outcomes. The qualitative data from the DZS survey, where alumni note that it is easier to find work in multinational companies, points directly to this mechanism. It suggests that graduates with higher CQ/GM are not just more employable in general, but are specifically more competitive for higher-quality, internationally oriented roles that likely offer better career progression and job satisfaction. Therefore, testing H2 is not just about confirming a link but also explaining the pathway to better careers. It posits that the "Competence Dividend" is realized when the human capital developed abroad allows graduates to access a higher tier of the labour market, moving beyond entry-level positions into roles where their global skills can be fully leveraged.

The implications of confirming these hypotheses are significant. For HEIs, it would validate the economic argument for investing in internationalization and provide a clear mandate to embed skills articulation into mobility programs. For employers, particularly in the tourism sector, it would provide empirical evidence that recruiting internationally experienced graduates is a sound investment in human capital that can address critical skills gaps. Finally, for policymakers, it would support the case for creating favourable visa and work permit conditions for international alums, framing them not as temporary visitors but as a strategic asset for enhancing the competitiveness and resilience of key economic sectors.

6 CONCLUSION

This study has established a comprehensive conceptual framework for investigating how international study experiences impact graduate employability and, by extension, national economic competitiveness. Synthesizing the literature and grounding the "Competence Dividend" model in a detailed case study of the Czech Republic provides a robust justification for empirically testing its core hypotheses. The research demonstrates that international graduates represent a strategic human capital resource, particularly for skill-intensive and growing sectors like tourism, and that understanding the mechanisms of competence development is key to unlocking their full economic potential.

The future research agenda stemming from this paper is clear and structured. The immediate next step is executing a multi-method empirical study designed to test the proposed hypotheses within the Czech context. This will involve three integrated components:

- Quantitative Survey (Sharp, 2003): A large-scale survey will be administered to mobile and non-mobile graduates from Czech universities. This instrument will gather data on their international experiences, self-assessed levels of ICC, CQ, and GM (using validated scales), and detailed employability outcomes, including salary, time to first job, and career satisfaction.

- Statistical Analysis: The survey data will be subjected to advanced statistical analysis. Regression models, including techniques like propensity score matching to control for self-selection bias (Kearns, 2013), will be used to test the causal relationships proposed in H1 and H2 rigorously.
- Qualitative Interviews: To add explanatory depth, in-depth, semi-structured interviews (Siedlecki, 2022) will be conducted with a subset of graduates and HR managers in the Czech tourism industry. These interviews will explore the lived experiences behind the data, providing rich, narrative context to the quantitative findings.

By pursuing this agenda, this research will move beyond correlation to provide a nuanced, evidence-based understanding of how internationalization creates value, significantly contributing to academic theory and the strategic practice of higher education, ultimately informing how nations can better leverage internationalization for global economic competitiveness.

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VALUING CUSTOMER DATA IN THE FINTECH SECTOR: A LITERATURE REVIEW

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Abstract

This literature review synthesizes academic discussions on valuing customer data as a strategic intangible asset, within the context of FinTech. Grounded in both the Resource-Based View (RBV) and Real Options Theory (ROT), the study claims that traditional models are quite inadequate in valuation, emphasizing the superiority of customer-centric models such as Customer Lifetime Value (CLV) and more dynamic frameworks like Real Options Analysis (ROA). The review concludes that value of data is much moderated by data decay, privacy regulation and network effects, calling for a holistic 'asset-liability' approach. The other key empirical and methodological gaps, which are highlighted by the review, set the stage for proposing a research agenda aimed at developing more robust integrated valuation models.

Keywords: *FinTech, Intangible Assets, Customer Data Valuation, Resource-Based View (RBV), Real Options Theory (ROT), Customer Lifetime Value (CLV)*

1 INTRODUCTION

1.1 The emergence of intangible assets in the digital economy

With the emergence of Financial Technology (Fintech), the current economic landscape is undergoing a major change in the way businesses create value. Traditional models are being replaced by new, often digital models. In the past, tangible assets such as property, plant and equipment were considered the foundation of business wealth. Today, the digital economy has put intangible assets to the forefront (Odonkor et al., 2023). Intangible assets like brand reputation, intellectual property (IP) now play a central role in value creation. Specifically for FinTech companies, proprietary technologies and data are critical in creating competitive advantage and market value (Odonkor et al., 2023). FinTech companies are the perfect example of this paradigm-shifting phenomenon since by nature, they are technology-driven and knowledge-intensive. The global economy of the 21st century is in the middle of a profound structural shift going from tangible to intangible assets based valuation (Dong & Doukas, 2025). In this new world, key drivers of firm value and sustainable competitive advantage are no longer physical capital—machinery, factories, and real estate—but nonphysical resources such as intellectual property, brand equity, technological know-how, and increasingly data (Das, 2024). This shift is most evident in the tech field where high-technology giants have overtaken traditional industrial firms at the top of global market capitalization. The value of these firms is derived less from their tangible asset base and more from their capacity to create new forms of intangible capital that generate sustainable cash flows (Dong & Doukas, 2025). A major outcome of this economic change is the growing gap between a company's book value reported on its balance sheet and its market value as set by the capital markets (Dong & Doukas, 2025).

The present accounting standards, the practice designed for an industrial economy, do not fully capture the actual economic value of internally created intangible assets, so these assets are

systematically undervalued or entirely omitted from the financial statements (Reilly & Schweih, 2016). This "valuation gap" poses a huge problem for managers, investors, and analysts who have to look beyond conventional financial reports to understand and assess the real drivers of value in modern companies.

1.2 The centrality of customer data and its valuation conundrum

The leadership of intangible assets can be best seen in the technological sector known as FinTech. Indeed, FinTech has facilitated a transformation within the global monetary system- it has broken the old models of banking and financial services by introducing advanced digital solutions (Payandeh & Babaei, 2025). Firms belonging to this new industry not only have agile organizational structures but also generate individualized offerings based on data that challenge traditional providers of institutional services (Senyo et al., 2021). Furthermore, disruption is enabled by a convergence of factors: rapid evolution in technology; customers demanding more digital-first, direct experiences; and supportive regulatory environments that encourage innovation (Payandeh & Babaei, 2025).

A key feature of the FinTech business model is an important intangible asset: customer data (Babina et al., 2022). Collecting, analyzing, and strategically using customer data is key to almost every part of FinTech operations. This information supports advanced lending risk assessments, helps with algorithmic trading and robo-advising, allows for hyper-personalized marketing, and promotes financial inclusion by enabling companies to work with previously unbanked or underbanked groups of customers (Siddiqui & Rivera, 2022). Essentially, customer data does not just come in as an input; it is the core strategic resource from which FinTech firms derive their competitive advantage and create economic value.

In spite of its obvious strategic importance, the problem of placing a credible, realistic monetary value on customer data is one of the most profound and complex. Data possesses characteristics as an asset class that render all traditional valuation methodologies somewhat deficient (Li, 2025). Data is non-rivalrous, meaning it can be used by one party without precluding use by another (Smedes et al., 2021). Its value depends greatly on context, quality, timeliness, and analytical capability. (Fleckenstein et al., 2023). Furthermore, according to Moody's (2023), data assets face unique risks: loss of relevance and accuracy over time (data decay); use can be curtailed by stringent privacy regulations; impacts on firm reputation and customer trust from ethical considerations. Likewise, the future use of a dataset is also very uncertain, filling it with great option value that static models fail to capture (Smedes et al., 2021). This paper conducts a literature review that maps, synthesizes, and critically evaluates the scholarly discussions regarding the valuation of customer data in the Fintech industry. It attempts to bring together the little bits of knowledge in this new field, moving beyond stories told to develop a structured understanding based on managerial finance theory.

1.3 Research objectives and the structure of the review

The paper aims to answer a set of core research questions designed to navigate the complexities of the topic:

- What are the prevailing conceptual frameworks for understanding customer data as a valuable intangible asset in FinTech?

- How do foundational theories in managerial finance, specifically the Resource-Based View and Real Options Theory, inform the valuation of these data assets?
- What particular valuation models and methodologies are used or suggested in the literature for customer data, and what are their strengths and weaknesses?
- What are the critical moderating factors—such as data decay, regulation, ethics, and network effects—that seriously influence the process of valuation?
- What are the most important gaps in the existing body of research, and what promising agenda can be identified for future inquiry?

2 LITERATURE REVIEW

2.1 Intangible assets: accounting vs. economic perspectives

The first step of valuation is to understand the broader category that intangible assets fall into. Nevertheless, major difficulty arises out of a very wide difference in the way accounting rules and economic theory define and recognize such assets, which further complicates the valuation. From an accounting point of view, the International Accounting Standards Board (IASB) gives a precise and restrictive definition in International Accounting Standard (IAS) 38. An intangible asset is described as "an identifiable non-monetary asset without physical substance" (Crouzet & Ma, 2023). For this asset to be acknowledged on a firm's balance sheet, it has to meet three strict criteria:

- **Identifiability:** the asset should be either separable, that is capable of being sold, transferred, licensed or rented, etc., or it should arise from contractual or other legal rights (Micah, 2022). This criterion has been laid to distinguish specific intangible assets from generalized goodwill.
- **Control:** the firm should have the ability to secure the future economic benefits flowing from the underlying resource and also to prevent others from utilizing those benefits. (Das, 2024).
- **Future economic benefits:** The asset should be anticipated to produce future economic benefits for the enterprise, such as enhanced revenues or lower costs. (Micah, 2022).

This accounting definition is deliberately conservative. It aims primarily to ensure that financial statements are reliable and verifiable. Therefore, most internally generated intangibles, especially those in the research phase, and whose future benefits are uncertain, will not be capitalized but rather expensed as incurred. (Das, 2024). This practice leads to a systematic underestimation of the real base of assets of the firm, particularly for knowledge-intensive firms such as FinTechs (Dong & Doukas, 2025). Conversely, the economic definition of intangible assets is much more expansive. Economists view intangible assets as all non-physical resources that a firm controls, which have resulted from past expenditures, and where such future private economic benefits are reasonably anticipated (Das, 2024). Such a definition embraces many more value-creating resources than IAS 38 can recognize; examples include internally created brand value, organizational capital, firm-specific human capital, and—most importantly in this context—internally developed customer databases (Dong & Doukas, 2025). The economic view concentrates on the ability of the asset to create value regardless of whether that asset can be

recognized on the balance sheet under more strict accounting criteria. This basic contrast between accounting's attention to reliability and economics' focus on value creation causes a big "valuation gap". The limiting nature of rules like IAS 38 means that many important value drivers for a FinTech company—its customer information and analysis skills, for example—are not seen on its balance sheet. (Li, 2025). This lack of visibility makes it harder to get financing using regular financial statements and shifts the burden onto strategic valuation methods to explain the real economic value of the company to investors and other stakeholders (Reilly & Schweih, 2016). Hence, the valuation process turns into a major task to help narrow the gap in information caused by the norms of accounting.

2.2 Customer data as a strategic asset

Within the broad class of intangibles, both frameworks recognize a specific subcategory of “marketing and customer-related assets”. This includes such assets as customer lists, order backlogs, customer contracts, and customer relationships (Crouzet & Ma, 2023). These assets are valuable because they correspond to an established connection to the income-generating base and hence lessen the future cost and uncertainty of gaining customers. (Wilson et al., 2019).

For FinTech firms, customer data is the digital representation of these customer-related intangibles. According to Li (2025), in essence, a customer list is an identifiers database while a customer relationship is the stream of interaction and transaction data. Nonetheless, the way the accounting standards treat these types of intangible assets is still problematic. If acquired in a business merger, their value may often be estimated and recorded on the balance sheet as part of goodwill (Pastor et al., 2017). But when these assets are created internally, which is typically the case for most Fintech companies, the associated costs (for example marketing, platform development, and storage) are typically expensed as incurred (Das, 2024). This accounting treatment effectively assigns a book value of zero to what may be the firm's most significant source of competitive advantage and so further worsens the valuation gap (Dong & Doukas, 2025).

The customer data has transcended the confines of accounting definitions and, in much more recent literature on managerial finance, is considered a strategic asset (Deloitte US, 2025). This perspective defines an asset not in terms of its physical substance or accounting treatment but with regard to its importance in corporate strategy and value creation. A strategic asset is a resource that is absolutely critical for a firm to successfully implement strategies to achieve competitive advantage and sustain it over time.

For the firms in the FinTech industry, customer data is a strategic asset since it directly fuels value capture. (Patil et al., 2025). FinTechs leverage data to create economic value through several identifiable mechanisms:

- Personalization and product development: Fintech firms can develop and offer highly personalized products and services thanks to the analysis of transaction histories and user behaviors. This ranges from tailored loan offers to customized investment advice, which increase customer satisfaction and willingness to pay (Brown et al., 2017).
- Dynamic pricing: Customer data permits advanced pricing tactics whereby firms differentiate customers according to their risk profiles, price sensitivity as well as lifetime value to maximize revenue from each customer relationship. (Patil et al., 2025).

- Improved risk management: Large datasets directly improve profitability by enabling the creation of more accurate credit scoring and fraud detection models, reducing loan defaults and operational losses (Siddiqui & Rivera, 2022).
- Enhanced customer retention: By understanding customer behavior, businesses can preserve long-term income streams by proactively tackling pain points, enhancing the customer experience, and reducing the churn rate (Visconti, 2024).

As a result, from a managerial finance perspective, customer data value is not an intangible concept but rather a measurable economic reality afforded by its direct contributions to a firm's revenue, cost, and risk profiles.

3 THEORETICAL FRAMEWORKS

To build a strong structure for assessing the worth of customer data, it is vital to base the study on well-known ideas of managerial finance. Two theories particularly stand out: the Resource-Based View (RBV), which tells us why data is valuable, and Real Options Theory (ROT), which gives us a way to value its future possibilities when there is uncertainty.

3.1 Resource-based view (RBV)

According to the Resource-Based View (RBV), firm-based sources of competitive advantage and superior performance do not depend primarily on a firm's position in its external market (Wright et al., 2001). Rather, they depend on the unique bundle of internal resources and capabilities. Proponents of RBV like Barney (1991) argue that: to achieve sustained competitive advantage, it should have four key attributes, known popularly as the VRIN or VRIO framework: it should be Valuable, Rare, Inimitable, and Non-substitutable (where the "O" in VRIO stands for Organization—the firm's ability to exploit the resource) (Liang et al., 2010). Applying this to customer data in the FinTech context highlights its strategic importance:

- Valuable: Consumer data is undoubtedly valuable. It helps FinTech firms take advantage of market opportunities like providing personalized credit to needy segments, and overcome threats such as lowering fraud risk or reducing customer turnover (Michaelis & Giebe, 2025). Data directly contributes to the firm's economic value by enhancing operational efficiency and revenue generation (Michaelis & Giebe, 2025).
- Rare: While raw data is seemingly abundant, that is actually not the case for the specific, proprietary, and curated datasets held by a FinTech firm (Harris, 2010). Rarity does not arise from the individual data points but from the particular combination of transactional, behavioral, and demographic data collected over time from a particular customer base. Additionally, there is a lack of advanced algorithms and specialized data science talent to efficiently analyze this data, which further restricts its competitors from effectively using it. (Michaelis & Giebe, 2025).
- Inimitable: There is no easy way for competitors to copy over or replicate a FinTech data asset. Inimitability occurs for several reasons. First, the data is path dependent; it comes with a unique customer interaction history that cannot be replicated overnight. (Miller, 2019). Second, often the value lies in what might be called the "data-network effect," wherein more data leads to better service, which in turn leads to more users being attracted, and thus even more data—a virtuous cycle creating a strong barrier to entry. (Cusumano,

2022). Third, advantage typically arises from the socially complex and causally ambiguous interactions between the data, the firm's proprietary algorithms, and an organizational culture of data-driven decision-making that outsiders have great difficulty understanding—much less imitating (Lubis, 2022).

- **Organizational:** Finally, to unleash the data's potential, the company has to be structured in such a way as to facilitate value capture from data. This means implementing not only technical infrastructure (data warehouses, analytics platforms) but also appropriate governance structures, business processes, and a corporate culture that encourages employees to use data in decision-making.

RBV sees customer data valuation not as a mere financial computation but as a strategic evaluation of its role in the firm's sustainable competitive advantage. The more VRIN attributes present in the data asset belonging to a firm, the more strategic value it has and consequently, its effect on long-term profitability.

3.2 Real Options Theory (ROT)

While RBV describes the static value of a resource, Real Options Theory (ROT) offers a dynamic framework of asset valuation under conditions of uncertainty and managerial flexibility (Mun, 2005). Traditional valuation methods, based on discounted cash flows, assume that the investment project will follow a single predetermined path. Whereas, the approach of ROT recognizes that managers are not passive; they can change their strategy as new information becomes available (Mun, 2005). This flexibility, sometimes referred to as the "real option"—has economic value that static models ignore.

Data assets fit very well with a real options analysis because the future uses of data assets are highly uncertain (Smedes et al., 2021). An upfront investment in building a customer data platform is perceived not just as an expenditure, but as the acquisition of a portfolio of real options for future growth (Coyle & Gamberi, 2024). The following options are included:

- **Option to expand:** This is the right, but not the obligation, to make further investments in scaling up a project or entering new markets. A company that compiles payments data, for example, gains the ability to expand into lending, insurance, or wealth management services by using that same data asset in the future (Mun, 2005). The initial data collection cost is thus the price of acquiring this growth option.
- **Option to defer:** This is the choice to put off an investment until extra information is at hand or market conditions are better. A company can gather and keep client data, putting off the large spending needed for full monetization until an aiding tech grows or a clear market chance comes (Mun, 2005). This "Option to defer" has value particularly in a fast-changing tech landscape.
- **Option to abandon:** It is the right to stop a project if it turns out to be unprofitable, thus limiting losses on the downside. A FinTech can initiate a pilot data-driven product and if it does not take off, the firm can abandon the project with loss limited to investment initially (Mun, 2005). This ability to cut losses is a valuable put option.

In his book "Real options: managerial flexibility and strategy in resource allocation" published in 1996, Trigeorgis highlighted that the sum value of an investment is its static NPV plus the value of the embedded real options ($\text{Expanded NPV} = \text{NPV} + \text{Option Value}$). For data assets, where the

future is highly uncertain, and the possibility for new applications are tremendous, the option value may be much greater than the value attributed to currently foreseeable cash flows. In this way, ROT offers an important theoretical perspective for capturing the strategic, forward-looking value of a FinTech's customer data.

4 A CRITICAL REVIEW OF VALUATION METHODOLOGIES, MODERATING FACTORS AND KEY CHALLENGES

The theoretical foundations that RBV and ROT provided emphasize the importance of valuation methodologies that can capture both the strategic nature and dynamic potential of customer data. In this section, the major valuation methodologies discussed in literature shall be critically assessed along with their applicability, advantages, and significant limitations in the FinTech industry.

4.1 Applicability and limitations of traditional models

Traditional business valuation typically relies on three primary approaches: cost, market, and income. Nevertheless, internally generated customer data is proprietary and these frameworks encounter substantial limitations primarily due to the intangible and non-transferable nature of such assets.

- **Cost approach:** This technique determines the value of an asset by computing the cost to reproduce or replace it (Visconti, 2020). For customer data, this might in theory cover the historical costs of marketing campaigns, platform development, and data storage necessary to accumulate such a dataset (Wilson et al., 2019). As a consequence, this approach is considered fairly inapplicable for a number of reasons. First of all, the historical cost of acquiring data often has little or no relation to its future capacity for generating economic value (Reilly & Schweihs, 2016). Second, the idea of “replacement cost” does not apply to a unique asset. A competitor cannot just “replace” a proprietary dataset that has been built up over years of specific customer interactions; the path-dependent nature of the data makes it inimitable. (Visconti, 2020).
- **Market approach:** this value method is determined by looking at what similar assets have recently sold for in an active market (Visconti, 2020). It works very well for assets that are standardized—like publicly traded shares or real estate—but fails almost entirely for customer data (Visconti, 2020). There is no active and open market for corporate proprietary datasets (Crouzet & Ma, 2023). Since each dataset is unique in its composition, quality, and context, no meaningful comparisons can be made (Fleckenstein et al., 2023). While data is sometimes sold, those are typically private transactions with undisclosed terms—not allowing reliable market multiples to be established (Visconti, 2020).
- **Income approach (Discounted cash flow - DCF):** This approach applies value to an asset by estimating what it will generate in future cash flows and discounting these to present value (Visconti, 2020). Because it links the asset directly to its ability to create economic value (Cheong et al., 2023), the DCF approach is the most theoretically sound of the traditional methods. Nonetheless, there remain two major practical difficulties in applying DCF to customer data. First, forecasting the incremental cash flows attributable only to the data asset is nearly impossible since the data has multiple, interacting, and often unforeseen future uses (Visconti, 2020). Second, setting the right discount rate to show the special risk

of a data asset such as technological obsolescence, regulatory risk, and high uncertainty, is an incredibly subjective task (Crouzet & Ma, 2023).

4.2 Customer-centric valuation: Customer Lifetime Value (CLV)

Traditional models have their limitations, and they are increasingly being replaced by a more granular customer-centric approach. This approach changes the unit of analysis from the firm or asset to the individual customer and directly links data to value creation.

- **Customer Lifetime Value (CLV):** CLV is the present value of all the profits a company expects to receive from a particular customer during the whole period of their relationship/lifetime (Visconti, 2024). It is calculated by using available data on customers, such as their purchase histories and frequencies, and engagement levels to predict future behavior (Roy & Roy, 2025). A simple calculation for CLV in a subscription model which is typical for many FinTechs is:

$$CLV = (ARPU \times \text{GrossMargin}) / \text{ChurnRate} \quad (\text{Farris, 2010}) \quad (1)$$

where ARPU is the average revenue per user, gross margin is the profit margin on that revenue, the churn rate is the percentage of customers who discontinue service in a given period. Through the focus on metrics such as Customer Acquisition Cost (CAC), and retention rates together with ARPU, the CLV model gives a simple, fact-based connection between customer behavior and financial value (Visconti, 2024).

- **Customer Equity:** Building on CLV, customer equity is the total value of a firm's customer base, calculated as the sum of the CLVs of all the firm's current and future customers (Wilson et al., 2019). In valuation terms, customer equity is the financial value of the customer-related intangible asset. It powers a highly essential framework for valuing the whole customer data asset since it aggregates how much value each individual relationship brings in (Visconti, 2024). This strategy will greatly benefit FinTechs because it immediately links value to the company's primary business model, which is gaining, keeping, and profiting from customer relationships. It is where value is created in a FinTech, so that it can continuously generate more and better value from its clients.

4.3 Advanced models for a dynamic environment

Though CLV and Customer Equity models give a strong income-based valuation, they can be static: in many cases, constant churn and margins are assumed. Advanced models seek to better incorporate the dynamism and uncertainty that characterize the landscape of FinTech.

- **Real Options Analysis (ROA):** This approach, which was considered to be the source of theoretical development, explicitly models and quantifies the value of managerial flexibility (Coyle & Gamberi, 2024). In practice, it means treating an investment in a data-driven project as a call option. For example, the strategic value of expanding into a new product line—facilitated by insights from an existing customer dataset—can be quantified using financial option pricing models, like the Black-Scholes formula (Coyle & Gamberi, 2024):

$$C = SN(d_1) - Ke^{-rt}N(d_2) \quad (2)$$

where C represents the option value, S signifies the value of the underlying asset (for example, the present value of the new product's expected cash flows), K indicates the exercise price (the cost to launch the new product), r is the risk-free rate, t stands for time to expiration, and $N(d1)$ and $N(d2)$ are cumulative normal distribution functions that relate to volatility (σ) of underlying asset returns (Coyle & Gamberi, 2024). The main difficulty in using ROA is to estimate these inputs, especially the volatility (σ) of the project's returns which has not been started—which usually needs simulation or dependence on proxies (Glantz & Mun, 2010). In spite of this complication, ROA remains the only method that can formally capture the strategic value of future opportunities embedded in a data asset (Coyle & Gamberi, 2024).

- The emerging role of AI and Machine Learning (ML) in Valuation: The latest advancement that has entered the valuation arena is the application of AI and ML, not as independent valuation approaches but rather as powerful enhancers of model inputs (MManga, 2024). None of these valuation approaches are mutually exclusive; in fact, they can be very symbiotically related. In this regard, advanced approaches like ROA and ML do not necessarily replace fundamental models such as DCF and CLV but rather serve to address the inadequacies of those models. A typical CLV calculation is based on assumptions about future customer behavior, for example, the churn rates and purchase frequency (Mercer Capital, 2018). These inputs are full of uncertainty. Machine Learning algorithms may be trained on large historical datasets of customers to make very accurate, probability-based forecasts for these inputs, replacing simple averages with advanced, individualized predictions (Roy & Roy, 2025). Similarly, Real Options Analysis also needs the present value of an underlying asset as a major input and is normally obtained through DCF analysis (Mun, 2005). With ML generating more robust cash flow forecasts for DCF, the resulting ROA is therefore more credible. This forms a state-of-the-art valuation hierarchy: M.L. models polish inputs for CLV and DCF models, whose outputs in turn feed the Real Options valuation reflecting the strategic and dynamic value of the customer data asset.

Table 1 summarizes the key properties among 5 valuation approaches.

Tab. 1 – Approaches in customer data valuation. Source: own research

Valuation Approach	Core principles	Key inputs	Application in fintech	Primary limitation
Cost approach	Value is based on the cost to create or replace the asset.	Historical development costs, marketing expenses, data storage costs.	Very low. Costs are often expensed and have little correlation with future value.	Replacement is often impossible for unique, path-dependent data. Cost is a poor proxy for economic value.
Market approach	Value is determined by prices of	Transaction prices of similar	Extremely low. Lack of an active, transparent	Inability to find truly comparable assets and

	comparable assets in market transactions.	data assets, market multiples.	market for proprietary data assets makes comparisons infeasible.	transactions. Uniqueness of each dataset.
Income approach (DCF)	Value is the present value of the future cash flows the asset will generate.	Forecasted incremental revenues and costs, discount rate.	Moderate. Theoretically sound but difficult to apply in practice.	High uncertainty in forecasting cash flows from multi-use data; subjectivity in determining the appropriate risk-adjusted discount rate.
CLV/Customer equity	Value is the sum of the net present values of all current and future customer relationships.	Customer acquisition cost (CAC), churn rate, average revenue per user (ARPU), gross margin.	High. Directly aligns with the customer-centric business model of FinTechs and uses readily available customer data.	Can be static if it doesn't account for changes in customer behavior or market dynamics over time.
Real Options Theory	Value includes the strategic worth of managerial flexibility to adapt to future uncertainties.	Value of underlying asset (from DCF), investment cost, time, volatility, risk-free rate.	High. Explicitly values the future growth opportunities and flexibility inherent in data assets, which is critical for innovative FinTechs.	High complexity; difficulty in accurately estimating key inputs, especially the volatility of future, non-traded opportunities.

4.4 Data decay and its implications for valuation

Unlike most traditional assets, data is exposed to a unique type of depreciation—data decay or data degradation. Data decay is defined as the process by which information loses its accuracy, relevance, and completeness over time (Moody's, 2023). For example, customer information changes constantly: people move, change their place of work, get new telephone numbers and so on. This type of degradation diminishes the economic value of the data asset directly because stale or incorrect data results in wrong analyses, misguided business decisions and marketing falling

flat—all of which eventually compromise the ability of the data to continue generating economic benefits.

Data decay is value-wise the economic equivalent of depreciation for tangible assets and must be explicitly modeled (Fleckenstein et al., 2023). Income-based valuation models such as DCF and CLV that do not take into account data decay will inevitably overvalue the asset. The impact of decay can be incorporated in several ways:

- Churn rate: In CLV models, the customer churn rate is an explicit metric of data decay, showing the losing rate of customer relationships (and their associated data streams) (Fader et al., 2005)
- Remaining Useful Life (RUL): Similar to the case of tangible assets, we can estimate an RUL for a dataset as the period during which it is expected to generate reliable economic benefits. This RUL will therefore define the forecast horizon in a DCF model (American Bankruptcy Institute, 2001). The value of an intangible is particularly sensitive to its RUL, especially when the remaining life is short (American Bankruptcy Institute, 2001).
- Decay function: More advanced models can use an explicit decay function, like an exponential decay model ($N(t)=N_0e^{-kt}$), for the expected future cash flows wherein the decay constant (k) denotes the rate at which the value of data decreases with time (Biørn, 2009).

Failure to model data decay is a serious, fundamental valuation mistake, not a little oversight. The ongoing costs that have to be factored in with regard to data cleansing, verification, and enrichment to combat decay must also be factored into any valuation as a recurring maintenance expense that further reduces the net value of the asset.

4.5 The regulation boundary

The rapidly changing landscape of data privacy regulation is perhaps the most significant external factor shaping the value of customer data. Major regulations, such as the General Data Protection Regulation (GDPR) in the European Union and the California Consumer Privacy Act (CCPA), have essentially changed the economics of data by setting strong rules and policies on how it can be collected, processed, and used (Johnson, 2022).

These rules have a significant influence on valuation in several ways:

- Direct financial costs: Such regulations have enormous direct financial costs to a firm in that it must spend money on new systems for managing data, legal advice, and periodic audits (Demirer et al., 2024). Moreover, not following the rules can lead to huge fines—up to 4% of a company's yearly worldwide income under GDPR—which is a big possible cost that has to be considered in any risk-adjusted valuation. (Ford et al., 2022).
- Constraints on data utility: Privacy rules limit the usefulness, and thus the value, of the data asset itself. Rules like data minimization (collect only necessary data), purpose limitation (only to use for the purpose for which it was collected) and explicit user consent have allowed firms only limited volume and variety of data collection and severely restricted its ability to apply that data for new applications (Sartor et al., 2020). It has been shown that GDPR compliance resulted in a significant decline in both documented e-commerce

revenue and website traffic, partly through restrictions on personalized marketing (Goldberg et al., 2024).

- Creation of reputational and ethical risk: Not only through legal compliance but also through ethical data management, customer trust is now being eroded. Algorithmic bias, lack of transparency in automated decision-making, and breaches of data are some factors that have brought tremendous reputational damage; therefore, resulted in customer attrition and investor backlash. This kind of reputational risk has a direct negative impact on the erosion of not only the value of customer-related intangibles but also the firm as a whole (Ransbotham et al., 2020).

This calls for a more sophisticated treatment of data as an asset. Customer data can no longer be valued just by looking at its upside in terms of revenue generation. A proper valuation has to treat data as an "asset-liability." The gross value attributed to monetization strategies must be netted against the present value of expected future liabilities relating to compliance costs under any applicable laws and regulations, the probabilistic cost of regulatory fines, and the potential financial impact of reputational damage due to unethical behavior or security breaches. This risk-adjusted approach gives a much more realistic picture of the net contribution of data to firm value.

4.6 The Influence of Platform Dynamics and Network Effects on Valuation

Many FinTech firms are platform businesses (e.g., payment systems, peer-to-peer lending, and investment platforms) where value is driven by a network effect (Hagiu & Wright, 2015). A network effect is when the value of a product or service increases to each user as more users join the network (Katz & Shapiro, 1985). In FinTech, customer data is the key driver of these effects. In a lending platform, for instance, more borrower data allows better modeling of credit risk which in turn attracts more lenders seeking reliable returns. More lenders offering better rates draws more borrowers, which creates a self-reinforcing growth loop (Cong et al., 2024).

Strong network effects create a significant challenge for the traditional models of valuation, which assumes linear growth and values assets in isolation (Cusumano, 2022). Network effects generate exponential, non-linear value. It is not simply the sum of individual customer data records; it lies in the aggregate dataset of the whole network that enables superior service quality and thus creates high barriers to entry (Cusumano, 2022). This means that valuation models for platform-based FinTechs must incorporate metrics that capture not only the size and growth but also engagement within the network, such as Monthly Active Users (MAUs), transaction volume, and platform-level cross-side network effect (p-CNE — the effect through which growth on one side of the platform drives growth on the other). If one neglects the multiplicative value created by network effects, the real value of the data asset will be significantly underestimated.

5 SYNTHESIS AND AGENDA FOR FUTURE RESEARCH

5.1 Summary of Key Findings and Identified Gaps

This review of literature on the valuation of customer data within FinTech shows a critically significant and intellectually emerging field. From existing research, several key conclusions can be drawn. First, the accounting treatment of customer data, most often given it zero book value, disconnects with its strategic role as one of the main sources of competitive advantage and firm value in FinTech industries. Second, managerial finance theories and especially the Resource-

Based View (RBV) and Real Options Theory (ROT) offer very useful conceptual frameworks to understand why information is valuable and how to frame its potential looking forward. Third, valuation methodologies are moving from inappropriate traditional models toward more advanced customer-centric (CLV, Customer Equity) and dynamic (ROA, AI/ML-enhanced) methods that can better reflect real data asset characteristics. Finally, the real economic value of consumer data is greatly tempered by a complex interaction of opposing factors that include the natural decay of data accuracy, the strict constraints set by privacy legislation, and the exponential value creation brought about by network effects.

However, even with these advancements, this review has found several key holes in the academic literature that show clear chances for upcoming study:

- The empirical gap: A prominent aspect of the recent works is the lack of large-scale empirical research. Much of the proposed valuation models, especially those based on Real Options, mainly remain theoretical or are shown with single-firm case studies (Sæterbø, 2019). There exists an urgent, pressing need for empirical research utilizing actual proprietary data from a cross-section of FinTech firms to test, compare and validate different methodologies in valuation and their accuracy and predictive capability. Without such validation, the models cannot be applied in practice to become useful tools for investors and managers.
- The methodological gap: Current research looks at valuation models and factors that moderate them separately. There remains an enormous need for the creation of integrated, multi-faceted frameworks for valuation. A truly robust model should be able to simultaneously quantify both the upside potential attributable to monetization and network effects, and systematically deduct the expected costs associated with data decay plus compliance plus ethical/reputational risks. No such widely used holistic "asset-liability" type model exists today.
- The theoretical gap: RBV and ROT have been very helpful, but the interplay between them has not been much explored. For example, how does the option value of a data asset fuel its status as a "valuable" and "rare" resource? More in-depth theoretical work is needed to bring these two views into a more unifying theory of intangible asset value. In addition, other relevant theories, like agency theory and signaling theory, have been nearly ignored in this particular context.

5.2 Proposing a Future Research Agenda

On the basis of these theoretical gaps, this paper sets forth a three-pronged agenda for future research that will help advance our understanding of how customer data is valued within FinTech:

1. Empirical pathways

- Model-testing studies: academics should pursue collaborations with FinTech companies to access their proprietary datasets in order to conduct large-sample studies testing model (e.g., CLV, DCF, ROA) valuation outputs against actual market outcomes (M&A transaction prices or funding round valuations).
- Event study analyses: the "liability" side of data assets financial impact can be quantified by event studies. The major data breaches or the announcement of significant regulatory

findings on the market valuations of affected FinTech firms can be analyzed by researchers to isolate the negative value component of data risk.

- Quantifying network effects: empirical work is needed to further sharpen models that quantify how much value network effects bring. Analyses such as the one evaluating platform-level cross-side network effects (p-CNEs) offer an excellent launching pad for connecting network metrics directly to platform survival and valuation (Cong et al., 2024).

2. Methodological pathways

- Creation of hybrid models: future work should be centered on the creation and testing of hybrid valuation models. One promising direction is the creation of ML-enhanced Real Options models, where machine learning algorithms help generate more robust inputs- for example, volatility, cash flow projections- for the option pricing formula.
- Quantitative risk frameworks: there is a need for methodological work to develop standardized quantitative frameworks in the assessment and pricing of the financial impact of data decay, regulatory non-compliance risk, and ethical lapses. This shall include the application of techniques coming from insurance (actuarial analysis) or credit risk modeling to estimate expected losses on such bases.

3. Theoretical pathways

- Integration of theories: scholars should strive to formally integrate RBV and ROT. For instance, research could delve into how having a VRIO data asset improves a firm's capacity to spot and carry out valuable real options.
- Application of new theories: other relevant financial theories could also be applied to the problem. For example, an analysis of the potential conflict between managers (who may have an incentive to monetize short-term data) and the shareholders bearing the long-term reputational risk could be conducted using agency theory. Another approach could be to apply signaling theory to understand how FinTech firms can credibly signal the value of their unobservable data assets to external capital markets-imperfectly informed about the true value of those assets-in order to overcome information asymmetry and thus lower their cost of capital.

6 CONCLUSION

Customer data in the FinTech industry is at an inflection point where traditional financial principles clash with new realities in the digital age. This paper has shown that while customer data is undoubtedly a key strategic asset, valuation is a very difficult and complex task, currently due to the inadequate conventional accounting, the very nature of data itself, and numerous powerful moderating factors. No simple application of cost, market, or even standard income-based approaches can really capture the true economic value of this dynamic and multi-faceted asset.

The path toward more credible valuation lies in a synthesis of approaches. It requires moving to more detailed, client-centered models that link data directly to income, like CLV and Customer Equity. It is important to note that in order to officially assess the enormous future potential and strategic flexibility that data assets provide, dynamic frameworks such as Real Options Theory must be used. The merge of artificial intelligence (AI) with machine learning offers an apt method

for enhancing the precision of these models—a shift in valuation from a subjective art to a science of data-driven foresight.

Finally, this review contends that there should be a change in the way customer data is conceptualized for valuation—not just as an asset, but as a complex "asset-liability." Its ultimate value is the net product of its enormous potential for value creation discounted by the significant and ever-present risks of decay, regulation, and reputational harm. By synthesizing existing literature that has been somewhat fragmented, and proposing clear agendas for future empirical, methodological, and theoretical research, this paper aims at providing a roadmap from the ground up for academics and practitioners who are interested in exploring this difficult yet important frontier in contemporary managerial finance.

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AI IN NEUROMARKETING WITHOUT UNDERSTANDING: THE RISKS OF FAST SOLUTIONS IN SLOW MARKETS

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Abstract

This paper explores the current use and limitations of artificial intelligence (AI) in neuromarketing, focusing on culturally specific contexts such as the Slovak market. While AI-powered tools such as NEURONS AI and REAL EYE are increasingly used to automate the interpretation of consumer reactions, their validity in smaller, linguistically and culturally diverse environments remains largely untested. The aim of this study is to critically assess the contextual reliability of such tools and to initiate an academic discussion about the risks of replacing traditional, human-based neuromarketing methods with automated systems.

Methodologically, the study adopts a pilot, exploratory approach that combines an analytical literature review with qualitative insights gathered from previous case studies and experimental observations conducted at NEUROLAB FMK UCM in Trnava. The research focuses on evaluating the performance of selected AI tools in processing emotional, linguistic, and visual stimuli and identifies methodological and ethical concerns related to their use in marketing practice.

Findings show that AI models often struggle to interpret local language and cultural nuances, leading to biased outputs and potentially misleading conclusions. Furthermore, commercial neuromarketing providers tend to overstate the effectiveness of such systems, despite lacking empirical validation in many regions. The study concludes that while AI offers useful functionalities, it should be integrated into neuromarketing with caution, ideally within a hybrid approach that respects psychological complexity, local specificity, and ethical responsibility.

Keywords: *Neuromarketing, artificial intelligence, consumer behaviour, cultural context, machine learning.*

1 INTRODUCTION

This study emerged as a result of a shared academic reflection on the rapidly expanding use of artificial intelligence in the field of neuromarketing. The initial impulse came from a personal experience of one of the authors (T. Darázs), who was invited as a keynote speaker at the NeuroAI by RULEZZ 2024 conference, representing the University of Ss. Cyril and Methodius, the academic guarantor of the event.

The event was visionary, energetic, and flawlessly organized—exactly what one might expect when artificial intelligence meets marketing ambition. But behind the polished surface, a different kind of conversation unfolded. In backstage discussions with fellow keynote speakers—many of them founders of companies offering AI-powered neuromarketing services—a quiet but essential question surfaced: how well do these tools, which generate fast and visually appealing outputs, truly understand local language, culture-specific emotional cues, or symbolic codes? And what if the “accuracy” they promise is more aesthetic than analytical?

Initially, the responses were cautious. One developer replied: “Clients don’t want to wait weeks for lab testing—they want results immediately.” Another admitted their system had never been tested in Slovak. But as the discussion deepened, a shift occurred. One CEO paused and said, “Maybe we are flying blind after all.”

That moment became the catalyst for this paper—not as a statistically generalizable study, but as a pilot reflection aimed at opening a much-needed academic discussion about what may be lost when consumer psychology is outsourced to algorithms. As a researcher working in neuromarketing and biometric consumer testing, I often find myself confronting uncertainty even when using the most sophisticated tools. I know that experimental results can be shaped by psychological mechanisms we still don’t fully understand—or even by the political climate, as shown in some of my previous studies, where the same advertisement evoked different emotional reactions under two successive governments.

Tools like Neurons AI and RealEye provide clean, aesthetically compelling outputs—but they rarely tell us how a consumer in a small, culturally and linguistically specific market actually thinks. And that becomes problematic when such outputs begin to drive real marketing decisions—not out of ill intent, but because the underlying AI models were never trained on the realities they now interpret. The real danger emerges when systems sound confident but lack contextual understanding.

While academic literature on this topic is growing, it continues to lag behind commercial development. Ferrell et al. (2025) highlight unresolved ethical concerns surrounding biometric AI. Peters and Carman (2024) identify cultural bias in explainable AI models. Ballı (2024) tracks the rising volume of neuromarketing-AI publications but also stress the lack of validation in smaller or underrepresented markets. Goncalves et al. (2024) go further, arguing that many startups simply lack the capacity to localize their tools for regions like ours—because it doesn’t yet pay off.

That is precisely why this study was written. In a context unlikely to become a priority for global neuroAI startups anytime soon, we believe it is essential to ask questions—before the pace of development makes it harder to do so. We do not seek to reject these technologies, but to understand them. And perhaps to slow down just enough to ask what it is they truly reveal.

2 LITERATURE REVIEW

The integration of artificial intelligence (AI) into neuromarketing has become a rapidly developing field, both in academic discourse and commercial application. Recent bibliometric analyses confirm a sharp rise in publications exploring the intersection of neuroscience, marketing, and machine learning, yet they also point to a growing gap between technological innovation and critical scientific validation (Ballı, 2024). Particularly in smaller or underrepresented markets, this gap is reinforced by the dominance of globally trained AI systems, which often lack sensitivity to local linguistic and cultural nuances (Peters & Carman, 2024).

The ethical implications of deploying such technologies have become a central topic in recent neuromarketing literature. Ferrell et al. (2025) emphasize that issues such as consumer privacy, informed consent, and the interpretability of biometric data are still unresolved, particularly when AI is used to infer subconscious or emotional reactions. Studies by Goncalves et al. (2024) further show that startup-driven AI solutions in neuromarketing frequently operate without culturally adapted training datasets, increasing the risk of misinterpretation—especially in regions like

Central and Eastern Europe where the commercial potential may not yet justify full-scale localization by global providers.

These insights underline the need to examine AI-driven neuromarketing tools not only in terms of technological sophistication, but also through the lens of ethical accountability and contextual relevance. This study contributes to this discussion by focusing on how such tools perform in a culturally specific environment, using Slovakia as a case example.

With the advent of artificial intelligence (AI), marketing has transformed significantly (Murár et al., 2024; Čábyová et al., 2024), including in the context of neuromarketing (Darázs, 2023; Darázs & Šalgovičová, 2019; Krajčovič & Darázs, 2021). In this era where technology enables fast and efficient analysis of consumer behaviour, traditional neuromarketing methods that involve long and difficult research with real people may seem outdated and ineffective. These approaches, while valuable, require manual data processing, which can slow down the speed of response in dynamically changing markets.

On the other hand, there are modern AI tools that can generate heatmaps based on machine learning and predict consumer behaviour, which until now has been provided by neuromarketing. These innovations offer promising opportunities for brands looking to maximize their effectiveness and accuracy in marketing campaigns (Ahmed et al., 2022). However, neuromarketing as such has many aspects of machine learning in it. For example, emotional responses, which were introduced by Paul Ekman, are used as the basis for training software that is able to recognise emotions based on a large database of samples. Newer software attempts to take these technologies even further and automate the evaluation process, increasing their usefulness in marketing applications (Alvino et al., 2020; Kakaria et al., 2023).

Despite these advances, however, the question of the effectiveness of AI tools remains open, especially when context is taken into account. Many of these technologies still struggle with the problem of understanding nuances in language and cultural context. For example, AI tools that rely on text analytics may confuse keywords such as “action” and “murder” for no good reason when presented in the same format and font size. This biases the results, which can have a major impact on consumer perception (Hsu & Chen, 2020).

This article focuses on examining how AI tools are impacting neuromarketing, and evaluates their ability to replace traditional methods of analyzing consumer behavior. Particular attention is paid to issues such as analyzing specific messages, differences between consumer groups, and evaluating results in the context of current political and economic conditions. In this way, we aim to contribute to a deeper understanding of the dynamics of the interaction between AI, neuromarketing and consumer behavior. Adding to the situation is the factor of a rapidly changing technological environment, where new trends such as virtual and augmented reality are beginning to influence the way consumers respond to marketing stimuli. This creates another layer of complexity that needs to be taken into account when analysing consumer behaviour.

This research aims to identify how AI tools, when applied to neuromarketing, can improve understanding of consumer needs and preferences, but also highlight their limitations and the risks they pose. The study will also focus on ethical issues that are inherent in the modern marketing environment. Given the increasing role of AI, it is important to discuss transparency, accountability, and potential biases that may affect the results of the analyses. Our goal is to develop a comprehensive view of how AI can push the boundaries of neuromarketing and how this technology should be integrated into broader marketing strategies that respect consumer

psychology and ethical standards. This article is therefore a step towards understanding the complex and dynamic relationship between AI and neuromarketing, which is proving crucial to the success of marketing campaigns in the 21st century.

3 METHODOLOGY

This pilot study adopts an explorative and practice-oriented research approach designed to examine the growing use of artificial intelligence (AI) in commercial neuromarketing services. As the adoption of AI tools accelerates in the business sphere, often outpacing academic validation, it is crucial to assess the reliability, contextual accuracy, and ethical implications of these technologies. This study does not aim to provide statistically generalizable conclusions; rather, it seeks to initiate academic reflection and identify early-stage challenges associated with AI-based consumer analysis.

The main objective is to critically evaluate the ability of selected AI neuromarketing tools—specifically NEURONS AI and REAL EYE—to function effectively within culturally and linguistically specific markets such as Slovakia. The study aims to highlight the risks associated with the use of under-trained models in localized contexts, where emotional, visual, and textual cues may be misinterpreted. Furthermore, the research addresses the broader methodological and ethical implications of outsourcing consumer insight to automated systems.

- The research is guided by the following questions:
- To what extent can AI-based neuromarketing tools reliably interpret consumer reactions in culturally and linguistically specific markets such as Slovakia?
- What are the potential risks and ethical concerns associated with replacing traditional neuromarketing methodologies with automated AI tools?
- How do commercial neuromarketing providers present the reliability and effectiveness of AI-driven analyses, and how does this align with scientific validation?
- Can localized observations and case studies reveal limitations in AI models that are not visible in generalized datasets or global applications?
- What are the implications of using under-trained AI models in marketing strategies that rely on emotion-based consumer targeting?

To address these questions, the methodology combines an analytical literature review with a qualitative assessment of selected case studies and pilot experiments conducted at NEUROLAB FMK UCM in Trnava. The focus lies on identifying the strengths and weaknesses of AI-powered neuromarketing tools when applied in different regional and linguistic contexts.

Publications such as Ahmed et al. (2022) and Tavishi (2024) emphasize that tools like NEURONS AI often struggle with language variations that are underrepresented in training datasets, which may affect the validity of the analysis. These findings were confirmed through our own case studies, where both NEURONS AI and REAL EYE failed to accurately process Slovak-language stimuli and interpret cultural nuances. Our observations are supported by the work of Hsu and Chen (2020), who argue that the incorrect interpretation of linguistic cues can lead to biased results and flawed marketing strategies.

Additionally, the study takes into account regional differences in consumer perception and the importance of context in emotional interpretation. We argue that classical neuromarketing methods—which rely on real participants, culturally sensitive design, and expert interpretation—remain more reliable in small and culturally specific markets.

Ethical considerations are also a key component of our methodological framework. Particular attention was paid to how misinterpretation by AI tools can influence marketing decision-making and consumer targeting. As emphasized by Darázs (2024a), transparency and methodological responsibility are essential to ensure that the implementation of AI does not compromise consumer well-being or distort behavioral insights.

In this way, the methodology supports a hybrid model of inquiry that integrates technological tools with qualitative interpretation and local expertise. Rather than advocating for or against AI, the study seeks to propose a reflective framework for its responsible and context-aware use in neuromarketing.

This study is conceived as a pilot and exploratory investigation and, as such, does not rely on the collection or statistical analysis of primary data. The findings are based on critical reflection, a structured review of relevant academic literature, and insights drawn from case observations and previous experiments conducted at NEUROLAB FMK UCM. While these sources provide valuable practical perspectives, they do not constitute a systematic empirical dataset. As a result, the study's conclusions should be interpreted as indicative rather than definitive.

The absence of new experimental data means that the arguments presented are primarily theoretical and practice-informed. The study aims to stimulate academic discussion and highlight the need for future empirical validation of AI-based neuromarketing tools, especially in culturally specific and linguistically diverse contexts. Further research involving controlled experiments and diverse participant groups will be essential to test and refine the hypotheses and reflections outlined in this work.

4 RESULTS

In order to effectively discuss the impact of artificial intelligence (AI) on neuromarketing, it is important to first explore the potential benefits of the discipline. The integration of AI into neuromarketing represents a significant shift that opens up new dimensions in understanding consumer behavior. AI can not only increase the accuracy and speed of analysis, but also provide deeper and more valuable insights that are derived from neuromarketing tools. Potential benefits of future AI in neuromarketing are also based on experimental experience from NEUROLAB FMK UCM in Trnava:

Increased Accuracy: AI algorithms can analyze neuroimaging data with high accuracy, reducing the likelihood of errors and bias in interpreting results. In this way, marketing teams can gain more accurate information about how consumers respond to different marketing stimuli. AI enables more efficient processing and analysis of complex data, leading to more accurate mapping of consumer preferences. Machine learning algorithms can identify behavioral patterns that human analysts might overlook.

Real-time Analytics: Thanks to AI, data collected from neuromarketing tools can be analyzed in real-time, providing immediate insights into consumer reactions. This is particularly useful for dynamic marketing campaigns where it is necessary to react quickly to changes in behavior. Rapid

analysis allows ads and marketing strategies to be adapted without unnecessary delays. The ability to adapt campaigns in real time can significantly increase their effectiveness and impact. Real-time data analytics empowers decision-making in marketing teams.

Predictive Analytics: This predictive approach is extremely valuable as it allows marketing teams to prepare for changes in consumer preferences and adapt their strategies in advance. Predictive analytics can also enable market segmentation based on anticipated reactions, improving campaign targeting. Marketing teams can use AI predictions to optimize product offerings.

Expanded Understanding of Emotional Reactions: AI technologies enable the analysis of emotional responses to marketing stimuli through sophisticated algorithms. These technologies can process data from multiple sources such as facial expressions, tone of voice, and physiological responses. In this way, researchers can gain a deeper understanding of the emotional dynamics that influence consumer decision-making. AI can analyze emotional responses with high accuracy, leading to a better understanding of consumer preferences.

Examples of existing AI integration in neuromarketing research include several innovative applications that enhance the analysis of consumer responses.

- **Emotion recognition software:** AI is used to analyse facial expressions (recorded via video) to gauge emotional responses to ads and products. This allows marketers to tailor their campaigns more effectively to reach their target audience.
- **AI in eye-tracking:** By combining eye-tracking technology with AI, researchers can track what consumers are looking at and determine the emotional and cognitive impact of what they see. Data collected in this way can provide valuable insights into how effectively ads capture attention.
- **Deep learning for consumer insights:** Deep learning models are used to analyse complex layers of data obtained from EEG and fMRI studies, revealing consumers' unconscious preferences and decision-making processes.

Key success stories:

Automotive campaigns: AI analysis of emotional reactions and physiological responses during car ads helped identify key emotional triggers that influenced purchase intent.

While AI can bring significant benefits in the field of neuromarketing, using it to predict consumer behavior—especially in heatmap generation and eye path analysis—can be risky. In particular, AI models may not be sufficiently trained to capture the linguistic and cultural nuances that are essential in such research. This can lead to inaccurate or skewed results, which is especially critical when sensitive or emotionally laden words are used in visuals. For example, if an AI system like Neurons AI analyzes a visual containing the word “murder” in a less commonly used language, it may interpret it similarly to the word “action” because it cannot discern the contextual or emotional weight of the terms. Neurons AI has gained popularity, especially in commercial applications, because its results are visually appealing and easy to sell. However, this ease of use may lead to serious issues when evaluating marketing campaigns, where precision and sensitivity to language are crucial.

Another potential problem arises when AI tools are applied to situations outside of their training scope. This doesn't concern only linguistic or cultural contexts, but also technological ones—such

as the emergence of new communication formats like interactive or virtual banners. These tools may not yet be adequately trained for such environments.

In support of the idea that AI faces significant challenges in neuromarketing, it is important to note that many tools, including Neurons AI, are trained on historical datasets that may be incomplete or inadequate for capturing specific cultural contexts. This becomes problematic because public perceptions of marketing communications can change rapidly over time. For instance, research by Darázs (2024) in Slovakia revealed that the public reacted very differently to the same anti-misinformation advertisement depending on the political climate: one version of the research was conducted during the liberal administration of Ľudovít Ódor, and another during the technocratic government of Róbert Fico, with only a three-quarter time gap between them. Without sufficiently diverse and representative datasets, AI can easily produce misleading outputs, leading marketing teams to make flawed decisions. This underscores the need to critically assess the use of AI in neuromarketing and develop strategies to mitigate its potential negative impacts.

Even experienced researchers may find it difficult to fully account for the various contextual factors that influence consumer responses. Although professionals are trained to analyze emotional and behavioral data, subtle nuances and cultural signals may escape their attention, leading to misinterpretations. In my recent work presented at the DOKBAT 2024 conference, I emphasized the importance of accounting for various contextual variables when applying neuromarketing techniques. For example, in the case of higher-order emotions such as empathy, it is crucial to incorporate qualitative research that offers deeper insight into consumer psychology (Darázs, 2024a).

The case studies I have conducted clearly show that not only automated AI systems but also locally trained human evaluators can provide inaccurate interpretations if they fail to consider the subjective representations and emotional nuances of individual viewers. For example, in a study analyzing advertisements for the Slovak retail brand COOP Jednota, we found that women responded more positively to the emotional elements of the ad, while men focused more on humor and clearly structured visual cues.

Such differences suggest that the effectiveness of AI may vary significantly depending on gender, age, or cultural contexts (Darázs, 2024). Another example is the analysis of the impact of colour schemes on consumer reactions. Neuromarketing tools that identified certain colours as positive proved to be insufficient when participants reported in interviews that specific colour combinations triggered feelings of anxiety. This discrepancy between physiological and subjective responses points to the need for in-depth analysis that can reveal nuances overlooked by automated tools (Darázs, 2024; Hsu & Chen, 2020). Combining technological solutions with expert analysis and human intuition is key to achieving accurate and effective results in neuromarketing. Kakaria et al. (2023) emphasize that even with advanced technologies such as AI and machine learning, it is imperative that experts integrate technological analysis with domain knowledge and experience in order to interpret complex consumer responses meaningfully.

5 DISCUSSION

The integration of artificial intelligence (AI) into neuromarketing is transforming the way consumer behaviour is analysed and marketing strategies are created. This development is supported by a wide range of literature that examines in detail the benefits, challenges, and applications of AI in neuromarketing. AI brings accuracy and efficiency to neuromarketing that

traditional methods cannot provide. These technologies enable the processing of large volumes of data, which increases the speed of analysis and reduces the risk of errors that can occur with manual data processing. AI can analyse consumers' emotional and cognitive responses to marketing stimuli and provide valuable insights that are essential for optimizing marketing strategies.

As stated by Tavishi (2024), technologies such as emotion recognition and eye-tracking are proving to be extremely valuable for understanding what consumers are feeling and how they react to different stimuli. These applications are able to provide real-time analysis of consumer reactions, helping brands quickly adapt to changing preferences and emotional states.

Despite the many benefits, there are also potential risks to consider. One of the biggest concerns is that AI systems, such as Neurons AI, may have difficulty interpreting linguistic and cultural nuances. This can lead to inaccurate or skewed results, as mentioned earlier. Hsu and Chen (2020) suggest that AI may overlook important emotional responses if trained on limited or inappropriate data. Additionally, the literature suggests that current AI applications often fail to capture the complexity and variability of emotional responses in different cultural contexts. A review by Kakaria et al. (2023) notes that many machine learning models are trained on historical data that may not be representative of current consumer trends and preferences. Such inaccuracies can lead to serious errors in the interpretation of consumer behavior and in strategic decisions made by marketing teams.

To improve the accuracy and efficiency of the analysis, it is essential to combine technological approaches with qualitative research. As Darázs (2024) states, the integration of qualitative methods such as interviews and discussions can complement quantitative data collected through AI. The results obtained in this way are more robust, as they also reflect emotional nuances and cultural factors. Case studies on the impact of colour schemes and demographic differences in response to marketing stimuli show that emotional responses are often complex and require in-depth interpretation (Darázs & Šalgovičová, 2019). Similarly, the interpretation of higher emotions such as empathy is difficult without sufficient context, reinforcing the need for a balanced approach that combines technological precision with expert insight.

6 CONCLUSION

In the conclusion of this study, we focused on evaluating the effectiveness of AI-based neuromarketing tools, such as NEURONS AI and REAL EYE, and their ability to respond appropriately to consumer behavioral dynamics. Our findings show that although AI technologies offer new opportunities in the field of consumer behavior analysis, their effectiveness varies significantly depending on context, cultural nuances, and language variations.

One of the main findings—addressing Research Question 1—is that classical neuromarketing, which relies on a deep understanding of local markets and cultural factors, remains far more effective than AI tools in smaller and local markets. This is due to the insufficient training of AI models on specific linguistic and cultural contexts, leading to misinterpretations and biases in the analysis of consumer responses. These findings demonstrate that AI-based tools still lack the contextual sensitivity required for accurate interpretation in culturally specific environments.

We also found—responding to Research Question 2—that AI's capacity to recognize and process emotional reactions is often limited. Despite technological progress, these tools frequently struggle to identify subtle affective cues, particularly those tied to complex or higher-order emotions. This

reinforces the need to combine automated methods with qualitative research practices that can capture the emotional depth and cultural meaning embedded in consumer responses.

Further analysis—addressing Research Question 3—confirmed that commercial neuromarketing providers often present AI-based tools as accurate and effective without acknowledging their methodological constraints. This misalignment between commercial claims and scientific validation raises concerns about the informed use of such technologies in practice. It underscores the importance of transparency and critical evaluation of AI tools before they are used for strategic decision-making.

With regard to Research Question 4, our study showed that localized observations and case studies are capable of revealing limitations in AI models that are not apparent in generalized datasets. Specifically, tools such as NEURONS AI demonstrated flawed interpretations when exposed to Slovak-language stimuli, supporting the argument that region-specific evaluation is essential to ensure reliability.

Finally, in line with Research Question 5, we found that using under-trained AI models in emotionally driven marketing strategies poses serious risks. Misinterpreting emotional triggers can lead to ineffective or even counterproductive campaigns, especially in culturally sensitive contexts. These insights emphasize the importance of refining AI training data to include diverse linguistic, emotional, and visual inputs relevant to specific markets.

Overall, this study suggests that while AI offers valuable tools and technological capabilities to enhance neuromarketing practices, traditional methods remain essential for accurately understanding consumer behavior—especially in culturally specific or localized contexts. We recommend that marketing teams adopt a hybrid approach, combining AI with traditional qualitative research, to obtain more accurate, meaningful, and contextually relevant insights. This integrative approach can support more adaptive and consumer-centered marketing strategies.

Moreover, our findings point to the importance of fostering greater interdisciplinary collaboration between technologists, psychologists, marketers, and ethics committees. Such collaboration is vital to ensure that AI tools are developed and implemented with ethical awareness and cultural sensitivity. Marketing teams must also invest in training and upskilling their personnel to effectively integrate AI into their workflows while preserving the human dimension in consumer analysis.

Future research should explore in greater depth how demographic variables—such as age, gender, and cultural background—influence consumer responses to marketing stimuli. A more nuanced understanding of these factors will enable the development of marketing strategies that are better tailored to the needs and preferences of diverse consumer groups.

At the same time, marketing strategies must adapt to emerging social and technological trends, including the growing demand for ethical and sustainable practices. Consumers increasingly expect brands to demonstrate social responsibility and align their actions with broader societal values. In this context, traditional neuromarketing methods that prioritize in-depth psychological insight remain indispensable for designing campaigns that are both ethically sound and culturally relevant.

In conclusion, the integration of AI into neuromarketing represents a compelling opportunity to improve the precision and adaptability of marketing strategies. However, it also necessitates a critical reflection on ethical boundaries and methodological limitations. The ultimate goal should

be to foster a marketing environment that not only leverages technological innovation but also deeply respects the complexities of human psychology and cultural diversity. By doing so, marketing strategies can become not only more effective, but also more meaningful and beneficial to both consumers and society at large.

It is important to acknowledge that the insights presented in this study reflect the current state of technological development and market application. As AI continues to evolve rapidly, it is entirely possible that within a few years, many of the limitations observed today may be significantly reduced or resolved. However, at this stage, it was essential to highlight the existing challenges and initiate a critical reflection within the academic and marketing communities. This is particularly important for smaller or linguistically specific markets, such as the Slovak and Czech regions, which may not yet be prioritized by global startups offering AI-based neuromarketing services. These regions risk being overlooked in model training and adaptation processes, which increases the potential for misinterpretation and misuse. Marketers and researchers operating in these environments must therefore remain cautious, analytically vigilant, and committed to contextual validation when adopting emerging AI tools.

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E-CRM: A SYSTEMATIC LITERATURE REVIEW

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Abstract

Due to the hypercompetitive, dynamic, and turbulent global business environment, customer relationship management (CRM) has become a popular managerial tool to gather extensive customer knowledge, maximize interaction profitability, and create long-term relationships with customers. Digital transformation has significantly altered customer relationship management. Information and Communication Technologies (ICTs) and e-commerce development encouraged many companies to employ electronic customer relationship management (E-CRM) instead of traditional CRM. Electronic customer relationship management, a web-based or Internet-based approach to customer relationship management, is believed to outperform traditional CRM in terms of profitability and value it brings. The paper aims to contribute to a comprehensive understanding of the role of electronic customer relationship management in modern businesses' success. A systematic literature review approach was employed to analyse existing papers in the Scopus and Web of Science academic databases. Based on the analysis of 41 articles, the key publication themes in E-CRM research are the effects of e-CRM on different variables and critical success factors of e-CRM implementation. Moreover, the most researched industries are banking, telecommunications, airline, retail/e-commerce, and tourism. The SLR revealed that although electronic customer relationship management has received a fair share of attention from academics in recent years, several areas still require further investigation. The article contributes to the academic literature on electronic customer relationship management. It highlights e-CRM's role in creating long-lasting relationships with customers and enhancing modern companies' performance regardless of size and industry.

Keywords: *e-CRM, E-CRM, electronic customer relationship management, SLR, customer loyalty.*

1 INTRODUCTION

Since customers are one of the most valuable assets of any organization, fostering a loyal customer base is a paramount objective for modern businesses (Haghighinasab et al., 2025; Herman et al., 2020; Kakeesh et al., 2021; Tsokota et al., 2021). Due to the hypercompetitive, dynamic, and turbulent global business environment, customer relationship management (CRM) has become a crucial strategy for companies to sustain long-term relationships with customers and achieve a competitive advantage, loyalty, steady revenue streams, and profitability (Abdi et al., 2020; Ali & Alfayez, 2024; Almahadeen & Al-Manasrah, 2022; Almajali et al., 2022; Alsheikh, 2023; Alshurideh, 2022; Auttri et al., 2023; Awad & Mahmoud, 2024; Chi, 2021; Eltahir et al., 2021; Haghighinasab et al., 2025; Herman et al., 2020; Hwang, 2022; Ivens et al., 2024; Kakeesh et al., 2021; Liu & Chen, 2022; Mahrinasari et al., 2023; Mohamed et al., 2023; Mokha & Kumar, 2022; Mokha & Kumar, 2024; Quyen & Sayapina, 2020; Rachbini et al., 2024; Sathyavani et al., 2025; Shabankareh & Sarhadi, 2023; Singh, 2022; Tsokota et al., 2021; Yang & Babapour, 2022).

Digital transformation has significantly altered customer relationship management in recent years. Nowadays, many companies integrate various technological developments, such as automation, the Internet, big data analytics, cloud computing, and artificial intelligence (AI) in their CRM

systems to gain competitive advantage, improve products/services and operational efficiency, increase sales efforts, predict future customer behaviours, intentions, preferences, patterns, and needs, create better- personalized experiences and targeted marketing campaigns, build more productive and healthier relationships with customers, and enhance their engagement, retention, and loyalty (Auttri et al., 2023; Almajali et al., 2022; Alshawawreh et al., 2024; Dehghanpouri et al., 2020; Dhinakaran et al., 2024; Ivens et al., 2024; Kamanghad et al., 2022; Liu & Chen, 2022; Quyen & Sayapina, 2020; Sathyavani et al., 2025; Singh, 2022; Tsokota et al., 2021).

The paper aims to contribute to a comprehensive understanding of the role of electronic customer relationship management in modern businesses' success by answering the following research questions:

- RQ1: What are the key publication themes in E-CRM research?
- RQ2: Which methods are most frequently employed in E-CRM studies?
- RQ3: Which industries have been the most researched in recent years?
- RQ4: What are the benefits of E-CRM implementation?
- RQ5: What are the future research directions?

This research employs a systematic literature review approach to analyse existing papers in the Scopus and Web of Science academic databases. The review uses the PRISMA reporting guidelines to increase transparency.

The article contributes to the academic literature on electronic customer relationship management (e-CRM). It highlights e-CRM's role in creating long-lasting relationships with customers and enhancing companies' performance regardless of industry. Furthermore, the research can provide valuable insights to practitioners interested in e-CRM and its implementation.

The article is organized as follows: after the introduction section, the paper presents a short literature review. Then, the authors present the research methodology, results, and discussion. Finally, the paper ends with a conclusion.

2 LITERATURE REVIEW

CRM is a popular managerial tool that is receiving great interest from academics (Alsheikh, 2023; Herman et al., 2020). Although the term “customer relationship management” (CRM) was introduced in the mid-1990s, its definitions and descriptions still vary significantly depending on the author (Kamanghad et al., 2022; Rachbini et al., 2024; Singh et al., 2022).

CRM is a multi-disciplinary approach exploiting different business aspects/ departments/function areas (i.e., marketing, sales, operations, customer service, human resources, R&D, finance, accounting, and IT) to gather extensive knowledge about firms' customers, maximize interaction profitability, and manage long-term relationships with them (Alshawawreh et al., 2024; Dehghanpouri et al., 2020; Herman et al., 2020; Kamanghad et al., 2022; Liu & Chen, 2022; Shabankareh & Sarhadi, 2023; Singh et al., 2022; Sitinjak et al., 2020; Yang & Babapour, 2022).

In practice, companies successfully implementing CRM can benefit from more analytical decision-making, increased customer acquisition, satisfaction, retention, lifetime value, and loyalty, reduced costs, and improved marketing effectiveness, performance, and profitability (Alshawawreh et al.,

2024; Alshurideh, 2022; Alsheikh, 2023; Eltahir et al., 2021; Haudi et al., 2022; Herman et al., 2020; Kamanghad et al., 2022; Liu & Chen, 2022; Mahrinasari et al., 2023; Mohamed et al., 2023; Rachbini et al., 2024; Sathyavani et al., 2025; Sawlani et al., 2022). However, CRM is not a magical solution- its implementation does not automatically guarantee achieving the abovementioned benefits.

2.1 Electronic Customer Relationship Management

Electronic customer relationship management (E-CRM) is a mainstream relationship marketing strategic paradigm in the e-world (Dehghanpouri et al., 2020; Karim et al., 2023; Suyanto et al., 2024). The evolution from CRM to e-CRM has been mostly attributed to the e-business/e-commerce that transitioned businesses from mass production and product-driven differentiation to mass customization and customer-based differentiation (Abdi et al., 2020; Al-Hawary & Alhajri, 2020; Almahadeen & Al-Manasrah, 2022; Awad & Mahmoud, 2024; Dehghanpouri et al., 2020; Hwang, 2022; Rachbini et al., 2024; Yang & Babapour, 2022). Furthermore, Information and Communication Technologies (ICT) development and the rapidly changing environment encouraged many companies to employ **electronic customer relationship management (E-CRM)** instead of traditional CRM to gain a competitive advantage, support and elevate their business strategies and marketing, achieve sustainability goals, improve/innovate their products and services, leverage customer knowledge, provide analytical insights and personalized interactions, create long-term relationships with valuable customers, increase customer satisfaction, retention, and foster loyalty (Al-Hawary & Alhajri, 2020; Ali & Alfayez, 2024; Almahadeen & Al-Manasrah, 2022; Almajali et al., 2022; Alsheikh, 2023; Alshurideh, 2022; Awad & Mahmoud, 2024; Chi, 2021; Dehghanpouri et al., 2020; Eltahir et al., 2021; Haghighinasab et al., 2025; Haudi et al., 2022; Herman et al., 2020; Hwang, 2022; (Kakeesh et al., 2021; Kamanghad et al., 2022; Khanh et al., 2022; Kumar et al., 2021; Kumar & Mokha, 2022; Kumar et al., 2021; Liu & Chen, 2022; Magatef et al., 2023; Mansour et al., 2024; Mohamed et al., 2023; Mokha & Kumar, 2021; Mokha & Kumar, 2022; Mokha & Kumar, 2024; Purnomo et al., 2021; Quyen & Sayapina, 2020; Rachbini et al., 2024; Radzi et al., 2021; Sasono et al., 2021; Sathyavani et al., 2025; Sawlani et al., 2022; Shabankareh & Sarhadi, 2023; Singh et al., 2022; Sitinjak et al., 2020; Tsokota et al., 2021; Yang & Babapour, 2022).

Electronic customer relationship management can be defined as a web-based or Internet-based approach to customer relationship management. It includes not only software, hardware, technology, management support, business processes, and techniques but also different concepts, platforms, topics, tools, applications, and practices, from appropriately designing digital goods and managing social media to pricing and loyalty programs (Abdi et al., 2020; Al-Hawary & Alhajri, 2020; Alsheikh, 2023; Kumar & Mokha, 2022; Sitinjak et al., 2020; Suyanto et al., 2024; Tsokota et al., 2021). Since e-CRM takes care of customers through the web, e-mail, call center, mobile, social media, and other electronic/ Internet-based touchpoints and reaches their demands at any time and place (Abdi et al., 2020; Al-Hawary & Alhajri, 2020; Ali & Alfayez, 2024; Eltahir et al., 2021; Haghighinasab et al., 2025; Haudi et al., 2022; Hwang, 2022; Kakeesh et al., 2021; Kumar & Mokha, 2022; Kumar et al., 2021; Mahrinasari et al., 2023; Mahrinasari et al., 2024; Mokha & Kumar, 2022; Singh et al., 2022; Tsokota et al., 2021), it is believed to outperform traditional CRM in terms of profitability and value (Eltahir et al., 2021; Haghighinasab et al., 2025). E-CRM success can be measured using metrics like customer acquisition, profitability, responsiveness, and efficiency (Dehghanpouri et al., 2020; Karim et al., 2023).

3 METHODOLOGY

A systematic literature review (SLR) was conducted to reach the research objective and contribute to a comprehensive understanding of the role of electronic customer relationship management in modern businesses' success. The review followed the PRISMA framework (Fig. 1)

The Scopus and Web of Science (WoS) — Core Collection databases were used to identify the publications for the systematic review. The publication date range was between 2020 and 2025. The search process took place in June 2025. The keywords were the same for both databases: Electronic CRM OR e-CRM OR electronic customer relationship management. Due to the vast amount of documents, search results were refined to receive more precise outcomes. The search was limited to articles and proceedings in the English language in the areas of Business, Management and Accounting; Economics, Econometrics and Finance; Social Sciences; Computer Science; Decision Sciences; and Engineering. The titles, abstracts, and keywords were screened to determine whether the papers were related to the research topic, i.e., if they were directly related to electronic customer relationship management in a business context. After that, 63 full-text articles were assessed for eligibility. Finally, 41 scientific articles were included in the systematic review.

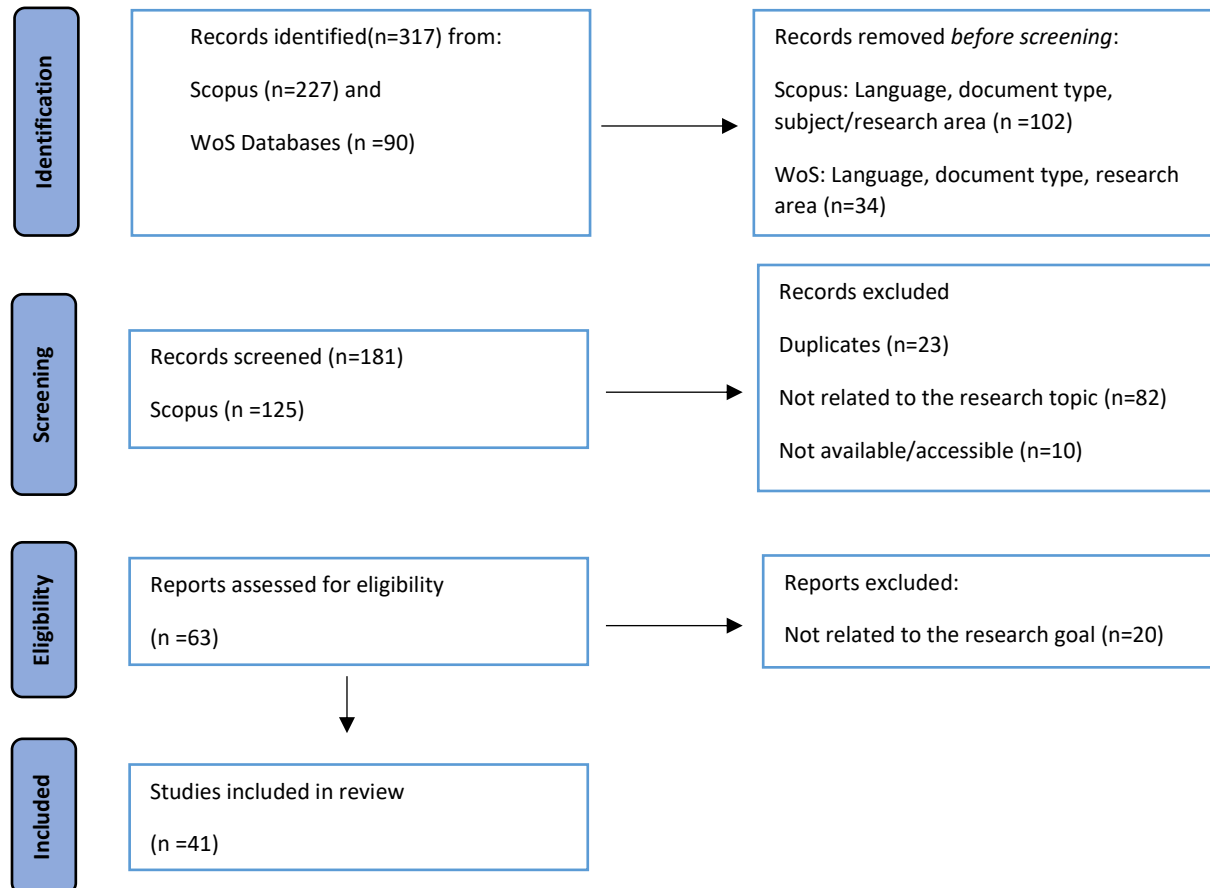


Fig. 1 – The Systematic literature review PRISMA flow diagram. Source: own research

4 RESULTS

Nowadays, e-CRM plays an important role in companies' performance and development regardless of size and industry. It has a positive effect on competitive advantage (Dehghanpouri et al., 2020; Sawlani et al., 2022), companies' performance (Haudi et al., 2022; Sawlani et al., 2022), innovative product creation and development (Chi, 2021; Herman et al., 2020), sustainability achievement (Mansour et al., 2024), and customer loyalty enhancement (Kakeesh et al., 2021; Sasono et al., 2021). It has been implemented not only in B2C and B2B companies from various industries but also in government agencies, government-linked companies (GLC), and the education sectors (Radzi et al., 2021).

E-CRM receives increasing attention from academics. The most frequently employed research method is quantitative (Table 1). The number of qualitative, mixed, and observational studies is limited.

Tab. 1 – Reviewed articles sorted by the research methods. Source: own research

Research method	Article count	Author(s)
Quantitative	36	Abdi et al., 2020; Al-Hawary & Alhajri, 2020; Ali & Alfayez, 2024; Almahadeen & Al-Manasrah, 2022; Almajali et al., 2022; Alshawawreh et al., 2024; Alsheikh, 2023; Alshurideh, 2022; Anaam et al., 2020; Anaama et al., 2022; Awad & Mahmoud, 2024; Chi, 2021; Dehghanpouri et al., 2020; Haghighinasab et al., 2025; Haudi et al., 2022; Herman et al., 2020; Hwang, 2022; Karim et al., 2023; Khanh et al., 2022; Kumar & Mokha, 2022; Kumar et al., 2021; Liu & Chen, 2022; Magatef et al., 2023; Mahrinasari et al., 2023; Mahrinasari et al., 2024; Mohamed et al., 2023; Mokha & Kumar, 2021; Mokha & Kumar, 2022; Mokha & Kumar, 2024; Quyen & Sayapina, 2020; Rachbini et al., 2024; Radzi et al., 2021; Sasono et al., 2021; Sawlani et al., 2022; Singh et al., 2022; Suyanto et al., 2024; Yang & Babapour, 2022
Qualitative	2	Kakeesh et al., 2021; Tsokota et al., 2021
Mixed	1	Mansour et al., 2024
Observation	1	Anna & Lazaros, 2020

The systematic literature review revealed that the most researched industries are banking, telecommunications, airline, retail/e-commerce, and tourism (Table 2).

Tab. 2 – Reviewed articles sorted by the industry. Source: own research

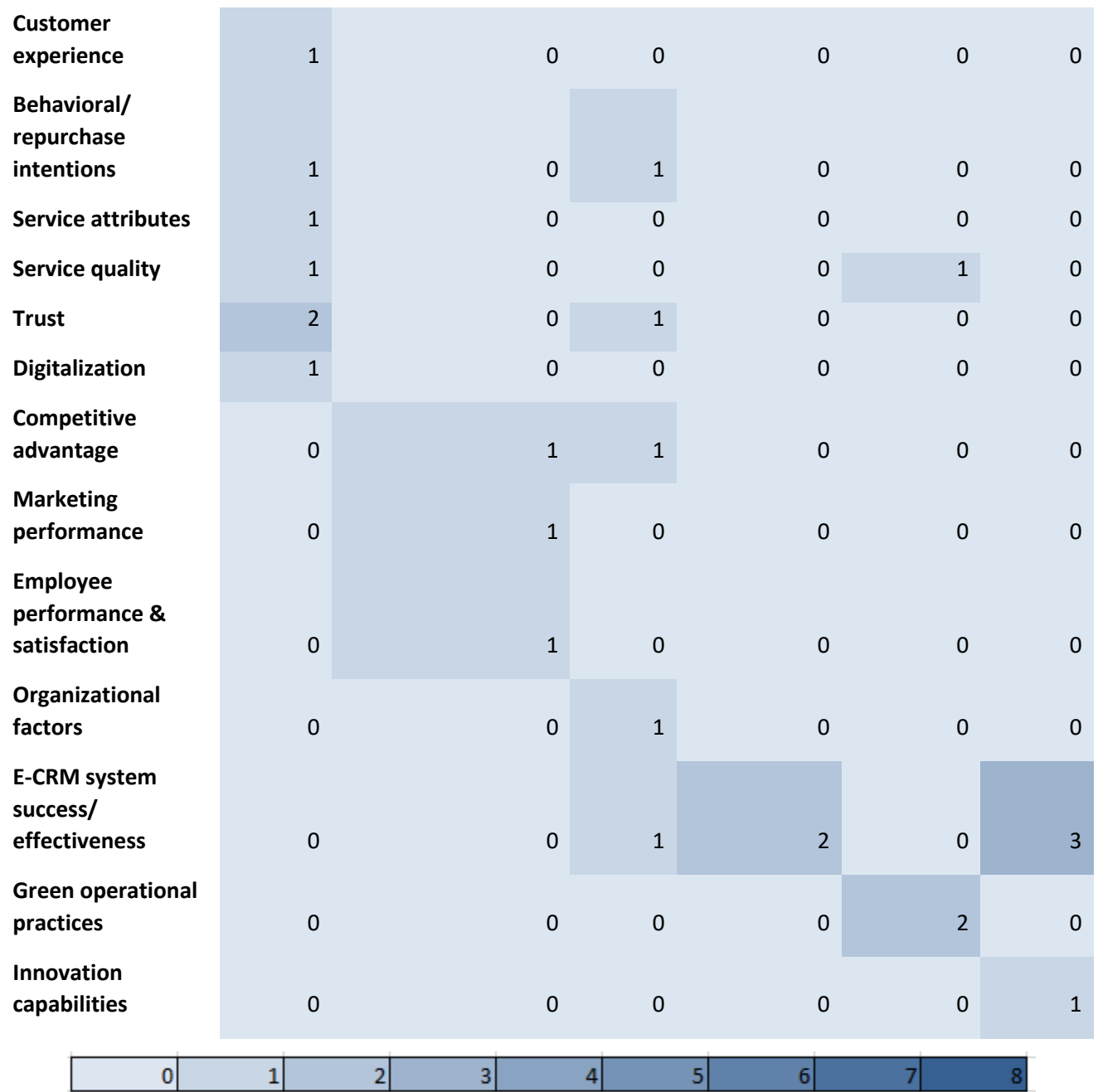
Sector/industry	Article count	Author(s)
Banking	11	Abdi et al., 2020; Alsheikh, 2023; Haghighinasab et al., 2025; Karim et al., 2023; Kumar & Mokha, 2022; Kumar et al., 2021; Mohamed et al., 2023; Mokha & Kumar, 2021; Mokha & Kumar, 2022; Mokha & Kumar, 2024; Quyen & Sayapina, 2020

Telecommunications	6	Al-Hawary & Alhajri, 2020; Almahadeen & Al-Manasrah, 2022; Alshawawreh et al., 2024; Anaam et al., 2020; Anaama et al., 2022; Magatef et al., 2023
Retail/e-commerce	4	Almajali et al., 2022; Hwang, 2022; Suyanto et al., 2024; Yang & Babapour, 2022
Airline	4	Ali & Alfayez, 2024; Awad & Mahmoud, 2024; Khanh et al., 2022; Rachbini et al., 2024
Healthcare	4	Alshurideh, 2022; Mahrinasari et al., 2023; Mahrinasari et al., 2024; Singh et al., 2022
Tourism	4	Anna & Lazaros, 2020; Chi, 2021; Liu & Chen, 2022; Tsokota et al., 2021
Food industry	1	Kakeesh et al., 2021
Petrochemicals	1	Radzi et al., 2021
Manufacturing	1	Sasono et al., 2021
Construction	1	Sawlan et al., 2022
Government (tax administration)	1	Dehghanpouri et al., 2020;
Several industries	1	Mansour et al., 2024
Not specified	2	Haudi et al., 2022; Herman et al., 2020

The identified key publication themes in E-CRM research include the effects/impacts of e-CRM on different variables/outcomes (competitive advantage, performance, customer loyalty, satisfaction, experience, trust, reputation, etc.) and pillars/critical success factors of e-CRM implementation. The heatmap (Figure 1) shows the researched topics by industry. The analysis reveals that several themes have been attracting attention across the industries. Customer loyalty is the most researched topic, particularly in banking and telecommunications. Customer satisfaction is another dominant topic in banking, retail and e-commerce, telecommunications, and healthcare. E-CRM system success/effectiveness has also received notable attention in tourism, retail and e-commerce, and airline industries. Conversely, other topics, e.g., trust, service quality, behavioural/repurchase intentions, competitive advantage, and green operational practices, were present but less distributed across industries.

Tab. 3 - Heatmap of research topics by industry. Source: own research

Topic / Industry	Banking	Telecommunications	Airline	Retail and e-commerce	Healthcare	Tourism
Customer Loyalty	8	2	1	2	1	0
Customer Satisfaction	3	1	0	3	1	0



4.1 E-CRM in the banking industry

Modern banks worldwide actively invest in electronic customer relationship management to achieve competitive advantage (Kumar et al., 2021; Mohamed et al., 2023; Quyen & Sayapina, 2020), improve e-service quality (Karim et al., 2023), increase volumes of customers' financial transactions (Abdi et al., 2020), market share, and profitability (Karim et al., 2023; Kumar & Mokha, 2022; Quyen & Sayapina, 2020) save time, efforts and resources, create better image and reputation (Quyen & Sayapina, 2020) and enhance customer engagement, satisfaction, trust, and loyalty (Abdi et al., 2020; Haghighinasab et al., 2025; Karim et al., 2023; Kumar & Mokha, 2022; Mohamed et al., 2023; Mokha & Kumar, 2022; Mokha & Kumar, 2024; Quyen & Sayapina, 2020).

E-CRM applications were developed with e-banking to care of the clients through the web, e-mail, call center, mobile, and other electronic touchpoints and reach their demands on time (Abdi et al., 2020; Kumar & Mokha, 2022; Kumar et al., 2021; Mokha & Kumar, 2022). E-CRM has gained more importance since digital-only banks appeared, as it is the only bridge between them and their customers (Haghighinasab et al., 2025). The successful implementation of e-CRM requires a proper strategy, information technology, customer orientation, human knowledge management, and involvement and support from senior leadership (Quyen & Sayapina, 2020).

E-CRM in the banking industry has been mostly capturing the attention of academics from Asia (Abdi et al., 2020; Alsheikh, 2023; Haghighinasab et al., 2025; Karim et al., 2023; Kumar & Mokha, 2022; Kumar et al., 2021; Mokha & Kumar, 2021; Mokha & Kumar, 2024). Pushpender Kumar and Anupreet Kaur Mokha have been investigating the relationship between E-CRM and various variables in the Indian banking industry for several years. For example, Mokha and Kumar (2021) confirmed the positive relationship between E-CRM and the technology acceptance model (TAM) variables (i.e., perceived usefulness and perceived ease of use), which, in turn, positively affect customers' attitudes and behavioural intentions to use E-CRM.

4.2 E-CRM in the telecommunications industry

Telecommunication organizations have been working hard to survive the demanding and changing environment and build long-lasting relationships with customers (Almahadeen & Al-Manasrah, 2022). Thus, they have started adopting e-CRM to improve market performance, increase competitive advantage (Alshawawreh et al., 2024), and influence employees' job satisfaction (Anaam et al., 2020; Anaama et al., 2022), customers' electronic satisfaction (Al-Hawary & Alhajri, 2020) and loyalty (Almahadeen and Al-Manasrah; 2022; Magatef et al., 2023). However, some telecommunication companies avoid implementing e-CRM or fail to implement it successfully (Anaama et al., 2022).

4.3 E-CRM in the airline industry

The airline industry is characterized by globalization, high local and international competition, increasing customer expectations, and decreasing customer loyalty (Ali & Alfayez, 2024; Awad & Mahmoud, 2024). E-CRM has become a primary tool to gain a competitive advantage, fulfil customers' requirements, influence their experience, trust, repurchase intentions, and loyalty, increase engagement, and establish long-term relationships in the airline industry (Ali & Alfayez, 2024; Awad & Mahmoud, 2024; Khanh et al., 2022; Rachbini et al., 2024). However, the successful implementation of e-CRM in the airline industry can be affected by different factors, including customer orientation, knowledge management, organizational factors, and technology (Khanh et al., 2022).

4.4 E-CRM in retail and e-commerce

Previous research regarding electronic customer relationship management in retail, online shopping, or e-commerce is scarce. Authors mainly discuss the effect of e-CRM on electronic satisfaction and/or loyalty (Hwang, 2022; Suyanto et al., 2024) and the factors affecting the effectiveness of e-CRM in online shopping (Almajali et al., 2022; Yang and Babapour, 2022).

According to Hwang (2022), online purchase e-CRM activities (i.e., e-Marketing, e-Sales, e-Support, and e-System) have a significant positive impact on e-customer satisfaction, which, in turn, significantly mediates the relationship between online purchase e-CRM activities and e-

loyalty. On the contrary, Suyanto et al. (2024) found no statistically significant relationship between e-CRM and e-satisfaction or e-loyalty.

Almajali et al. (2022) suggested that user satisfaction affects the effectiveness of E-CRM in online shopping. Similarly, Yang and Babapour (2022) proved that customer (user) satisfaction significantly and positively influences E-CRM systems' effectiveness.

4.5 E-CRM in the healthcare industry

Although e-CRM plays a significant role in the healthcare industry, the research is still limited (Mahrinasari et al., 2023; Singh et al., 2022). Alshurideh (2022) suggested that electronic customer relationship management has a significant positive influence on service quality in private hospitals in Jordan. Furthermore, Singh et al. (2022) proved that E-CRM services have a significant positive effect on customer trust, value, satisfaction, and loyalty in the Indian private healthcare industry. Moreover, Mahrinasari et al. (2023) confirmed a correlation between E-CRM practices and patient satisfaction and the moderating role of green social influence in the relationship in Indonesian hospitals. Finally, in another research about hospitals in ASEAN countries (Indonesia, Malaysia, and Singapore), Mahrinasari et al. (2024) also demonstrated that E-CRM significantly and positively influenced patient satisfaction, which, in turn, influences operational performance.

4.6 E-CRM in the tourism industry

E-CRM remains crucial to any firm's success, including companies from the tourism industry (Tsokota et al., 2021). Adopting e-CRM tools helps companies gain innovation capabilities and foster long-term relationships with customers (Chi, 2021), reduce business costs, increase sales, enhance customer service and satisfaction, and improve profitability (Tsokota et al., 2021).

According to Tsokota et al. (2021), the pillars of e-CRM implementation are investment (financial resources), employee buy-in, guidance, customer education, and organizational structure. In the research of Anna and Lazaros (2020), the critical success factors of the e-CRM implementation are web policy, security, business content, navigation, payment, and interactivity in sport tourism hotels in the Peloponnese region. Finally, Liu and Chen (2022) suggested that buyer behaviors, consumer-driven innovation, product lifecycle, and customer feedback management positively affect E-CRM prosperity.

5 DISCUSSION

As can be noted, the key publication themes in E-CRM research are the effects/impacts of e-CRM on different variables/outcomes (competitive advantage, performance, customer loyalty, satisfaction, experience, trust, reputation, etc.) and pillars/critical success factors of e-CRM implementation.

Authors have consistently demonstrated the influence of e-CRM on various aspects, including competitive advantage and performance (Dehghanpouri et al., 2020; Haudi et al., 2022; Sawlani et al., 2022), service attributes and quality (Abdi et al., 2020; Alshurideh, 2022; Mohamed et al., 2023), customer (electronic) loyalty (Abdi et al., 2020; Ali & Alfayez, 2024; Almahadeen & Al-Manasrah, 2022; Alsheikh, 2023; Haghighinasab et al., 2025; Haudi et al., 2022; Hwang, 2022; Kakeesh et al., 2021; Karim et al., 2023; Kumar & Mokha, 2022; Magatef et al., 2023; Mohamed et al., 2023; Mokha & Kumar, 2022; Mokha & Kumar, 2024; Sasono et al., 2021; Singh et al., 2022; Suyanto et al., 2024), customer experience (Kumar et al., 2021); satisfaction (Abdi et al.,

2020; Al-Hawary & Alhajri, 2020; Anaam et al., 2020; Dehghanpouri et al., 2020; Kumar et al., 2021; Mahrinasari et al., 2023; Mahrinasari et al., 2023; Mohamed et al., 2023), trust (Abdi et al., 2020; Mohamed et al., 2023; Rachbini et al., 2024) repurchase (Rachbini et al., 2024) and behavioural intentions (Mokha & Kumar, 2021), innovation capabilities (Chi, 2021; Herman et al., 2020), and achieving sustainability (Mansour et al., 2024).

Another topic discussed in the academic literature is the critical success factors of e-CRM success. Depending on the author, these factors include: trust, customer satisfaction, and the quality of service (Dehghanpouri et al., 2020), customer orientation, knowledge management, organizational factors, and technology (Khanh et al., 2022), individual, technology, and organization factors (Anaam et al., 2021); technology adoption, process automation, and staff empowerment (Kakeesh et al., 2021).

Based on the systematic literature review, the most researched industry is banking. Researchers encourage bank managers and decision-makers to adopt e-CRM to improve their relationship with clients, acquire new customers, retain existing profitable customers, and improve their experience, satisfaction, and (electronic) loyalty (Alsheikh, 2023; Haghighinasab et al., 2025; Karim et al., 2023; Kumar & Mokha, 2022; Mohamed et al., 2023; Mokha & Kumar, 2022; Mokha & Kumar, 2024).

6 CONCLUSION

The article tried to contribute to a comprehensive understanding of the role of electronic customer relationship management in modern businesses' success using a systematic literature review. Based on the results, e-CRM has a paramount role in companies' performance and development, regardless of the size and industry. The benefits of E-CRM include (Alsheikh, 2023; Al-Hawary & Alhajri, 2020; Almahadeen & Al-Manasrah, 2022; Alshawawreh et al., 2024; Anaam et al., 2020; Anaama et al., 2022; Chi, 2021; Dehghanpouri et al., 2020; Eltahir et al., 2021; Haghighinasab et al., 2025; Haudi et al., 2022; Herman et al., 2020; Kakeesh et al., 2021; Karim et al., 2023; Khanh et al., 2022; Kumar & Mokha, 2022; Kumar et al., 2021; Liu & Chen, 2022; Mansour et al., 2024; Mohamed et al., 2023; Mokha & Kumar, 2022; Mokha & Kumar, 2024; Purnomo et al., 2021; Radzi et al., 2021; Sathyavani et al., 2025; Sitinjak et al., 2020; Tsokota et al., 2021):

- Achieving competitive advantage and sustainable goals
- Elevated strategies, marketing, and innovation capabilities
- Improved business profitability and reduced costs
- Improved performance, operational efficiency, and decision-making using a data-driven approach
- Effective interaction platform for fostering long-term relationships with customers
- Personalized/customized/tailored offerings to each customer segment
- Enhanced reputation, customer experience, engagement, satisfaction, trust, and loyalty.

Overall, the article contributes to the academic literature on electronic customer relationship management (e-CRM). It highlights e-CRM's role in creating long-lasting relationships with customers and enhancing modern companies' performance regardless of industry. Furthermore,

the research can provide valuable insights to practitioners interested in e-CRM and its implementation.

6.1 Limitations

The article is not without limitations. Firstly, the literature review only included studies published in recent years (2020-2025), which may have omitted earlier foundational research regarding E-CRM. Second, the review considered publications available only on Scopus and Web of Science, which may have excluded grey literature or regional studies from other databases. Finally, choosing the keywords and refining search results may have overlooked critical perspectives on e-CRM.

6.2 Future research directions

The SLR showed that although electronic customer relationship management has received a fair share of attention from academics in recent years, several areas still require further investigation. Future research should focus on other industries besides banking, telecommunications, airline, retail/e-commerce, and tourism. Furthermore, academics can study different topics connected to e-CRM, e.g., negative effects, outcomes, or risks of implementing E-CRM, such as data privacy issues and customer and employee resistance. Finally, since most studies are quantitative, it is suggested that researchers conduct qualitative (e.g., case studies) and mixed studies.

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ENHANCING SME OPERATIONAL EFFICIENCY THROUGH RISK MANAGEMENT: A SYSTEMATIC REVIEW AND THEMATIC SYNTHESIS

Hawree Dizaye

Abstract

Small and Medium-sized Enterprises (SMEs) face significant challenges in adopting effective risk management practices due to limited funding, lack of support, and insufficient structured approaches. These constraints hinder their ability to manage uncertainties, foster resilience, and remain competitive. This study aims to investigate risk management practices in SMEs and assess their impact on operational performance, with a particular focus on how such practices can enhance innovation, internal capabilities, and sustainable development. The paper conducts a comprehensive review of existing literature on SME risk management, identifying key frameworks, strategies, and innovation linkages. Findings indicate that SMEs can benefit from efficient risk management across various operational activities by systematically identifying, evaluating, and mitigating potential risks. Well-structured frameworks significantly improve the capacity to manage uncertainties and adapt to market changes. Additionally, integrating risk management with innovation practices fosters creativity and improves competitiveness. The study enriches the existing literature by synthesizing best practices in SME risk management and highlighting the interplay between risk management, innovation, and operational performance. The research provides actionable strategies for SMEs to adopt structured risk management frameworks, thereby enhancing their resilience, competitiveness, and long-term sustainability.

Keywords: *enterprise risk management, SMES, operation risk, performance, efficiency, resilience*

1 INTRODUCTION

Small and Medium-Sized Enterprises (SMEs) are widely acknowledged as crucial players in the development of the global economy. Their capacity to foster innovation, create jobs, and adapt swiftly to changing market conditions highlights their significance in both developed and developing countries. Nevertheless, in spite of their economic importance, SMEs encounter a disproportionately higher level of operational risks due to limited resources, restricted managerial capabilities, and insufficient formalized systems compared to larger companies (Testorelli et al., 2022).

The primary objective of this study is to investigate how structured risk management practices can enhance the competitiveness and sustainability of SMEs, addressing the identified research gap in current literature.

Operational efficiency—the capability to provide products and services in a cost-effective manner while preserving quality and competitiveness—is crucial for SMEs aiming to maintain growth in increasingly unstable markets. Risk management (RM) has become a key tool in achieving this goal. Proper RM allows SMEs to identify potential disruptions, allocate resources effectively, and respond proactively to uncertainties (Marcelino-Sádaba et al., 2014). However, research indicates that many SMEs do not fully leverage formal RM practices due to challenges such as lack of

awareness, insufficient expertise, and minimal institutional support (Snieška et al., 2020; Alquier & Tignol, 2006).

The COVID-19 pandemic further highlighted the weaknesses of SMEs, demonstrating that a lack of strong RM systems can significantly impede operational performance. During such disruptions, SMEs frequently focus on immediate survival rather than long-term strategic planning, which may hinder their capacity for innovation and sustainability (Leopoulos et al., 2006; Santoro et al., 2020). Thus, implementing structured and context-specific RM frameworks is essential rather than a secondary concern.

Although, interest in risk management (RM) within small and medium-sized enterprises (SMEs) is growing. The current literature is still lacks clarity on how specific risk management models and practices can improve operational efficiency. There are ongoing uncertainties about the extent to which RM helps with process optimization, resilience, and sustained performance improvements in SMEs, especially in resource-limited environments (Pertheban et al., 2023).

With a thorough systematic review that examines how RM improves operational efficiency in SMEs, this study aims to close these gaps. It seeks to address a central research question: How can risk management techniques be applied successfully to raise operational effectiveness in SMEs in various industries and geographical areas? Peer-reviewed researches from 2006 to 2025 is highlighted in the review, which also reveals important themes, success factors, persistent difficulties, and empirical evidence.

This paper attempts to integrate insights that will improve the understanding of RM in SMEs and provide useful advice for managers, policymakers, and researchers by closely examining 39 carefully chosen articles from prestigious journals. It focuses especially on how RM impacts small business decision-making effectiveness, supply chain resilience, process continuity, and resource allocation.

Finally, by elucidating the strategic significance of RM in enhancing SME operations, this systematic review advances both scholarly discourse and real-world applications. It also establishes the framework for future research into how RM can support SMEs operating in a more unpredictable global environment in terms of innovation, competitive positioning, and long-term value creation.

2 METHODOLOGY

2.1 Systematic Review Design

For the comprehensive synthesis of current knowledge, this study uses a systematic review methodology based on the framework developed by Tranfield, Denyer, and Smart (2003). This approach is frequently used in management studies. This review's primary goal is to locate, evaluate, and incorporate conceptual and empirical research on the contribution of risk management (RM) to increased operational effectiveness in small and medium-sized businesses (SMEs). Transparency, reproducibility, and the integration of pertinent, high-caliber research are all ensured by this methodology.

2.2 Research Questions

To direct the systematic review process, the following research questions (RQs) were developed:

Each research question is supported by scholarly literature; for example: RQ1 addresses the risk identification gap highlighted by Alquier & Tignol (2006) and Dankiewicz et al. (2020), who stress that SMEs often lack structured RM processes, which in turn affects operational efficiency. RQ2 builds on the models and prioritization frameworks discussed by Leopoulos et al. (2006) and Testorelli et al. (2022), who outline effective RM tools and strategies to minimize operational disruptions in SMEs. RQ3 responds to the barriers identified by Banerjee et al. (2023) and Jobo & Phyllis (2020), who examine organizational, resource, and knowledge constraints hindering RM adoption, and propose context-specific remedies.

- RQ1: In what ways does the adoption of risk management practices enhance the operational efficiency of SMEs?
- RQ2: Which specific RM models or strategies have been most effective for SMEs in reducing operational disruptions?
- RQ3: What obstacles hinder the successful implementation of RM in SMEs, and how can these issues be addressed?

2.3 Search and Database Approach

Scopus databases were the main tool used for the literature search. These platforms were selected because they offer extensive coverage of peer-reviewed journals in economics, management, and business. To capture the evolution and recent advancements in risk management within the context of SMEs, the search was limited to studies published between 2006 and June 2025.

Using Boolean operators, a structured search string was created to increase the precision and applicability of the results. The following terms were utilized:

("enterprise risk management" OR "risk management" OR "operational risk") AND ("small and medium enterprises" OR "SMEs") AND ("performance" OR "capability" OR "resilience" OR "efficiency" OR "operation").

Keywords, abstracts, and article titles were searched. By tracking pivotal articles' backward and forward citations, more records were found.

2.4 Inclusion and Exclusion Criteria

Particular inclusion and exclusion criteria were used to guarantee the coherence and applicability of the chosen studies. Studies that were written in English, published in peer-reviewed journals between 2006 and 2025, and that addressed small and medium-sized businesses (SMEs) in relation to operational risk management were considered. As long as the research was listed in Scopus, both theoretical and empirical studies, whether qualitative or quantitative, were taken into consideration. Theses, book chapters, editorials, conference papers, and research unrelated to risk management or operational efficiency were all excluded based on certain criteria. Furthermore, studies that only looked at big businesses were not included.

2.5 PRISMA Flow and Study Selection

There were 216 articles found in the first search. 59 articles were selected for a full-text review after titles and abstracts were screened. The quality assessment criteria led to the inclusion of 39 articles out of these. The selection process was documented and made transparent using the

Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 framework (Page et al., 2021). The screening process is depicted in a PRISMA flow diagram (Figure 1).

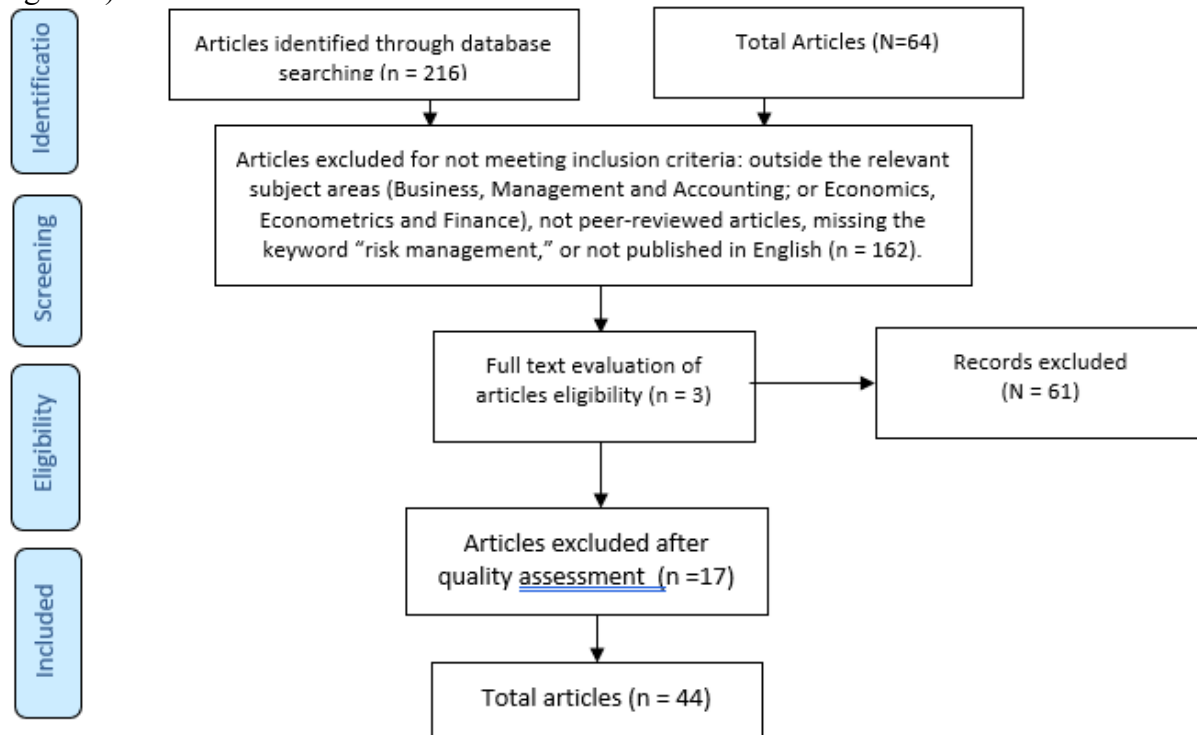


Fig. 1 –Flow Diagram from selected, screened, and included studies. Source: author’s processed results

2.6 Evaluation of Quality

A quality assessment checklist, modified from Gough (2007) and Tranfield et al. (2003), was used to evaluate the methodological rigor of each study that was part of the review. The following topics were covered by this checklist:

- Clarity regarding the research aims and design.
- Relevance to Risk Management (RM) and the operational efficiency of Small and Medium Enterprises (SMEs).
- Transparency in methodology.
- Contribution to theoretical frameworks or practical applications.

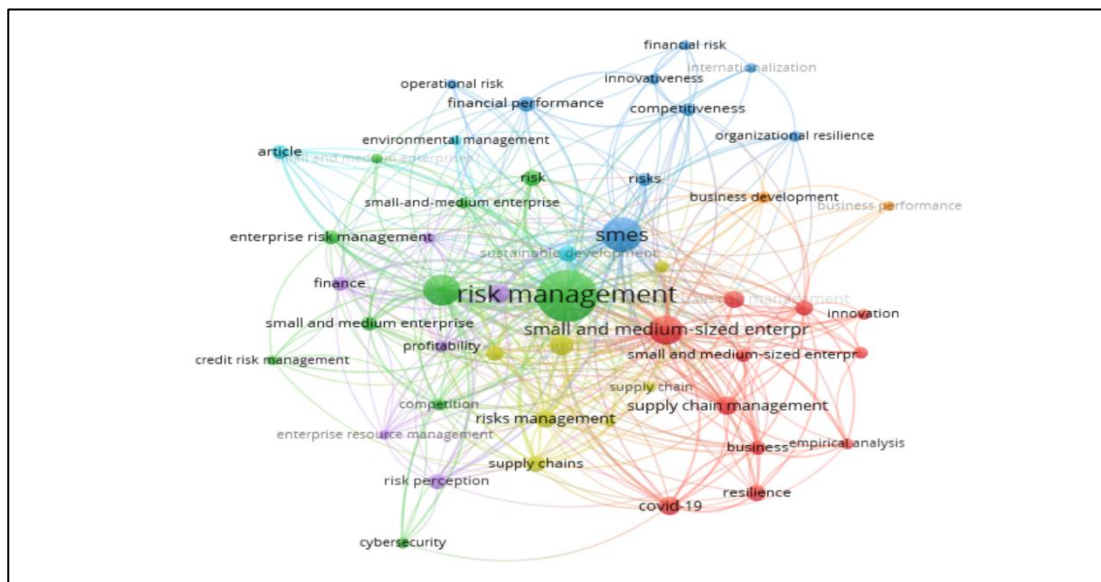
Studies were only included if they met a minimum quality benchmark, such as receiving at least 60% of the possible points on the evaluation criteria. To maintain scholarly integrity, articles from low-impact or non-indexed journals were not included.

2.7 Extraction and Synthesis of Data

Key information from each chosen study, such as the author or authors, the year of publication, and the country of origin, was gathered using a methodical data extraction form. The study's goals and methodology, the kinds of risk management (RM) practices that were looked at, the

operational effectiveness findings, and any significant conclusions or limitations were also recorded in the form. A narrative approach was used to synthesize the data, enabling the integration of findings from various study designs. As suggested by Petticrew and Roberts (2006), this approach made it easier to find, classify, and interpret recurrent themes that were consistent with the study questions.

To enhance the qualitative synthesis, a bibliometric analysis was performed using VOSviewer to visualize the co-occurrence of keywords and thematic clusters in the selected literature. This analysis assisted in identifying the intellectual frameworks and trends within the field by highlighting important terms related to RM and SMEs, such as "supply chain," "operational risk," "innovation," and "resilience."



relationship. Source: own research

2.9 The Methodology's Limitations

The review has certain limitations even with the rigorous methodology used. It's possible that pertinent research published in other languages was overlooked by limiting the scope to English-language publications. Furthermore, the narrow focus on peer-reviewed journal articles may have missed excellent institutional reports or working papers, particularly those that were behind paywalls, which would have restricted access to potentially insightful information. However, the methodical approach taken guarantees that the final synthesis provides a solid and thorough understanding of how risk management helps SMEs increase operational efficiency.

3 RESULTS AND ANALYSIS

The results of the 39 carefully chosen and examined studies are compiled in this section, offering insights into how risk management (RM) techniques enhance operational effectiveness in SMEs. The findings are arranged based on methodological approaches, geographical focus, theoretical frameworks, thematic patterns, and the development of scholarship over time.

Tab. 1 – Summary of Theory/ Framework and Research Main Contribution Management Risks in SMEs. Source: own research

ID	Author(s)	Year	Theory/Framework	Main Contribution	Country/Region
R1	Yang et al.,	2018	ERM & Financial Literacy	Demonstrates that ERM and financial literacy boost competitive advantage.	Pakistan
R2	Rustiarini et al.	2023	Competitive Advantage Theory	Explores how RM and intellectual capital improve SME competitiveness during COVID-19.	-
R3	Gao et al.	2013	Cognitive Capital Theory	Explains how SMEs develop risk capabilities through learning and communication.	China
R4	Przychodzen & Przychodzen	2015	Eco-Innovation & Financial Performance	Links eco-innovation activities to SME financial performance in Poland and Hungary.	Poland, Hungary
R5	Dankiewicz et al.	2020	Endogenous & Exogenous RM	Explores how SMEs perceive and manage internal and external risks.	Poland
R6	Wong et al.	2024	AI-driven RM (PLS-SEM + ANN)	Demonstrated AI-enhanced RM significantly boosts supply chain agility in SMEs.	Malaysia, China, UK, USA, Taiwan
R7	Jobo & Phyllis	2020	Environmental Uncertainty & Risk Perception	Studies green innovation risk behavior under environmental uncertainty.	South Africa
R8	Rehman & Anwar	2019	ERM as Mediator in Business Strategy	Found that ERM partially mediates the relationship between strategy and performance in Pakistani SMEs using SEM.	Pakistan

R9	Snieska et al.	2020	Industry 4.0 Risk Perception	Analyzes risk perceptions of Industry 4.0 among Slovak and Polish SMEs.	Slovakia, Poland
R10	Li et al.	2020	Blockchain-Driven SCF Framework	Proposed a blockchain-driven supply chain finance platform; analyzed models and validated with real cases.	China
R11	Rodriguez et al.	2010	Internationalization Process Model	Explores internationalization risk tools in SME knowledge management.	-
R12	González Calzadilla et al.	2022	Internationalization Risk Management	Analyzes risk strategies used by Spanish SMEs during international expansion.	Spain
R13	Dey et al.	2024	AI-driven Supply Chain Resilience Framework	Showed AI-based risk practices strengthen resilience in Vietnamese manufacturing SMEs.	Vietnam
R14	Temel & Durst	2021	Knowledge Risk Management	2020 Identifies knowledge risks in tech adoption and proposes preventive strategies.	-
R15	Alquier & Tignol	2006	Management by Risk	Introduces RM as a global process for business innovation in SMEs.	-
R16	Rozsa et al.	2021	CSR and Personnel Risk Management	Explored how CSR perception influences optimism around personnel risks and performance; based on 1,585 SME responses.	V4 (CZ, SK, PL, HU)
R17	Santoro et al.	2020	Open Innovation Theory	Investigates openness in innovation and entrepreneur influence in SMEs.	-
R18	Banerjee et al.	2023	Grey-DEMATEL	Mapped post-pandemic resilience barriers in Indian MSMEs using Grey-DEMATEL.	India
R19	Testorelli et al.	2022	Project RM Framework	Proposes an expanded project RM framework with communication strategies.	Italy
R20	Marcelino-Sádaba et al.	2014	Project RM Methodology	Presents simple, practical RM tools for SME project risk management.	-
R21	Qiao & Zhao	2023	Supply Chain Risk Management	Analyzed how supply chain RM capabilities improve SME financing performance.	-
R22	Leopoulos et al.	2006	Quantitative RM Tools	Shows how risk tools improve efficiency and reduce costs in SMEs.	Greece
R23	Nayal et al.,	2024	Digital Supply Chain Capability Framework	Found that digital supply chain capabilities during COVID-19 mitigated disruptions and bolstered competitive advantage.	-
R24	De Matteis et al.	2023	Business Continuity Management & Resilience	Showed that BCM practices significantly enhance organizational resilience in SMEs.	-
R25	Civelek et al.	2024	Resource-Based View	Explores internal risk capabilities and export intentions in SMEs.	Europe
R26	Zeiringer et al.	2022	Risk Behaviour Typology	Categorizes SME risk behavior in supply chains using cluster analysis.	Europe

R27	Kaivanto & Stoneman	2007	Sales Contingent Claim Finance	Analyzes SCC-based financing for SME innovation and growth.	-
R28	Dvorsky et al.	2022	Risk Perception Comparative Analysis	Found owners and managers differ significantly in perceiving market and regulatory risks; study used Kruskal–Wallis tests on 1,585 SMEs.	V4 (CZ, SK, PL, HU)
R29	Prioteasa et al.	2020	Structured RM Approach	Highlights structured RM's role in boosting SME operational performance.	Romania
R30	Prakash et al.	2016	Supply Chain Collaboration & RM	Uses TOPSIS to evaluate SME supply chain collaboration under risk.	-
R31	Foli et al.	2024	Supply Chain RM Framework	Links SCRM with innovation performance under tech turbulence in SMEs.	-
R32	Dvorský et al.	2020	Multi-Risk Framework	Analyzes various risks and their impact on SME performance; financial risk had the highest effect.	-
R33	Foli et al.	2023	Grey-DEMATEL	Identified operational knowledge risks in SMEs; outsourcing, communication, knowledge application critical.	Estonia / Spain
R34	Chowdhury et al.	2019	Operational Supply Risk	Shows social capital and integration reduce supply risk and improve performance.	Bangladesh
R35	Abudaqa et al.	2023	Supply Chain Design & Risk Collaboration	Demonstrated how SCD, risk management, and collaboration build resilience in manufacturing SMEs in Dubai.	UAE
R36	Hanggraeni et al.	2019	Financial & Marketing Risk	Shows risk assessment in finance/marketing improves SME operations.	Indonesia
R37	Maalouf et al.	2025	SME Crisis Strategy Framework	Developed a framework on SME survival strategies in polycrisis environments using qualitative interviews in Beirut.	Lebanon
R38	Crespo et al.	2025	Financial & Marketing Risk	Identified the dual role of planned and adaptive resilience and highlighted a significant research gap in emerging economies like Ecuador. Called for mixed-methods future research.	-
R39	Khadka et al.	2025	Quantitative Regression Model	Identifies key success factors for Nepalese SMEs—record-keeping and market responsiveness drive perceived success; RM had no direct significance.	Nepal

3.1 Risk Management's Impact on Operational Effectiveness

The operational efficiency of SMEs is positively impacted by risk management, according to the majority of the reviewed studies. Key discoveries include:

Proactive Risk Identification and Assessment: SMEs that place a high priority on scenario planning and early risk identification are better prepared to handle outside disruptions, which reduces downtime and stabilizes production rates (Marcelino-Sádaba et al., 2014; Rustiarini et al., 2023).

- **Operational Continuity and Resilience:** Strong RM systems help SMEs maintain operations in the face of unforeseen circumstances or crises, like depressions or international health crises (De Matteis et al., 2023; Snieška et al., 2020; Dankiewicz et al., 2020).
- **Cost-effectiveness:** By averting losses due to mishaps, delays, and regulatory noncompliance, Enterprise Risk Management (ERM) and other well-structured RM frameworks help lower operating costs.
- **Cost Efficiency:** By avoiding losses due to mishaps, delays, and regulatory noncompliance, well-structured RM frameworks, such as Enterprise Risk Management (ERM), assist in lowering operating costs (Prakash et al., 2016; Zeiringer et al., 2022).
- **Financing & Supply Chain Optimization:** Supply chain RM capabilities benefit financing efficiency and operational speed by reducing supply disruptions (Qiao & Zhao, 2023).
- **Supply Chain Agility:** Research, including studies by Wong et al. (2024), shows that RM improves supply chain agility, especially when paired with AI tools, allowing SMEs to adapt to logistics disruptions and market demands.
- **Supply Chain Agility:** AI-enhanced RM, as shown by Nayal et al. (2024) and corroborated by Wong et al. (2024), equips SMEs to swiftly adapt to logistics challenges and volatile markets.
- **SME Resilience Post-Pandemic:** Grey-DEMATEL analyses, such as Banerjee et al. (2023), pinpoint organizational barriers and design resilience systems to support post-pandemic operational stability.

3.2 Theoretical Underpinnings of Research on Risk Management

The reviewed literature investigates RM implementation in SMEs using a range of theoretical frameworks, including:

- **The Resource-Based View (RBV):** The RBV is used in a number of studies to support the claim that internal capabilities, such as technological infrastructure, risk-aware culture, and skilled workers, serve as strategic assets that increase a company's competitiveness and export readiness (Civelek et al., 2024; Rodriguez et al., 2010).
- **Social Capital Theory:** Gao et al. (2013) found that relational trust and informal networks are important for advancing RM practices, especially in developing nations where official institutional support may be scarce.
- **Resource Orchestration Theory and the Knowledge-Based View (KBV)** emphasize how RM can enhance learning, innovation, and knowledge integration—all of which are critical for SMEs competing in markets that are continuously changing (Temel & Durst, 2021; Zeiringer et al., 2022).

3.3 Geographic Distribution of Studies and Contextual Insights

Tab. 2 – Geographic Distribution of Studies. Source: own research

Area	Country	Authors	Total
Europe	Italy	Testorelli et al., 2022	1
	Poland & Hungary	Przychodzen & Przychodzen, 2015	1
	Multi Countries in Europe	Civelek et al., 2024; Zeiringer et al., 2022	2
	Poland	Dankiewicz et al., 2020	1
	Spain	González Calzadilla et al., 2022; Marcelino- Sádaba et al., 2014; Rodríguez et al., 2010	3
	Czech, Slovakia and Poland	Snieska et al., 2020, Dvorský et al., 2020, Dvorsky et al., 2022	3
	Romania	Prioteasa et al., 2020	1
	Greece	Leopoulos et al., 2006	1
	V4 (CZ, SK, PL, HU)	Rozsa et al., 2021	1
	India	Prakash et al., 2016; Banerjee et al., 2023	2
Asia	China	Gao et al., 2013	1
	Indonesia	Rustiarini et al., 2023, Hanggraeni et al., 2019	2
	Vietnam	Dey et al., 2024	1
	Malaysia	Wong et al., 2024	1
	Bangladesh	Chowdhury et al., 2019	1
	Pakistan	Yang et al., 2018; Rehman & Anwar, 2019	2
Africa	South Africa	Jobo & Phyllis, 2020	1
Middle East	UAE	Abudaqa et al., 2023	1
Global	Not specified	Temel & Durst, 2021; Crespo et al., 2025; Santoro et al., 2020; Qiao & Zhao, 2023; Nayal et al., 2024; Kaivanto & Stoneman, 2007; De Matteis et al., 2023; Foli et al., 2023; Foli et al., 2024; Maalouf et al., 2025; Khadka et al., 2025; Alquier & Tignol, 2006; Li et al., 2020	13

The reviewed literature offers insights into regionally specific RM practices and spans a variety of geographic contexts:

- Europe: Studies carried out in Hungary, Poland, and Spain (e.g., Przychodzen & Przychodzen, 2015; González Calzadilla et al., 2022) show a strong correlation between RM and financial performance, especially in eco-innovative SMEs.
- Asia: Research in Malaysia and Indonesia highlights the function of digital tools in RM and their impact on both the growth of intellectual capital and operational agility (Wong et al., 2024; Rustiarini et al., 2023).
- Africa: Jobo and Phyllis's (2021) research emphasizes the need for more structured RM to handle particular operational risks in the region by concentrating on maritime hazards and infrastructure deficiencies.
- Middle East: Although there is less literature in these regions, Abudaqa et al.'s (2023) demonstrated how risk management and collaboration build resilience in manufacturing SMEs

3.4 Notable Articles and Foundational Works

Among the most significant contributions:

Tab. 3 – Notable Articles. Source: own research

Authors	Citations
Marcelino-Sádaba et al., 2014	481
Przychodzen & Przychodzen, 2015	457
Yang et al., 2018	406
Wong et al., 2024	241
Gao et al., 2013	217
Rehman & Anwar, 2019	190
Hanggraeni et al., 2019	184
Alquier & Tignol, 2006	181
Chowdhury et al., 2019	118
Leopoulos et al., 2006	128
Dey et al., 2024	146
Li et al., 2020	101
Santoro et al., 2020	91
Dankiewicz et al., 2020	75
Temel & Durst, 2021	74
Banerjee et al., 2023	63
Rodriguez et al., 2010	65
Rozsa et al., 2021	58
Kaivanto & Stoneman, 2007	48
Snieska et al., 2020	44
Nayal et al., 2024	40
Qiao & Zhao, 2023	30
Testorelli et al., 2022	30
Foli et al., 2024	26
Zeiringer et al., 2022	16
Jobo & Phyllis, 2020	16
González Calzadilla et al., 2022	13
Abudaqa et al., 2023	13
Dvorsky et al., 2022	12

Prakash et al., 2016	12
Rustiarini et al., 2023	12
Foli et al., 2023	6
Civelek et al., 2024	5
Prioteasa et al., 2020	5
Dvorský et al., 2020	3
De Matteis et al., 2023	31
Maalouf et al., 2025	10
CRESPO et al., 2025	1
Khadka et al., 2025	1

The table then displays the most frequently cited articles in this area to provide an overview of the impact and contribution of research in the area of risk management and SMEs. The selection of articles is determined by the quantity of quotes they accept, which indicates their relevance and influence among community scholars.

Commonly cited articles in the fields of risk management and SMEs. The SMEs and articles with the highest field management risks are shown in the above table. With 481 quotes, the article by Marcelino-Sádaba et al. (2014) holds the top spot and has a substantial literary impact. The significance of research in the field is further supported by the sufficient quotes, 457, 406 and 241 citations, respectively, in other articles, such as Przychodzen & Przychodzen (2015), Yang et al. (2018), and Wong et al. (2024). High quotes demonstrate that it is effective. are frequently cited by scholars, indicating their importance and noteworthy contribution to development theory and risk management practice in the context of SMEs. Even though they may be more specific or novel in academic discourse, articles that have been slightly quoted still make significant contributions.

3.5 Methodological Approaches

Drawing from a broad range of research on risk management practices in SMEs, this paper emphasizes the application of multiple methodological approaches, each of which offers a unique perspective on the relationship between risk management and strategic outcomes and operational efficiency.

The behavioural and cognitive components of risk are frequently investigated using qualitative methods like case studies, interviews, and thematic analysis. For instance, Calzadilla et al. (2022) illustrated how internationalization strategies impact performance through risk management practices, while Gao et al. (2013) showed how SMEs unofficially develop risk capabilities through cognitive and social capital. Temel and Durst (2021) looked at knowledge-based risks in technological innovation and suggested mitigation strategies, while Alquier and Tignol (2006) presented the PRIMA method, a proactive framework aimed at risk in the product life cycle.

Through the measurement of correlations between variables, quantitative approaches offer empirical validation. According to Yang et al. (2018), financial literacy acts as a moderator in the relationship between enterprise risk management (ERM) and firm performance, while competitive advantage mediates it. Dvorský et al. (2020) examined how various business risks, particularly

financial ones, affected the performance of SMEs. According to Chowdhury et al. (2019), social capital and supplier integration greatly lower operational supply risks, enhancing performance. Hanggraeni et al. (2019) investigated how ERM, external, and internal practices work together to improve performance in micro and small businesses. While more recent models employing tools like PLS-SEM and artificial neural networks investigate AI's impact on supply chain risk agility, Roper and Tapinos (2016) evaluated the relationship between perceived environmental risk and green innovation willingness.

A more thorough understanding is provided by mixed-method designs. A conceptual model connecting risk and knowledge management in internationalization projects was created by Rodriguez et al. (2010). Zeiringer et al. (2022) provided practical insights into behavioural risk management by using a mixed method to categorize SME risk behaviours into four different typologies.

However, current SME risk management research often relies heavily on qualitative assessments or generic risk matrices, which may not provide adequate prioritization in resource-limited contexts. This study suggests integrating structured multi-criteria tools, such as the Analytic Hierarchy Process (AHP), and recommends future research into hybrid models and longitudinal studies to assess long-term impact, as discussed in Chapter 4.7.

Methodologies based on literature reviews (e.g., Leopoulos et al., 2006; Testorelli et al., 2022) synthesize current frameworks and tools to identify research gaps and best practices that are pertinent to SMEs. When taken as a whole, these studies show that sound risk management, whether it be qualitative, quantitative, or mixed, is not only necessary for SMEs to survive but also promotes efficiency, innovation, and strategic expansion.

3.6 Emerging Themes and Practical Implications

A number of significant themes that are essential to efficient risk management (RM) in SMEs were identified by the synthesis of the reviewed literature. Digital transformation is a major theme, whereby the incorporation of technologies like big data and artificial intelligence improves SMEs' capacity to anticipate and address risks more effectively. The establishment of a risk-aware culture which highlights the significance of integrating RM practices into the organizational mindset through leadership commitment and focused employee training, is another crucial component. The review also emphasized RM's role in financial risk mitigation by demonstrating how different tools assist SMEs in managing working capital, exchange rate fluctuations, and credit-related uncertainties. Lastly, it was discovered that by lowering the uncertainty surrounding product development, investment choices, and market expansion, RM strategically supports innovation. Collectively, these themes show how RM helps SMEs grow and remain stable in increasingly unstable environments.

4 DISCUSSION AND IMPLICATIONS

The systematic review's findings demonstrate how important good risk management (RM) is to raising small and medium-sized businesses' (SMEs') operational effectiveness. The literature emphasizes RM as a strategic enabler for improving performance, encouraging innovation, and raising competitiveness, in addition to being a tool for threat mitigation. Key themes, theoretical ramifications, and practical considerations drawn from the reviewed literature are covered in this section.

4.1 Risk Management and Operational Efficiency in SMEs

The review consistently demonstrates that SMEs can optimize their internal processes, resource allocation, and flexibility with the support of robust RM systems. Risk-averse SMEs are better able to manage expenses, react to market shifts more adeptly, and carry-on during emergencies (Marcelino-Sádaba et al., 2014; Rustiarini et al., 2023). Such operational improvements are essential for SMEs, especially those with limited resources and high levels of environmental uncertainty.

Studies by Dankiewicz et al. (2020) and Prakash et al. (2016) demonstrate that SMEs can anticipate disruptions and create backup plans when they integrate RM into their operational strategies. Increased production stability, supply chain continuity, and dependable service delivery are the outcomes of this structured approach, and they all have a favourable impact on operational efficiency.

4.2 RM as a Driver of Innovation and Performance

RM has proven to be effective in encouraging innovation and learning in SMEs in addition to protecting against risks. Proactive risk managers are more likely to experiment with new business models, procedures, and technologies. Implementing RM, particularly through digital technologies like AI and data analytics, enhances operational agility and fosters innovation across a range of functions, according to research by Wong et al. (2024) and Zeiringer et al. (2022). For SMEs seeking to stand out from the competition, the ability to innovate while managing uncertainty offers a substantial advantage. According to Otache (2024), SMEs with established RM frameworks exhibit higher resilience and are better able to adapt and grow during times of external disruptions or economic downturn.

4.3 The Significance of Organizational Culture and Social Capital

Relational and cultural factors have also become important in the implementation of RM. SMEs are more likely to successfully transform RM into operational improvements when they cultivate a risk-aware organizational culture characterized by open communication, leadership support, and an emphasis on learning (Gao et al., 2013; Santoro et al., 2020). Social capital, which includes informal networks and relationships based on trust, helps disseminate RM practices and knowledge, especially in environments with limited resources. Research from developing nations (such as South Africa and Indonesia) supports this idea by showing that social networks help SMEs overcome the lack of formal infrastructure by providing them with access to outside knowledge and collaborative risk management techniques (Rustiarini et al., 2023; Jobo & Phyllis, 2021).

4.4 Contextual Factors Related to Sector and Region

The reviewed studies suggest that contextual factors, including industry sector, regulatory environment, and national economic conditions, impact the effectiveness of RM. For example, manufacturing-oriented SMEs in Europe gained a lot from RM in terms of inventory control and quality assurance (Przychodzen & Przychodzen, 2015), while service-oriented businesses in Asia emphasized the value of customer retention and supply chain resilience. This dependence on context implies that RM frameworks must be modified to accommodate risk characteristics unique to a given industry. Furthermore, cross-national comparisons, like those

between Europe and Southeast Asia, show disparities in RM maturity and digital preparedness, suggesting the need for regional policy initiatives to support SMEs' adoption of RM.

4.5 Contributions to Theory

This review highlights the importance of the Resource-Based View (RBV) from a theoretical perspective by showing that internal risk capabilities are useful, distinct, and inimitable resources that improve SMEs' competitive advantages. In a similar vein, combining RM with theories of innovation management highlights how risk management and creative exploration work together to improve performance.

Furthermore, applying Social Capital Theory and the Knowledge-Based View (KBV) provides insights into how SMEs use relational networks and internal knowledge to develop adaptive RM systems. These theoretical frameworks offer a multifaceted perspective on how RM contributes to operational excellence.

4.6 Methodological Observations and Future Research Directions

A thorough understanding of RM practices is provided by the literature review, which uses a variety of methodological techniques, including mixed methods, quantitative modelling, and qualitative case studies. There are still noticeable gaps, though. Few studies have used longitudinal analyses to assess the long-term effects of RM on the performance of SMEs. Future research should use panel data to examine the following:

- The causal relationships between RM practices and sustained operational efficiency.
- The impact of new technologies on the development of SME risk frameworks, such as blockchain and the Internet of Things.
- The goal of cross-sectoral and cross-regional studies is to set standards for best practices in RM.
- Training programs and experimental interventions aimed at improving SME managers' RM competency.

4.7 Practical Implications

The results emphasize the urgent necessity for practitioners to put structured risk management (RM) frameworks into practice. Small and medium-sized business (SMEs) leaders should make risk management (RM) training a top priority, integrate RM into strategic planning procedures, and use digital tools for risk detection and response. The RM maturity of SMEs can be further strengthened by fostering a culture that places a high priority on risk awareness and forming partnerships with outside parties like banks, governmental agencies, and research groups. By offering incentives for the adoption of RM practices, expanding access to RM consultants and resources, and incorporating RM training into entrepreneurship education programs, policymakers can support this development. By linking financing terms to the presence of strong RM systems, financial institutions can also contribute.

5 CONCLUSION

The impact of risk management (RM) on improving operational efficiency in small and medium-sized businesses (SMEs) was investigated in this systematic review, which looked at 39 peer-reviewed studies published between 2006 and 2025. The findings show that SMEs' internal capabilities, capacity for innovation, and long-term competitiveness are significantly increased by an organized and proactive approach to RM. SMEs are better equipped to handle resource constraints and environmental uncertainties when they use effective RM. They are also more likely to adopt innovative practices and maintain business continuity.

The Resource-Based View (RBV) is strengthened by the theoretical components of this study, which highlight RM as a fundamental internal capability essential to achieving long-term competitive advantage. Furthermore, the relationship between RM and knowledge-based and innovative theories offers a promising foundation for developing hybrid models that capture the intricacies of managing SMEs in unstable environments.

Practically speaking, the findings provide policymakers, managers, and owners of SMEs with insightful advice. Integrating RM into SMEs' strategic and operational framework requires a number of crucial steps, including developing a risk-aware organizational culture, investing in workforce training, leveraging technology, and creating robust social and professional networks. These tactics have the potential to boost innovation, supply chain agility, and decision-making—all of which are essential for raising operational effectiveness.

Future research should build on this work by conducting cross-sectoral and longitudinal studies, developing integrative models that connect RM to performance metrics, and empirically evaluating intervention strategies. Studies of this nature will improve our comprehension of the effects of RM and provide SMEs with useful guidance on how to manage progressively challenging business issues.

In conclusion, this review contributes theoretical and practical perspectives to the discourse on the development of SMEs. It supports the idea that RM is a potent tool that, when used properly, fosters operational excellence and strategic expansion rather than merely serving as a safeguard.

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THE IMPORTANCE OF CITY BRANDING: LITERATURE REVIEW

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Abstract

In an era of increasing global competition and urban transformation, city branding has emerged as a strategic governance tool used by municipalities to differentiate themselves, attract investment, and foster community engagement. This literature review aims to synthesize current academic research on city branding, with a particular focus on its role in public administration, stakeholder involvement, and regional development. The study applies a systematic review methodology guided by the PRISMA 2020 framework. Articles were selected from four elite academic journals ranked in the Academic Journal Guide 2021. Thirteen studies were analyzed to identify thematic trends, methodological approaches, and empirical findings relevant to city branding as a multidimensional governance strategy.

The results reveal that successful city branding depends heavily on stakeholder participation, cultural coherence, and strategic alignment with policy frameworks. Participatory branding initiatives foster stronger place identity and public support, whereas top-down efforts often encounter resistance and fail to resonate with local communities. Additionally, digital media and social platforms offer new opportunities for engagement but require integration with offline strategies to create coherent brand narratives. The review also highlights that effective branding can enhance institutional trust, improve tourism outcomes, and support regional development objectives. This paper contributes to a more integrated understanding of city branding and offers practical insights for policymakers seeking to design inclusive, effective, and context-sensitive branding strategies.

Keywords: *City Branding, Governance, Stakeholder Engagement, Place Identity, Regional Development, Public Administration*

1 INTRODUCTION

In an increasingly globalized and competitive world, cities face growing pressure to differentiate themselves, attract investment, foster tourism, and retain skilled residents. As traditional economic and political boundaries become more fluid, the identity and image of a city have emerged as strategic assets in urban development. This shift has given rise to the practice of city branding, a complex process through which cities construct and communicate distinctive identities to both internal and external audiences (Jansson & Power, 2010; Wæraas et al., 2014).

City branding now extends well beyond conventional marketing functions. It operates as a strategic governance tool that intersects with economic planning, public policy, stakeholder engagement, and cultural representation (Klijn et al., 2012; Stevens et al., 2021). Increasingly, local governments use branding not only to promote tourism and attract businesses, but also to foster civic pride, enhance institutional trust, and legitimize governance processes (Karens et al., 2016; Ripoll González et al., 2023). This reflects broader trends in public management, where narrative and symbolic tools are used to influence perception, mobilize support, and coordinate collective action.

Despite the growing interest in city branding among practitioners, the academic field remains conceptually fragmented. Key debates persist regarding the effectiveness of top-down versus participatory branding models (Pugh & Andersson, 2023; Nathan et al., 2019), the strategic integration of branding within governance frameworks (Wæraas et al., 2014), and the role of digital media and stakeholder co-production in shaping authentic and resonant brand identities (Corradini et al., 2023; Klijn et al., 2022). These topics underscore the need for a comprehensive review of existing literature to clarify the evolving role of branding in public administration and regional development.

This paper aims to address that gap by systematically reviewing the academic literature on city branding, with a focus on its application as a governance strategy. Guided by the PRISMA 2020 framework (Page et al., 2021), the review includes thirteen peer-reviewed articles selected from four top-rated journals listed in the Academic Journal Guide 2021. The selected journals cover the fields of public administration and regional planning, offering a multidisciplinary perspective on city branding practices across diverse geographic and institutional contexts.

The research question guiding this review is: How is city branding conceptualized and applied as a governance tool in contemporary academic literature, and what are the implications for stakeholder engagement, legitimacy, and regional development?

By synthesizing findings from these studies, the review identifies core themes such as stakeholder involvement, branding legitimacy, cultural alignment, and the use of digital channels. The article contributes to a more integrated understanding of city branding and offers practical insights for urban policymakers, branding professionals, and scholars interested in the intersections of narrative, governance, and regional development.

2 LITERATURE REVIEW

The literature review presents a multi-dimensional analysis of public branding strategies, focusing on how different entities, from cities to regions, employ branding as a governance tool, and the various outcomes these strategies create.

2.1 Public Branding as a Strategic Tool

Public branding has increasingly become a strategic tool for cities and regions to enhance their global reputation, attract businesses, and engage citizens. Thomas (2022) explores the partnership between Nike and the City of New York (USA), highlighting the cultural and financial ties that support successful public branding initiatives. The study emphasizes that the success of this branding effort depends on the deep cultural connections between the brand and the city. The research highlights the potential for such agreements to inspire broader adoption of public branding strategies across other cities, provided there is meaningful public engagement and alignment with existing cultural narratives. These findings align with broader literature on place branding, which suggests that authentic and culturally resonant branding efforts are more likely to be successful (Jansson & Power, 2010). The New York-Nike partnership serves as an example for other cities considering similar agreements, as it shows that leveraging existing cultural assets can be a powerful strategy in public branding.

Jansson and Power (2010) and Nathan et al. (2019) provide insights into global and digital place branding strategies. Jansson and Power (2010) explore how cities like Milan (Italy) use various brand channels to establish themselves as global fashion and design hubs. Their study underscores

the importance of interconnected branding efforts, including high-profile events, flagship stores, and media presence, in maintaining and evolving a city's global image.

Stevens et al. (2021) further explore public branding from a governance perspective, analyzing how cities like Rotterdam (the Netherlands) use branding to engage companies as coproducers of the brand. Their findings underscore the importance of transparency and stakeholder involvement in enhancing the legitimacy and effectiveness of branding campaigns. This perspective aligns with Ripoll González et al. (2023), who demonstrate that increased stakeholder participation in place branding correlates with higher levels of Brand Citizenship Behaviour (BCB), thereby fostering stronger place identity and more active brand support.

Karens et al. (2016) extend this discussion to the European Union (EU), examining how EU branding in policy communication can increase citizen trust. Their experimental study reveals that effective branding can influence public perception and trust, even in contexts where the overall sentiment towards the organisation may be negative such as the example of the Netherlands. This finding underscores the power of strategic branding in shaping citizen attitudes and the importance of focusing branding efforts on specific policies rather than the whole organisations.

2.2 Stakeholder Involvement and Its Impact on Branding Effectiveness

The involvement of stakeholders in the branding process is another critical factor highlighted across several studies. Stevens et al. (2021) and Klijn et al. (2012) both emphasize that stakeholder engagement is crucial for the success of place branding initiatives. Stevens et al. (2021) demonstrate that companies in Rotterdam's Makers District prefer to be co-producers of the brand, a process that enhances the legitimacy and effectiveness of the branding campaign. Similarly, Klijn et al. (2012) find that stakeholder involvement, when combined with targeted marketing activities, significantly enhances the effectiveness of city branding efforts. These findings suggest that branding is most effective when it is an inclusive process that engages key stakeholders as active participants.

This idea is further supported by Ripoll González et al. (2023), who find that stakeholder participation in place branding correlates with higher levels of Brand Citizenship Behaviour (BCB). The positive relationship between participation and brand support underscores the importance of involving stakeholders not just in the branding process but in the ongoing development and refinement of the brand. This aligns with the broader discourse on public governance, where transparency and participation are seen as key to achieving policy success (Karens et al., 2016). However, Klijn et al. (2022) who examined the role of collaboration in achieving output legitimacy in place branding campaigns argues that even though collaboration is often emphasized, it is not a necessary condition for legitimacy. The research shows that Dutch-oriented companies benefit from both collaboration and place identity, whereas internationally oriented companies rely more on place dependency. This study suggests that while collaboration is valuable, it should be considered alongside other contextual factors such as place identity and place dependency to optimize branding strategies.

2.3 The Challenges of Top-Down Branding Efforts

While stakeholder involvement is generally beneficial, some studies highlight the challenges associated with top-down branding efforts. Pugh and Andersson (2023) discuss the difficulties Karlskoga (Sweden) faces in leveraging Alfred Nobel's legacy for place branding. The branding strategy, dominated by a small group of powerful stakeholders, risks alienating other segments of

the community and suppressing local identities. This top-down approach contrasts with the more participatory models discussed earlier and suggests that branding strategies that do not adequately engage diverse stakeholders may struggle to achieve their objectives.

Similarly, Nathan et al. (2019) explore the limitations of the top-down Tech City branding initiative in East London (England). While the branding helped elevate London's profile as a tech hub, its impact on local tech firm growth was less significant, and it faced challenges such as rising rents and displacement of local firms. These findings highlight the tension between top-down branding initiatives and the organic development of place identities, suggesting that branding efforts need to be carefully managed to avoid unintended negative consequences.

2.4 Strategic Integration of Branding and Governance

The literature review also reveals that successful place branding requires a strategic integration of branding efforts with broader governance and policy frameworks. Wæraas et al. (2014) propose a multi-dimensional approach to municipal branding, combining place branding, organisation branding, and democracy branding strategies. The study of Norwegian municipalities highlights that the municipalities, which function not only as geographic entities but also as service providers and political institutions may prioritize different branding strategies depending on their specific challenges and goals. The study's findings advocate for a nuanced understanding of place branding that goes beyond basic marketing to include the full range of governance activities.

2.5 The Role of Social Media and Digital Channels in Place Branding and Sustainable Tourism

Corradini et al. (2023) and Van der Zee et al. (2024) explore the role of social media and sustainable tourism in place branding. Corradini et al. (2023) analyze the effectiveness of social media communication in promoting European entrepreneurial ecosystems, finding that while social media increases visibility, it often fails to create distinct and emotionally resonant place brands. The literature points to the need for a more strategic approach to digital branding, where social media efforts are integrated with broader branding strategies to create cohesive and impactful place identities.

Van der Zee et al. (2024) examine the impact of the UNESCO World Heritage Site (WHS) label on sustainable tourism in Europe. Their study shows that WHS-labeled locations receive higher tourist satisfaction ratings and offer a broader range of activities, contributing to regional development goals. However, the challenges in managing increased tourist traffic highlight the need for integrated place branding and tourism management strategies that involve all local stakeholders.

2.6 Synthesis and Research Gap

Despite the growing body of literature, city branding research remains conceptually fragmented. While some studies emphasize participatory and stakeholder-driven approaches (Stevens et al., 2021; Ripoll González et al., 2023), others point to the relative effectiveness of top-down approaches under certain institutional or market conditions (Thomas, 2022; Nathan et al., 2019). This tension reveals an ongoing debate about the optimal balance between stakeholder co-creation and centralized strategic control in city branding.

Moreover, while individual case studies provide valuable insights into place-specific branding practices, there is limited comparative synthesis across geographic and policy contexts. Key questions remain underexplored, including how branding efforts align with broader governance objectives, how digital tools are integrated into long-term branding strategies, and how outcomes such as legitimacy or regional development are evaluated.

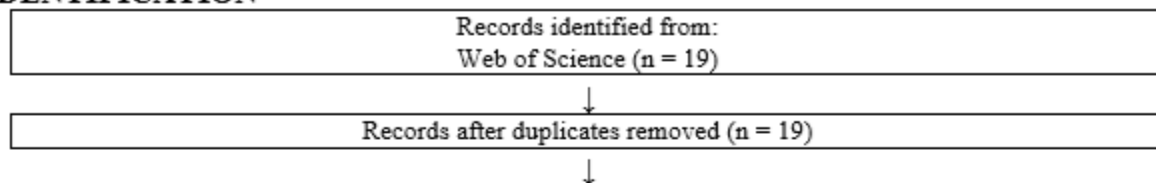
These gaps underscore the need for a systematic review that integrates insights across disciplines and policy contexts. Such a synthesis can clarify how city branding functions as a governance tool and its implications for stakeholder participation, legitimacy, and regional development.

3 METHODOLOGY

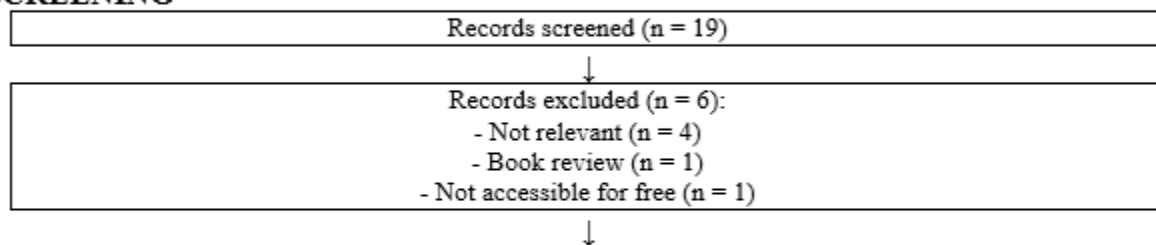
The literature review is based on the PRISMA 2020 statement that provides a reporting guidance for systematic literature reviews Page et al. (2021). The aim was to critically review high-quality, peer-reviewed studies that explore city branding as a strategic governance tool.

The selection of research journals was intentionally limited to those ranked with four stars in the Academic Journal Guide 2021, issued by the Chartered Association of Business Schools. This criterion was applied to ensure the academic quality, methodological precision, and relevance of the reviewed studies. Moreover, selected journals had to include research articles directly focused on the topic of city branding. This combined focus on ranking and topical relevance was chosen to strengthen the validity and depth of the literature review.

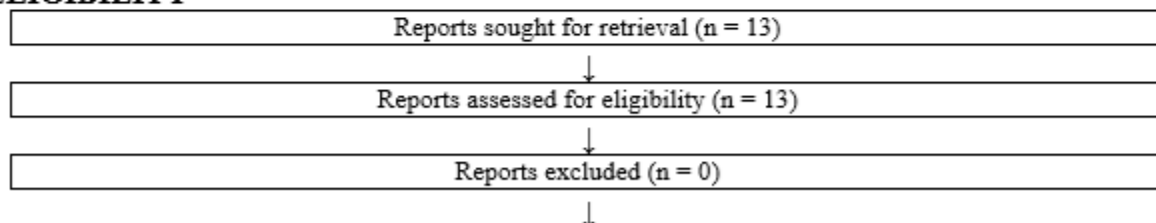
IDENTIFICATION



SCREENING



ELIGIBILITY



INCLUDED

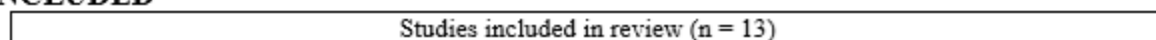


Fig. 1 – PRISMA 2020 Flow Diagram Source: Page et al. (2021)

The literature search was conducted in the Web of Science database using the keyword “city branding.” Four high-ranking journals were identified based on relevance to the topic and subject area: Public Administration Review and Public Management Review (focused on public sector and governance), and Regional Studies and Journal of Economic Geography (focused on spatial planning and regional development). Only English-language articles available as open access were considered, to ensure both accessibility and research transparency.

The total of nineteen articles was identified. Each article was manually screened by reviewing its title and abstract. The screening resulted in elimination of six articles. Four of them were not relevant, one was a book review and not a research article and one article was not accessible for free. The total of thirteen articles was reviewed.

The selected studies were then examined using qualitative content analysis. Each article was analyzed in terms of its aims, research methodology, thematic focus, and geographic or institutional context. This analysis enabled the identification of common patterns, key insights, and conceptual frameworks that inform the thematic structure of the results section. Key areas of focus included stakeholder engagement, digital branding strategies, governance integration, and the effectiveness of top-down versus participatory branding approaches.

4 RESULTS

The systematic literature review identified thirteen high-quality peer-reviewed research articles published in 4-star academic journals according to the Academic Journal Guide 2021. These articles span diverse geographical contexts, research methodologies, and disciplinary perspectives, offering a comprehensive understanding of city branding.

The reviewed studies cover a broad temporal and geographic range. The publication years span from 2010 to 2024, reflecting both foundational contributions and the latest advancements in the field. The geographical focus includes countries from Western and Northern Europe (e.g., Netherlands, Norway, Sweden, Italy, England), North America (USA), and multi-country European contexts, including comparative studies involving Belgium, Poland, and pan-European regions. The Netherlands appears most frequently as a national context or author affiliation, indicating a strong academic presence in city branding and governance studies. Several articles, including those by Klijn et al. (2012, 2022) and Ripoll González et al. (2023), offer insights into Dutch regional branding initiatives, suggesting a particularly rich empirical ground for stakeholder-driven and governance-based approaches.

Tab. 1 – Aim and objective of the reviewed articles. Source: own research

Author	Year	Country	Aim and Objective
Corradini et al.	2023	Europe (20 cities)	To assess the role of social media communication in promoting entrepreneurial ecosystems and city branding.
Jansson & Power	2010	Italy	To examine how global city brand channels contribute to Milan’s status as a fashion hub.
Karens et al.	2016	Belgium, Poland, Netherlands	To investigate whether EU branding in policy communication increases citizen trust.
Kasabov & Sundaram	2013	England	To propose a stakeholder-based approach to branding industrial clusters.

Klijn et al.	2012	Netherlands	To assess the effect of stakeholder involvement, brand concept, and marketing activities on branding effectiveness.
Klijn et al.	2022	Netherlands	To analyze conditions under which collaboration influences output legitimacy in place branding.
Nathan et al.	2019	England	To analyze how the Tech City branding shaped spatial imaginaries and affected tech cluster development in East London.
Pugh & Andersson	2023	Sweden	To evaluate the challenges of branding Karlskoga around Alfred Nobel's legacy.
Ripoll González et al.	2023	Netherlands	To examine the relationship between stakeholder participation and Brand Citizenship Behaviour (BCB).
Stevens et al.	2021	Netherlands	To explore how companies perceive and respond to public branding strategies in Rotterdam.
Thomas	2022	USA	To analyze how apparel licensing agreements (e.g., NYC and Nike) influence city branding through cultural and financial ties.
Van der Zee et al.	2024	Europe	To assess the impact of the UNESCO World Heritage Site label on sustainable tourism and regional development.
Wæraas et al.	2014	Norway	To explore municipal branding strategies across place, organisation, and democracy dimensions.

The review revealed five principal thematic findings that collectively highlight the strategic significance, challenges, and outcomes of place branding initiatives:

- Strategic Use of Branding in Governance
- Stakeholder Engagement as a Determinant of Branding Success
- Tensions in Top-Down Branding Models
- Digital Media, Communication, and Identity Co-Creation
- Branding Outcomes: Trust, Tourism, and Regional Development

4.1 Strategic Use of Branding in Governance

The reviewed literature confirms that city branding is increasingly adopted as a strategic governance tool aimed at enhancing a city's global visibility, competitiveness, and attractiveness. Municipalities, such as those in Norway and the Netherlands, have integrated branding within their policy frameworks to address demographic decline, stimulate economic development, and foster civic engagement (Wæraas et al., 2014; Klijn et al., 2012). The New York City-Nike licensing agreement (Thomas, 2022) demonstrates how cities can leverage corporate partnerships to foster cultural identity and global reach, provided there is alignment with local narratives.

4.2 Stakeholder Engagement as a Determinant of Branding Success

A frequent finding across the studies is the critical role of stakeholder participation in enhancing the legitimacy, coherence, and effectiveness of branding initiatives. Branding efforts that incorporate local businesses, residents, and civil society organisations tend to foster stronger place identity and support, as evidenced by the positive correlation between stakeholder involvement

and Brand Citizenship Behaviour (Ripoll González et al., 2023; Stevens et al., 2021). In contrast, top-down or exclusionary branding strategies may disengage local communities, weakening both the relevance and resonance of the brand, as evidenced by the cases of Karlskoga and East London (Pugh & Andersson, 2023; Nathan et al., 2019).

4.3 Tensions in Top-Down Branding Models

Several case studies illuminate the tensions and limitations inherent in top-down branding strategies. In East London's Tech City initiative, while the brand succeeded in raising the area's global profile, it fell short in stimulating localized tech firm growth and triggered displacement pressures (Nathan et al., 2019). In the case of Karlskoga, efforts to build a city brand centered on Alfred Nobel's legacy were undermined by a lack of broad community participation and disagreements over how his history should be represented (Pugh & Andersson, 2023). These cases underscore the importance of participatory branding processes that reflect the diversity and complexity of local identities.

4.4 Digital Media, Communication, and Identity Co-Creation

The integration of digital media and social platforms into city branding presents both opportunities and challenges. Social media enhances visibility and allows for broader participation but often fails to establish emotionally resonant or differentiated place identities (Corradini et al., 2023). The analysis suggests that social media efforts must be strategically aligned with offline branding and governance activities to support coherent identity construction. Furthermore, digital branding initiatives are most effective when they foster co-creation and narrative inclusion among stakeholders rather than focusing solely on promotional content.

4.5 Branding Outcomes: Trust, Tourism, and Regional Development

Effective branding not only shapes external perceptions but can also produce tangible outcomes in terms of trust, tourism, and regional growth. Empirical evidence from the European Union branding study (Karens et al., 2016) indicates that branding policy messages can enhance citizen trust, even in skeptical contexts. Moreover, the UNESCO World Heritage Site (WHS) designation has been shown to positively influence tourist satisfaction and service diversification, aligning with sustainable development goals (Van der Zee et al., 2024). These findings reinforce the potential of strategic branding to serve as a catalyst for broader public value creation.

The reviewed literature demonstrates that successful city branding is a multi-dimensional effort that requires strategic governance integration, active stakeholder involvement, contextual sensitivity, and coherent communication strategies. While top-down models may generate short-term visibility, long-term brand resilience and effectiveness are more likely when branding processes are inclusive, participatory, and aligned with local identities and development goals.

5 DISCUSSION

The findings of this literature review highlight the evolving role of city branding as an integral component of urban governance and strategic planning. Across diverse geographical contexts and methodological approaches, the reviewed studies reveal how city branding is no longer limited to marketing or tourism promotion but functions as a multi-layered governance instrument aimed at fostering economic growth, social cohesion, and global competitiveness.

One of the most consistent themes across the literature is the critical importance of stakeholder involvement. Studies by Stevens et al. (2021), Ripoll González et al. (2023), and Klijn et al. (2012) demonstrate that inclusive branding processes that engage businesses, residents, and civil society actors tend to result in more coherent brand narratives, stronger place identity, and higher levels of support through Brand Citizenship Behaviour (BCB). These findings confirm that place branding is most successful when it is collaborative and participatory, functioning as a co-produced governance tool rather than a top-down promotional exercise.

In contrast, cases such as East London's Tech City and Karlskoga's Nobel-centered branding illustrate the challenges of top-down approaches. Although these initiatives raised the external profile of the particular locations, their limited engagement with local communities led to resistance, fragmentation, and questions about legitimacy. In Karlskoga, for example, the attempt to center the city's identity on Alfred Nobel's legacy struggled because of insufficient local involvement and conflicting interpretations of Nobel's historical image. These findings suggest that top-down branding efforts may risk disconnecting from the lived experiences and expectations of local populations, ultimately weakening the brand's authenticity and effectiveness.

Furthermore, the discussion of digital platforms and social media underscores the dual-edged nature of these technologies. While they facilitate broader dissemination and participatory engagement, as Corradini et al. (2023) show, their potential remains underutilized in generating emotionally resonant and distinct city brands. The integration of online and offline branding strategies is essential to build cohesive place narratives that resonate both locally and globally.

The literature also supports the notion that place branding can generate tangible governance outcomes. Karens et al. (2016) provide evidence that effective branding can enhance citizen trust in public institutions, even in contexts where institutional legitimacy is challenged. Similarly, Van der Zee et al. (2024) highlight the contribution of UNESCO World Heritage Site labels to sustainable tourism and regional development. These findings suggest that when properly aligned with governance goals, city branding can serve as a catalyst for public value creation.

Finally, several authors call for a more nuanced, context-sensitive approach to place branding. Wæraas et al. (2014) propose a multi-dimensional model that considers municipalities as places, service providers, and political institutions. This framework underscores the need to adapt branding strategies to specific local challenges, capacities, and audiences. The mixed results across case studies further reinforce the argument that there is no one-size-fits-all solution in city branding. Effective branding depends not only on the tools and strategies used but also on how well they are included in broader policy, governance, and socio-cultural contexts.

Despite the recurring themes, the literature is not without inconsistencies. While several studies emphasize the importance of stakeholder co-production and participatory branding (Stevens et al., 2021; Ripoll González et al., 2023), other research illustrates that top-down approaches, despite their limitations, have contributed to increased visibility or generated certain economic advantages (Thomas, 2022; Nathan et al., 2019). These contrasting outcomes suggest that the effectiveness of branding strategies is highly context-dependent, influenced by local governance models, cultural narratives, and institutional frameworks.

A clear trend in the reviewed literature is the growing integration of digital media and data-driven tools in city branding efforts (Corradini et al., 2023; Nathan et al., 2019). However, there remains a gap between technological potential and practical implementation, especially in translating online visibility into authentic place identity.

The implications of these findings can be understood on two levels: theoretical and practical. From a theoretical perspective, they encourage a reconceptualization of city branding as a governance mechanism rather than merely a communication tool (Wæraas et al., 2014). This calls for more integrative frameworks that combine public administration, regional development, and identity politics. In practical terms, the review offers guidance for policymakers, urban managers, and branding professionals to prioritize stakeholder engagement, transparency, and narrative coherence as foundations for resilient city brands.

This study also has limitations that should be acknowledged. The review was limited to articles published in 4-star journals as ranked by the Academic Journal Guide 2021, which may have excluded relevant insights from other reputable but lower-ranked or interdisciplinary sources. The focus on English-language, open-access articles further narrows the scope. Additionally, the review does not include grey literature or practitioner reports, which could provide valuable real-world perspectives. Future research should consider expanding the range of sources and incorporating empirical case studies to capture a more holistic view of branding practices.

In summary, the literature reviewed in this study reveals both the promise and the complexity of city branding as a governance tool. Future research should continue to explore the interplay between branding, stakeholder governance, and regional development, particularly in the context of digital transformation and demographic change. These dynamics are reshaping how cities compete, collaborate, and communicate in increasingly complex environments, making it essential to understand how branding strategies can respond to and anticipate such structural shifts.

Equally important is the need to develop evaluative frameworks that can assess not only the visibility of branding efforts but also their social, economic, and institutional impacts. Without robust assessment tools, city branding risks remaining a symbolic or promotional exercise, lacking evidence of its long-term value for governance, inclusion, or regional competitiveness.

6 CONCLUSION

The literature review has examined the evolving role of city branding as a complex governance strategy, drawing from thirteen studies published in elite academic journals. The findings emphasise that city branding is no longer a peripheral marketing activity but a cross-cutting strategic tool that relates to urban governance, economic development, stakeholder engagement, and identity construction.

A key conclusion emerging from the review is that inclusive stakeholder participation is a fundamental determinant of branding success. Branding efforts that engage local actors - such as businesses, residents, and institutions - tend to foster stronger place identity and increase long-term legitimacy through mechanisms like Brand Citizenship Behaviour (BCB).

The review also underscores the strategic role of digital platforms and social media, while cautioning against over-reliance on them without a clear narrative and offline engagement. Although these tools enhance visibility, they may fall short in building lasting city identity unless integrated within broader policy and communication frameworks.

Finally, the literature confirms that effective city branding can deliver measurable public value, including citizen trust, improved tourism, and regional development, especially when branding aligns with policy goals and authentic local narratives.

Despite these benefits, persistent gaps remain - particularly regarding inclusivity, local adaptability, and long-term evaluation. More empirical studies are also needed to evaluate long-term impacts and to develop tools for assessing branding success beyond visibility metrics. This is essential to distinguish short-term promotional effects from deeper contributions to governance, identity, and community development.

Future research should also further explore how city branding intersects with governance and regional development goals, particularly in relation to demographic shifts, digital engagement, stakeholder management, and the challenges of attracting and retaining new residents. Such research could guide the creation of branding models that are better equipped to respond to the complexity and volatility of modern urban environments.

In conclusion, city branding holds considerable promise as a strategic asset for modern cities, but its effectiveness relies on participatory governance, alignment with local culture, and policy integration. Cities that embrace these principles are more likely to cultivate resilient, inclusive, and globally recognized urban identities.

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MEAN-VARIANCE PORTFOLIO OPTIMIZATION BASED ON COMPLEX NETWORK CONSTRAINTS

Qian Gao

Abstract

This study develops an integrated decision-making framework that combines complex network analysis with portfolio optimization and empirically validates its effectiveness using constituent stocks of the Dow Jones Industrial Average (DJIA). The framework begins by applying the Ledoit-Wolf shrinkage estimator to construct a robust stock correlation network, which serves as the basis for identifying significant community structures and influential hub nodes. A range of complex network metrics are subsequently calculated and embedded within the portfolio optimization process. A key innovation of this research lies in the introduction of two novel constraints that guide portfolio construction: one restricts the overall allocation to highly central assets, defined as those exceeding a specified centrality percentile, in order to mitigate concentration risk. At the same time, the other imposes a structural diversification constraint by limiting the total weight assigned to any single detected community. Out-of-sample testing, based on a 70/30 train-test split, reveals that the proposed network-constrained strategy yields superior performance relative to the traditional mean-variance model. Moreover, the empirical results reveal that the portfolio constrained by the sparsest network configuration achieves the best performance, suggesting that retaining only the strongest and most stable correlations provides a more reliable topological foundation. This enhances the effectiveness of the imposed constraints and mitigates the detrimental impact of noisy or transient relationships commonly present in lower-threshold networks on the optimization outcomes.

Keywords: *Complex network, portfolio optimization, community structure constraints, centrality measures, out-of-sample test*

1 INTRODUCTION

In the realm of modern finance, the pursuit of optimal portfolio allocation remains a cornerstone for investors aiming to maximize returns while mitigating risk. Traditional portfolio optimization techniques, notably the Mean-Variance (MV) framework introduced by Markowitz, rely heavily on statistical measures such as expected returns and covariance matrices. While foundational, these methods often operate under assumptions of asset independence or simple linear relationships, potentially overlooking the intricate, dynamic interdependencies that characterize real-world financial markets. As markets become increasingly interconnected and volatile, a deeper understanding of these complex relationships is imperative for developing more robust and resilient investment strategies.

The burgeoning field of complex network theory offers a powerful lens through which to analyze and model these intricate financial interdependencies. By representing financial assets as nodes and their relationships (e.g., correlations) as edges, a financial market can be transformed into a quantifiable network structure. This topological perspective allows for the identification of central assets, community structures, and other systemic properties that are not readily apparent through traditional statistical analysis. Such network insights can illuminate hidden risks, reveal

diversification opportunities, and provide a more nuanced understanding of how shocks propagate through the system, thereby offering a richer context for investment decisions.

This study proposes an innovative approach to portfolio optimization by integrating the analytical power of complex network theory directly into the MV framework. We move beyond conventional constraints by introducing network-based constraints that explicitly account for the market's structural properties. Specifically, our methodology incorporates constraints that regulate the concentration of investments in highly central assets—those identified as having significant influence or connectivity within the network—and promotes diversification across different asset communities.

To demonstrate the efficacy of this novel approach, we employ a rigorous out-of-sample backtesting methodology. This involves constructing the financial network and optimizing portfolios using a training dataset and then evaluating the performance of these portfolios on an unseen test dataset. We benchmark the proposed network-constrained MV strategy against both a standard MV-optimized portfolio and a simple, equally weighted portfolio. This comparative analysis, assessing key performance metrics such as annualized returns, volatility, and Sharpe ratios, aims to highlight the tangible benefits of leveraging network insights for superior risk-adjusted returns in real-world investment scenarios.

The remainder of this paper is organized as follows. Section 2 provides a systematic review and critique of the relevant literature, highlighting the key findings and existing gaps. Section 3 presents the core methodology of this study along with the main mathematical formulations. Section 4 applies the proposed method to empirical data, followed by a detailed analysis of the results. Section 5 offers an in-depth discussion of the main findings. Finally, Section 6 concludes the paper by summarizing the research, methodological contributions, and empirical insights, and outlines directions for future research.

2 LITERATURE REVIEW

In recent years, the application of complex networks in modeling financial asset relationships and optimizing portfolio allocation has garnered increasing attention, particularly in the context of asset pricing and the detection of systemic risk. Empirical evidence suggests that the strength of nonlinear correlations can significantly expand investment exposure, and network effects become markedly more prominent during financial crises, facilitating the identification of systemic vulnerabilities (Haluszczynski et al., 2017). Furthermore, networks constructed using full cross-correlation matrices and global movement matrices effectively filter out market noise, revealing that peripheral nodes often exhibit higher profitability and greater diversification potential than their central counterparts (Li et al., 2019).

Building upon these insights, a growing body of literature has explored the direct integration of network-derived metrics into portfolio optimization frameworks. Konstantinov et al. (2023) highlight that real-world financial networks typically exhibit sparsity, clustering, and non-random connectivity—structural properties closely linked to the dynamics of information diffusion and the propagation of systemic risk. While portfolios composed of peripheral assets tend to achieve higher cumulative returns, they are generally accompanied by greater volatility and reduced risk resilience; in contrast, portfolios centered around core assets demonstrate superior stability (Huang et al., 2024). These findings underscore the potential of incorporating neighborhood constraints

and local clustering coefficients into optimization objectives, thereby enhancing structural risk control (Ricca & Scozzari, 2024).

Simultaneously, complex network methodologies have been widely employed in the development of asset selection and allocation strategies. For instance, Yan et al. (2021) introduced a "fundamental network" that integrates fundamental indicators and financial ratios to identify stocks characterized by lower volatility and greater resilience. By leveraging random walk processes within the network, assets associated with nodes of higher visitation frequency are prioritized, resulting in improved return performance under equivalent risk conditions. Moreover, it has been shown that negatively correlated edges promote diversification, whereas positively correlated edges are more conducive to concentrated investment strategies (Freitas & Bertini, 2023).

In the broader context of portfolio construction, the design of constraint mechanisms plays a critical role in shaping optimization outcomes. Liagkouras and Metaxiotis (2018) investigated the behavior of multi-objective evolutionary algorithms under multiple constraints, emphasizing how classification-based restrictions can indirectly reshape the bounds of asset weights. Complementary findings by Castilho et al. (2019), who integrated echo-state prediction with weighted link forecasting, demonstrated the superiority of data-driven approaches over traditional mean-variance (MVA) strategies, highlighting the efficacy of network learning mechanisms in enhancing investment performance.

Finally, with the expansion of research across multiple asset and market dimensions, the role of network centrality in asset selection has become increasingly significant. Wang et al. (2024) constructed a cross-market correlation network comprising 86 assets and systematically evaluated various centrality measures, identifying PageRank, eigenvector, and hybrid centralities as the most informative for portfolio decisions. Similarly, Yan et al. (2024) integrated DuPont decomposition with graph theory to construct an ROE-based network, uncovering intricate links between profitability structure, industry heterogeneity, and network clusters. The study shows that inter-cluster diversification reflects differences in business models. In contrast, intra-cluster diversification enhances sectoral balance, which exhibits a linear relationship with out-of-sample portfolio performance.

3 METHODOLOGY

This study proposes a network-constrained portfolio optimization framework that incorporates complex network topology into the classic mean-variance model. The approach involves estimating asset correlations, constructing a threshold-based financial network, and incorporating network-derived constraints into the portfolio optimization process. To ensure the robustness and stability of the input covariance matrix used in portfolio optimization, this study adopts the Ledoit-Wolf shrinkage estimator, a widely accepted method designed to address the inherent estimation errors of the sample covariance matrix, particularly when the number of assets is large relative to the sample size. The corresponding equations are presented in (1),

$$\hat{\Sigma}_{LW} = \hat{\delta} \cdot F + (1 - \hat{\delta}) \cdot S, \quad (1)$$

where S denotes the sample covariance matrix, F represents the structured target matrix (typically the identity matrix), $\hat{\delta}$ is the shrinkage intensity determined by minimizing the Frobenius norm, and $\hat{\Sigma}_{LW}$ refers to the Ledoit-Wolf shrinkage covariance matrix. This approach enhances the

conditioning of the covariance matrix by shrinking the sample estimator toward a structured and well-behaved target, often chosen as the identity matrix scaled by the average variance or a constant correlation matrix. The shrinkage procedure effectively balances the trade-off between bias and variance, yielding a more stable estimator that is less sensitive to sampling noise.

This study proposes an enhanced mean-variance portfolio optimization model constrained by complex network features. Building upon the traditional mean-variance framework of Markowitz (1952), the model innovatively incorporates topological constraints derived from stock correlation networks, thereby formulating a network-driven portfolio optimization strategy. The corresponding formulation is presented in equation (2),

$$\begin{aligned}
& \max_{\mathbf{w}} \quad \mu^\top \mathbf{w}, \\
& s. t. \quad \sum_{i=1}^N w_i = 1, \\
& \quad \quad w_i \geq 0, \forall i, \\
& \quad \quad \sum_{i \in \mathcal{H}} w_i \leq \alpha \cdot \frac{|\mathcal{H}|}{N}, \\
& \quad \quad \sum_{i \in \mathcal{C}_k} w_i \leq \beta \cdot \frac{|\mathcal{C}_k|}{N} \forall k,
\end{aligned} \tag{2}$$

where μ denotes the expected return vector, $\mathbf{w}$ represents the asset weight vector, $\mathcal{H}$ refers to the set of highly central assets, α is the centrality constraint factor, β is the community constraint factor, and $\mathcal{C}_n$ denotes the set of assets belonging to the n th community. These network features are translated into portfolio constraints: on the one hand, the weights allocated to highly central nodes are capped to prevent excessive concentration in the structural core of the network; on the other hand, the proportion of portfolio weights assigned within each community is controlled to ensure sufficient diversification across distinct correlation-based clusters.

Betweenness centrality measures a node's ability to act as an intermediary along the shortest paths between other nodes in the network, reflecting its role in bridging information or influencing the transmission of information. It is defined as shown in equation (3),

$$C_B(v) = \sum_{s \neq v \neq t \in V} \frac{\sigma_{st}(v)}{\sigma_{st}}, \tag{3}$$

where σ_{st} denotes the total number of shortest paths between nodes s and t , while $\sigma_{st}(v)$ represents the number of those paths that pass through node v . This measure reflects the extent to which node v controls the shortest-path connectivity within the network, with higher values indicating a more critical and influential position.

Eigenvector centrality measures a node's influence within the network by accounting for the importance of its neighbouring nodes. Unlike simple degree-based metrics, it assigns higher scores to nodes that are connected to other highly influential nodes, thereby capturing the recursive nature of influence. The formal definition is provided in equation (4),

$$C_E(v) = \frac{1}{\lambda} \sum_{u \in N(v)} A_{uv} \cdot C_E(u), \tag{4}$$

where λ denotes the corresponding eigenvalue, $C_E(v)$ represents the eigenvector centrality vector, and A_{uv} is the weighted adjacency matrix of the network. Typically, the eigenvector associated with the largest eigenvalue is selected. This centrality measure emphasises the position of a node about other influential nodes, making it particularly suitable for identifying structurally core assets and sources of systemic influence within the network.

The clustering coefficient describes the local density of connections in a network and measures the extent to which a node's neighbours form tightly knit triangular structures. It is defined in equation (5),

$$C(v) = \frac{2 \cdot E_v}{k_v \cdot (k_v - 1)}, \quad (5)$$

where E_v denotes the number of triangles that include node v as a vertex, and k represents the degree of node v , the number of its directly connected neighbours. The clustering coefficient ranges from 0 to 1, with higher values indicating tighter connections among a node's neighbours. This measure is handy for identifying tightly knit subgroups within local markets or clusters of highly coupled assets.

4 RESULTS

The empirical result utilises daily adjusted closing prices of the 30 constituent stocks of the DJIA, spanning from January 2019 to December 2024. This period captures a range of market conditions, including episodes of both relative stability and heightened turbulence. The data is divided into 0.7 and 0.3 for the training period and test period (out-of-sample period), respectively. To ensure robustness in correlation estimation, the Ledoit-Wolf shrinkage estimator is applied, providing a more stable input for subsequent network construction.

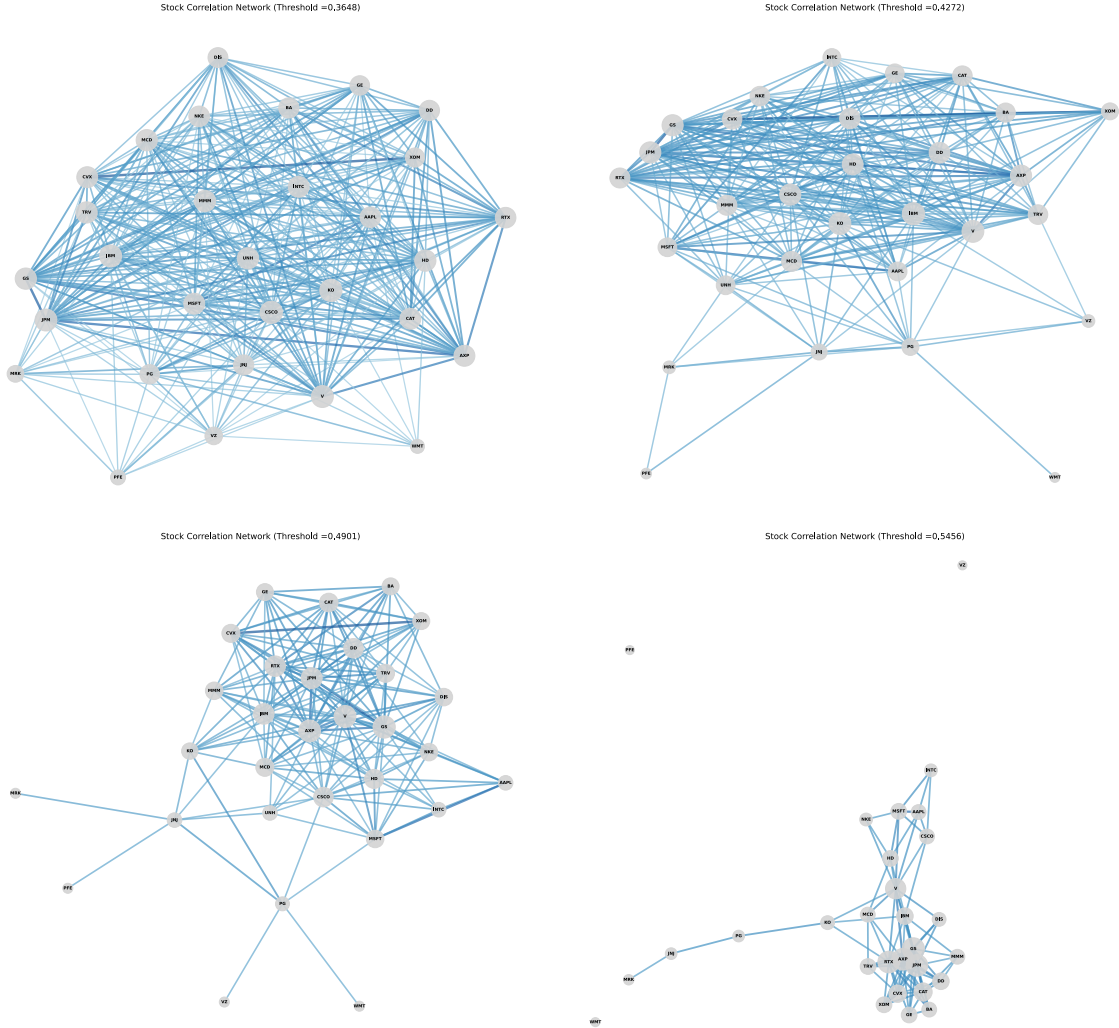


Fig. 1 – Force-directed complex networks constructed under varying threshold levels. Source: own research

Figure 1 presents force-directed layout networks constructed under varying correlation thresholds. As the threshold increases, the network evolves from a densely entangled configuration into a sparser and more modular structure, where weaker correlations are deliberately filtered out to retain only the most significant inter-asset connections. Under low-threshold settings, nodes appear tightly clustered, reflecting a high degree of market-wide connectivity in which nearly all assets exhibit at least moderate levels of correlation. This dense architecture suggests a more systemic market environment in which shocks can propagate broadly. Conversely, at higher thresholds, the network fragments into more distinct clusters, with diminished or absent inter-cluster connections, thereby revealing latent structural segmentation within the market. These transformations are not merely visual but signal a transition from homogenised market behaviour to more heterogeneous and potentially diversified dynamics.

Moreover, these topological shifts have direct implications for portfolio construction beyond changes in community structure. In low-threshold networks, the spatial concentration of nodes around dominant hubs suggests that a small number of assets may exert a disproportionate influence on systemic behaviour, thereby increasing the risks of concentration and contagion. As

the threshold rises, the weakening gravitational pull of these central nodes and the increased spacing among peripheral assets reflect a redistribution of influence and a reduction in systemic coupling. This decoupling is critical for achieving structural diversification, as it implies the presence of relatively independent asset groupings. The fragmentation observed in high-threshold networks aligns with the theoretical objective of identifying robust diversification opportunities: by focusing solely on strong and stable correlations, the resulting asset clusters are more likely to reflect underlying economic fundamentals rather than transient co-movements.

Tab. 1 – Evaluation indicators of complex networks under different thresholds. Source: own research

Q	CT	N	E	ABC	AEC	ACC
0.2	0.3648	30	348	0.0071	0.1784	0.8942
0.4	0.4272	30	260	0.0172	0.1690	0.7946
0.6	0.4901	30	174	0.0300	0.1600	0.6067
0.8	0.5456	30	87	0.0345	0.1383	0.5278

Note: Q represents the quantile, CT denotes the correlation threshold, N is the number of nodes, E is the number of edges, ABC refers to the average betweenness centrality, AEC to the average eigenvector centrality, and ACC to the average clustering coefficient.

Table 1 illustrates how the topology of stock correlation networks evolves with increasing quantile thresholds (Q) and the corresponding correlation thresholds (CT), under otherwise constant conditions. As Q rises from 0.2 to 0.8 and CT increases from 0.3648 to 0.5456, the network undergoes progressive sparsification. The number of edges (E) drops significantly from 348 to 87, while the number of nodes (N) remains constant at 30, indicating a shift toward retaining fewer but more robust correlations. This structural sparsity enhances the visibility of potential modular organization within the network, as weak and possibly noisy correlations are eliminated, allowing dominant relationships to shape the topology more explicitly. As the network becomes increasingly sparse, the average betweenness centrality (ABC) rises substantially from 0.0071 to 0.0345, suggesting a growing concentration of control within a limited set of nodes that now function as critical bridges. These nodes emerge as pivotal channels for the flow of information or influence, implying that with higher thresholds, the network's vulnerability to disruption becomes more node-specific.

Simultaneously, the average eigenvector centrality (AEC) declines steadily from 0.1784 to 0.1383, indicating a reduction in the influence of globally central nodes within the network. As the correlation threshold increases, highly connected hub nodes lose part of their dominance, reflecting a flattening of the hierarchical structure typical of densely connected financial systems. This transition implies a more even distribution of influence among peripheral nodes, even though the increase in ABC suggests that a few nodes still dominate in terms of structural brokerage. The average clustering coefficient (ACC) also experiences a pronounced decline from 0.8942 to 0.5278, signifying the weakening of local triangular relationships. The reduction in local cohesion implies the fragmentation of tightly knit groups, potentially limiting the speed and intensity of local shock transmission. From a portfolio optimization perspective, these topological transitions are critical: a sparser, less clustered network implies a more modular financial structure, thereby supporting more effective diversification. However, the concurrent rise in betweenness centrality

highlights the necessity for constraint-based strategies that limit exposure to structurally critical nodes, thereby balancing systemic vulnerability and diversification potential.

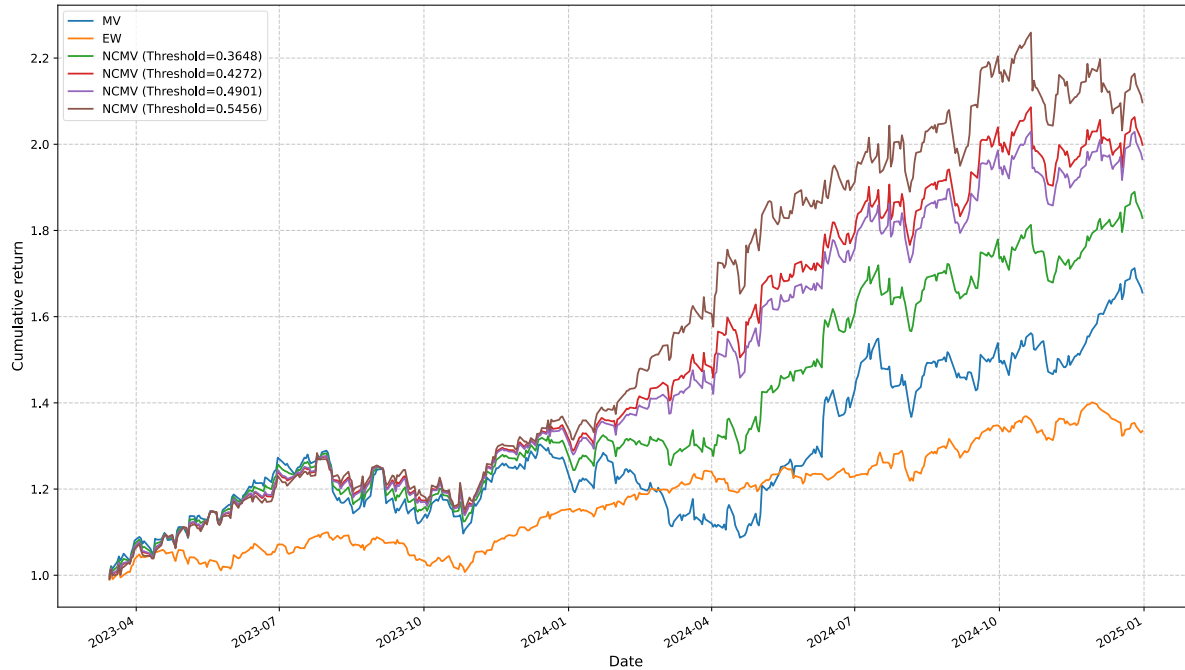


Fig. 2 – Cumulative out-of-sample returns under different strategies and thresholds. Source: own research

Figure 2 illustrates the out-of-sample cumulative returns of five portfolio strategies under identical market conditions, including the equally weighted (EW) benchmark, the traditional mean-variance (MV) model, and four variants of network-constrained mean-variance (NCMV) strategies constructed under increasing correlation thresholds. All NCMV portfolios outperform the two benchmark strategies throughout the testing period, demonstrating the effectiveness of integrating complex network structures into the optimization process. By penalizing highly central assets and enforcing diversification at the community level, network-based portfolios introduce an additional layer of systemic awareness that is absent from the conventional MV framework. This structural sensitivity enables the NCMV portfolios to detect latent patterns of co-movement and systemic concentration, resulting in superior risk-adjusted return trajectories. While the cumulative growth of EW and MV portfolios remains relatively flat and more volatile, the NCMV strategies exhibit consistently upward trends, indicating greater robustness and adaptability to evolving market dynamics.

Among the NCMV strategies, the portfolio constructed under the highest correlation threshold of 0.5456 achieves the best cumulative performance, followed by those based on thresholds of 0.4272, 0.4901, and 0.3648. This ranking reveals a non-monotonic relationship between network sparsity and portfolio performance. Although lower thresholds produce denser networks that capture broader asset correlations, they may also incorporate noisy or less stable relationships, diminishing the effectiveness of structural constraints. In contrast, networks constructed at the 0.8 quantile threshold emphasize only the strongest and most persistent connections, allowing the optimization model to focus on the core interdependencies of the market. This concentrated and topologically informative architecture enhances the precision of constraint enforcement, particularly in identifying and managing exposure to structurally influential assets and cohesive

communities. Consequently, the superior performance of the sparsest NCMV portfolio suggests that carefully filtering the correlation network to retain only high-confidence links can improve both interpretability and return outcomes.

5 DISCUSSION

Empirical results demonstrate that incorporating network-based constraints into the classical mean-variance optimization framework can significantly enhance out-of-sample portfolio performance. Notably, under identical market conditions, all four variants of the network-constrained mean-variance (NCMV) portfolios outperform both the equally weighted and the unconstrained mean-variance strategies. This performance advantage is attributable to the topological awareness embedded within the NCMV framework, which leverages complex network features—such as centrality and community structure—to guide portfolio construction. By limiting exposure to systemically central assets and enforcing diversification at the community level, the NCMV approach mitigates implicit concentration risks that traditional models often overlook. These findings suggest that conventional diversification based solely on return and risk metrics can be effectively augmented through structural constraints derived from inter-asset correlation networks.

An intriguing and perhaps counterintuitive insight emerges from the ranking of cumulative returns under different correlation thresholds. Contrary to the expectation that denser networks (associated with lower thresholds) might support more stable constraint structures, the best-performing NCMV portfolio is based on the sparsest network, constructed using a correlation threshold of 0.5456. This result implies that retaining only the strongest correlations—those more likely to be robust and persistent—can yield a more precise and more reliable topological foundation for constraint implementation. In contrast, networks at lower thresholds may incorporate transient or noisy relationships, thereby weakening the effectiveness of structural penalties and reducing portfolio efficiency. The observed non-monotonic relationship between network density and performance underscores the critical importance of threshold selection, suggesting that the informational content and stability of the underlying network structure are more consequential than mere connectivity. This underscores the necessity for further investigation into data-driven thresholding mechanisms to ensure alignment between network topology and underlying market dynamics.

6 CONCLUSION

This study proposes and validates a novel portfolio optimization framework that integrates complex network constraints into the classical mean-variance model. By constructing correlation-based asset networks and embedding node-level centrality and community-level diversification constraints, the framework introduces structural awareness into portfolio allocation decisions. Empirical analysis of DJIA constituent stocks demonstrates that network-constrained portfolios consistently outperform traditional benchmarks in terms of out-of-sample cumulative returns, confirming the practical value of incorporating topological features into financial decision-making.

The findings further highlight that the effectiveness of network constraints is sensitive to the quality and sparsity of the underlying correlation structure. Portfolios derived from sparse, high-threshold networks exhibit superior performance, suggesting that focusing on strong and stable correlations can enhance both interpretability and return potential. These results contribute to the

literature on network-based financial modelling and offer concrete pathways for developing structurally informed investment strategies. Future extensions may explore dynamic network construction, multilayer correlation modelling, or integration with alternative forms of systemic risk indicators to strengthen the robustness of network-aware portfolio design further.

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A BIBLIOMETRIC LITERATURE REVIEW OF ETHICAL CONSUMPTION AND I-B GAP AMONG GEN-Z

Shovan Nasim Haider

Abstract

This study provides a comprehensive bibliometric analysis of 88 peer-reviewed articles published between 2002 and 2025, systematically examining ethical consumption and the intention-behavior (I-B) gap among Generation Z. Employing tools such as BibliometrixR and PRISMA frameworks, the analysis maps publication trends, highlights thematic developments, and uncovers the intellectual structure underpinning this emerging field. Findings reveal that research on Gen Z's ethical consumption has surged since 2021, fueled by global sustainability concerns and Gen Z's rising societal influence. However, a persistent disconnect remains between ethical intentions and actual behaviors, with digital platforms and peer influences emerging as key yet understudied mediators. While India leads in publication volume, Western countries (notably the USA and UK) dominate citation impact, indicating an imbalance in global scholarly influence. Methodologically, the field is characterized by a reliance on quantitative approaches like PLS-SEM and the continued prominence of the Theory of Planned Behavior (TPB), although integration with broader sustainability frameworks is limited. The bibliometric mapping also spotlights emerging research niches, including technological mediation (such as augmented reality) and cultural factors (like trust), suggesting fertile ground for interdisciplinary collaboration. As one of the first studies to systematically map the I-B gap in Gen Z's ethical consumption, this work synthesizes contributions from 241 authors across 54 journals and highlights overlooked areas such as digital mediation, cross-cultural insights, and crisis-driven consumption while offering strategic recommendations and a replicable methodology for future research.

Keywords: *Ethical consumption, Intention-behaviour gap, Gen-Z, Bibliometric literature review*

1 INTRODUCTION

The persistent intention-behavior gap (I-B gap) in ethical consumption where consumers' stated sustainability values fail to translate into purchasing decisions fundamentally impedes progress toward UN Sustainable Development Goal 12 (SDG 12) on responsible consumption and production (Kara & Min, 2023; Tomşa, Romonţi-Maniu & Scridon, 2021). This challenge is critically relevant for Generation Z (Gen Z), defined as individuals born between 1995 and 2010 (Chaney, Touzani & Ben Slimane, 2017; Priporas, Stylos & Fotiadis, 2017), who constitute approximately a quarter of the global population (Derbani, Rabiatul & Zulaikha, 2022) and wield increasing market influence. As digital natives, Gen Z's worldview and consumption patterns are profoundly shaped by ubiquitous internet access, smartphones, and social media immersion from an early age (Dolot, 2018). Consequently, this cohort demonstrates heightened awareness and concern for ethical and environmental issues, largely fueled by constant exposure to online information and activism (Djafarova & Foots, 2022). However, a significant paradox persists: despite strong ethical intentions, empirical evidence consistently reveals a substantial disconnect between Gen Z's aspirations and their tangible consumption behaviors (Casais & Faria, 2021; Robichaud & Yu, 2021). This I-B gap stems from a complex interplay of economic rationality,

moral obligations, social symbolism, contextual constraints, and habitual responses (Steg & Vlek, 2009; Bhutto, Ertz, Khan & Sun, 2022), presenting a major obstacle to achieving sustainable consumption at scale.

While research on ethical consumption and the I-B gap among Gen Z has surged exponentially post-2021, driven by global sustainability imperatives and this generation's rising influence (Jeong & Kim, 2023; Kara & Min, 2023), the literature remains fragmented. Existing studies often focus narrowly on isolated aspects (i.e., specific products or regions) or rely predominantly on quantitative cross-sectional designs like PLS-SEM. This fragmentation obscures the field's intellectual structure, impedes identification of thematic trajectories and knowledge gaps, and limits actionable insights for bridging the I-B gap (Chekima, Chekima, Wafa, Igau & Sondoh, 2015; Chaturvedi, Kulshreshtha & Tripathi, 2020). A systematic synthesis of this evolving landscape is therefore imperative.

To address this critical need, this study conducts the first comprehensive bibliometric review focused explicitly on mapping the literature concerning ethical consumption and the I-B gap within the Gen Z demographic. The rationale of this study is threefold:

- (1) Gen Z's unique digital socialization and value formation (Dolot, 2018; Djafarova & Foots, 2022) necessitate distinct investigation;
- (2) the rapid growth of publications demands systematic consolidation to reveal structural patterns; and
- (3) pinpointing specific antecedents, mediators (i.e., eWOM, trust), and barriers underlying Gen Z's I-B gap is essential for effective interventions. Consequently, this research aims to:
 - Synthesize the evolution, scope, and key contributors within this literature.
 - Map the intellectual structure using bibliometric science to identify dominant themes, collaborative networks, and emerging trends.
 - Critically evaluate predominant theoretical frameworks (e.g., Theory of Planned Behavior) and methodological approaches.
 - Identify unresolved research challenges and underexplored domains.

This analysis delivers significant academic and practical value. Academically, it provides an objective, foundational map of the field, clarifying conceptual boundaries and evolutionary pathways (Chaturvedi et al., 2020; Chekima et al., 2015). It definitively identifies critical knowledge voids, including the role of digital mediators (e.g., influencer impact; Djafarova & Foots, 2022), cross-cultural variations (Derbani et al., 2022), crisis impacts, and the scarcity of longitudinal studies (Jeong & Kim, 2023). Practically, by consolidating evidence on factors enabling or impeding Gen Z's ethical actions (e.g., social norms, trust mechanisms), the findings offer actionable intelligence for marketers (Halibas, Akram, Hoang & Thi, 2025; Bhutto, Ertz, Khan & Sun, H. 2022) and policymakers (Robichaud & Yu, 2021) to design strategies that bridge the I-B gap and accelerate progress toward SDG 12.

The importance of ethical consumption study can be traced to SDG-17 goals (SGD 12- responsible consumption and production) that the United Nations (UN) aims to meet by 2030. People born between 1995 and 2010 are called Gen-Z (Chaney et al., 2017; Priporas, Stylos, Fotiadis, 2017). A significant number, if not at least a quarter of the global population, belongs to this group (Derbani et al., 2022). Interestingly, the internet boom has also begun in the late 1990s. Born in

the age of information technology, fast-expanding internet facilities, smartphones, and such developments have significantly shaped their unique characteristics (Dolot, 2018). In their study, Djafarova & Foots (2022) claimed that Gen-Z shows a strong awareness and desire towards ethical and environmental issues mainly due to unlimited exposure to social media platforms and online resources. However, such pro-environmental behavior is influenced by several factors, Steg and Vlek (2009) argued. These factors are rational choices based on economic cost-benefit analysis, moral obligations (psychological), symbolism (social status), various environmental factors, and routinized response behavior.

The scope of the study encompasses examining the existing scientific studies on the dynamics influencing Gen Z's ethical consumption and the I-B gap. This study aims to conduct a bibliometric analysis of the existing literature on the intention-behavior gap in ethical consumption among Gen Z consumers. The objectives include synthesizing the breadth of existing research, identifying prevailing themes, and critically examining both established advancements and prospective avenues for future inquiry in Gen-z's ethical I-B gap in ethical consumption phenomena.

The importance of this study lies in its potential to inform both academic research and practical applications in promoting sustainable consumption behaviors among young consumers. By identifying research gaps and emerging trends, this bibliometric analysis can guide future studies and develop more effective interventions to bridge the intention-behavior gap (Kara & Min, 2023; Tomşa et al., 2021). Furthermore, the findings can assist marketers and policymakers in designing targeted strategies that address Gen Z consumers' unique challenges and motivations in adopting ethical consumption practices (Bhutto et al., 2022; Robichaud & Yu, 2021).

This study holds notable significance for academic research by offering a structured synthesis of existing knowledge on Generation Z's ethical consumption behaviors. Systematically mapping current literature clarifies dominant themes, trends, and pivotal studies, establishing a foundation for understanding this generation's evolving priorities. A critical aspect of the research lies in its bibliometric analysis, which identifies gaps in the field and emphasizes emerging areas requiring deeper exploration. For instance, the role of digital influencers and social media platforms in shaping ethical choices, as highlighted in recent work by Djafarova and Foots (2022), emerges as an under-examined yet vital dimension.

Additionally, the study enriches the longstanding discourse on the gap between ethical intentions and actual behaviors, a challenge well-documented across multiple contexts (Casais & Faria, 2021). Consolidating diverse findings reveals recurring contradictions and patterns, offering fresh perspectives to address this gap. Furthermore, the research evaluates methodological approaches and theoretical frameworks employed in prior studies, guiding scholars to design robust investigations into sustainable consumption, as seen in recent explorations by Jeong and Kim (2023) and Kara and Min (2023). Beyond theoretical contributions, the findings hold practical value, proposing actionable strategies to align Gen Z's values with their consumption habits. Insights from studies such as Chaturvedi et al. (2020) and Chekima et al. (2015) could inform interventions to foster sustainable behaviors, bridging the divide between awareness and action. This work advances scholarly understanding while supporting real-world efforts to cultivate ethical consumption practices among younger generations.

2 LITERATURE REVIEW

2.1 Ethical consumption and Intention-Behaviour gap among Gen-z

One of the fundamental theories studying human behavior is the theory of planned behavior, or TPB, which was developed by Ajzen and Fishbein (1991). However, TPB is considered the extension of their earlier theoretical work, named the theory of reasoned action or TRA, in 1975. In core to these theories, the authors have claimed that behavioral intention is the direct antecedent of the performance of a behavior. Moreover, individuals' attitudes towards the behavior influence the intention (the positive or negative evaluation of a person about performing the behavior), the subjective related to the behavior (he perceived social pressure to perform or not perform the behavior), and perceived behavioral control (the extent to which an individual believes they can perform the behavior easily or with difficulty).

Ethical consumption literature has garnered heightened academic attention (Carrington, Neville & Whitwell, 2010; Strong, 1996). However, in this context, the studies by Wicker (1969) and Carrington et al. (2010) have found that general attitudes are weak in predicting specific behavior, and a gap exists between consumers thinking intention and behavior.

The intention-behavior gap or I-B gap in ethical consumption among Gen-Z consumers is a complex phenomenon that has garnered significant attention in recent research. Studies have shown that while Gen-Z expresses strong intentions toward sustainable and ethical consumption, translating these intentions into actual behavior remains challenging (Liang et al., 2022; Liu-Lastres et al., 2025). This phenomenon, often called the "Gen-Z Paradox," highlights the discrepancy between young consumers' intentions to make ethical purchases and their buying behaviors (Hassan et al., 2014). Despite strong awareness and desire towards ethical and environmental issues, Generation Z's purchasing decisions are often constrained by financial limitations and lifestyle choices (Djafarova et al., 2022).

Interestingly, subjective norms and peer influence significantly impact Gen-Z's purchase intentions towards ethical products (Robichaud & Yu, 2021). This aligns with the notion that ethical consumption can be used as a communication tool among peers to project personal values and influence others. However, barriers, i.e., limited resources, high costs, and lack of knowledge, often impede the translation of intentions into action (Liu-Lastres et al., 2025). Implementing practical strategies, including financial incentives and better access to sustainable options, may help bridge this gap (Carrington et al., 2010; Liu-Lastres et al., 2025). Environmental awareness also plays a crucial role in shaping Gen-Z's ethical consumption intentions. It positively influences personal norms and corporate social responsibility expectations linked to green purchase intentions (Lin et al., 2023). However, the relationship between intentions and behavior is mediated by plans and habits and moderated by commitment and sacrifice (Casais & Faria, 2021). This suggests that having ethical intentions is insufficient to drive sustainable consumption behaviors.

Research has shown that while Gen Z consumers demonstrate high levels of environmental awareness and express intentions to engage in sustainable consumption, translating these intentions into action remains challenging (Liu-Lastres et al., 2025). This gap between intention and behavior is influenced by various factors, including limited resources, high costs, lack of knowledge, and the interplay between personal norms, corporate social responsibility expectations, and shopping motivations (Lin et al., 2023; Liu-Lastres et al., 2025). To address the intention-behavior gap, researchers suggest cultivating green consumption intentions,

environmental responsibility, and environmental values among Gen-Z consumers (Liang et al., 2022). Additionally, considering the role of gender identity in ethical intentions could provide valuable insights, as femininity has been found to increase ethical intent while masculinity has the opposite effect (Pinna, 2019).

Existing studies have primarily focused on identifying the factors influencing ethical consumption intentions among Gen Z consumers. However, comprehensive research examining the specific mechanisms that lead to the intention-behavior gap remains unexplored (Casais & Faria, 2021; Hassan et al., 2014). The role of mediating and moderating variables in bridging this gap also remained underexplored, particularly in the context of Generation Z's unique characteristics and consumption patterns (Casais & Faria, 2021; Nguyen et al., 2018). Nevertheless, the bibliometric study by Li and Hassan (2023) has only analyzed the purchasing behavior of Gen-Z and overlooked the intention behavior gap dynamics, which is extensively debated and mentioned in such academic studies.

2.2 Bibliometric literature review

There are relatively few bibliometric studies on Generation Z (Li, Hassan, 2023), while none has been conducted on the I-B gap in ethical consumption among gen-z consumer group combining citation database and subject area/publication database as a primary data source.

Several research gaps exist in conducting a bibliometric analysis on this topic:

- Limited empirical evidence quantifies the intention-behavior gap in ethical consumption, particularly for Gen Z (Hassan, Shaw & Shiu, E 2014). Research has identified multiple constraints affecting Gen Z's ethical consumption decisions, including cognitive dissonance and social comparison, yet these constraints are often treated in isolation rather than as interconnected factors (Seyfi, Hall, Saarinen, Zaman, & Vo-Thanh 2024)
- There is a lack of systematic examination of factors influencing the extent and magnitude of the gap (Hassan et al., 2014; William & Hodges, 2020).
- Insufficient longitudinal studies assessing the complex relationship between intention and behavior over time (Hassan et al., 2014).
- There is a need for integrating interdisciplinary collaboration and multiple theoretical frameworks, such as the Theory of Planned Behavior, Norm Activation Model, and consumption value theory, to comprehensively understand Gen Z's ethical decision-making process (Loso, Nofirman & Muhtadi, 2024; Djafarova & Fouts, 2022; Lin et al., 2023).
- Understanding these constraints is crucial for addressing the I-B gap, as they can significantly influence purchasing decisions (Casais & Faria, 2021).

Ortiz-Pimentel, Molina, and Ronda-Pupo (2020) have analyzed the focus of generations (namely Generation X, Y, and Z, Baby Boomers, and the Silent Generation) based on the Web of Science database through a bibliometric analysis of intergenerational papers in business and management journals. They indicate that most of the studies are mainly concentrated in economically developed countries and regions, and there is a lack of qualitative research on Generation Z (Ortiz-Pimentel et al., 2020). To better understand Gen Z in the labor market, Benítez-Márquez, Sánchez Teba, Bermúdez-González & Núñez-Rydzman (2022) used bibliometrics techniques to evaluate 102 Web

of Science papers on Gen Z employees from 2009 to 2020 and found that research in this field has been attracting widespread attention since 2018. However, the stability of research keywords in each period is low, and all aspects must be further developed (Benítez-Márquez et al., 2022). Thus, a bibliometric measurement of publications in Gen Z's I-B gap in ethical consumption must be conducted as they are an extensive consumer group.

In this study, the research impact and study benefits of bibliometric literature review are unquestionably accepted as bibliometric study has become a trend in academic research (Khan, Pattnaik, Ashraf, Ali, Kumar, Donthu, 2021; Donthu, Kumar, Pattnaik, 2020; Donthu, Kumar, Pandey, Lim, 2020, Donthu, Kumar, Mukherjee, Pandey, Lim, 2021; Ellergaard, Wallin, 2015). Historically, the term bibliometrics was coined by Belgian documentarist Otlet (Rousseau, 2014) in the early 1930s. Nevertheless, bibliometric methods have been firmly established as a scientific specialty and have become integral to research evaluation methodology (Ellergard et al., 2015). The benefit of the bibliometric method is that it generates a quantitative analysis of written publications (Egghe & Rousseau, 1990; Ruthven, 2004). The qualitative approach to conducting literature reviews often experiences criticism as quantitative studies are claimed to capture better generalizability of any study. On the contrary, bibliometric analysis is increasingly gaining importance in academia with highly available and applicable bibliometric analysis software and databases, and such techniques are increasingly gaining attention (Passas, 2024).

3 RESEARCH METHODOLOGY

Draper, Young, and Fenich (2018) argue that bibliometric analysis is a structured approach that reviews published articles and other scientific literature. It involves micro and deep text analysis of the literature to uncover trends and projections for future research (Mehraliyev et al., 2020). Bibliometric research is a complex field that considers journal ranking, the assessment of research quality, bibliometric literature review, and the analysis of trends and patterns (Leong et al., 2020).

This study is focused on accessing publications from peer-reviewed and high-impact journals from Web of Science, Scopus, and Emerald databases. A bibliometric study of such research interest in analyzing Gen-Z purchasing behavior has previously used Scopus as the data source (Li, Hassan, 2023). Because they are large databases, these sources are often used as data sources for metrological literature analysis (Van Eck & Waltman, 2010). Effectively, this approach helped to map and identify the most relevant articles. Articles identified in WOS, Scopus, and indexed journals are widely regarded as highly reputable citation indexing databases; academic institutions frequently utilize them because they provide comprehensive citation data (Li et al., 2018). The article selection criteria have the following eligibility indicators: 1. Peer-reviewed journal articles of mature and comprehensive reports 2. Articles that are published in the English language 3. Articles that are developed around business economics research area 4. Articles only focused on ethical consumption in the intersection of the I-B gap among gen-z and 5. Articles that are published between 2001 and 2024(See Table 1).

Tab. 1 – Inclusion and Exclusion criterion. Source: authors own research

Criterion	Eligibility	Exclusion
Article class	Journal articles, Case study	Book chapter, Conference paper
Language	English	Other languages

Research subject area	Business economics	Other
Focus of study	Ethical consumption, I-B gap, Gen-Z, Consumer behavior	Other
Year of publication	2001 to 2024	Published before 2001

The reviewing process was conducted in February 2024 and has been done in four stages: identification, screening, eligibility, and analysis. The review protocol is crucial for a rigorous systematic and bibliometric review (Xiao, Watson, 2019). At first, the databases for primary data collection are identified. Different databases offer various options to procure the presentation of basic bibliographic data, abstracts, full texts, citations, etc. Furthermore, these databases offer custom search options according to the search criteria.

Three databases were chosen: Web of Science, Scopus, and Emerald. Subject-specific journals often cover niche areas that may be underrepresented in WOS and Scopus, particularly in fields like Social Sciences and Arts and Humanities (Mongeon & Paul-Hus, 2015). By including these journals, researchers can capture a broader spectrum of knowledge and trends within specific disciplines, leading to more representative bibliometric analyses (Echchakoui, 2020). These databases are selected based on their frequent use by other researchers in social science studies and accessibility through university login. Nevertheless, using a mix of citation and publisher/subject-based databases is also being ensured in the primary data identification stage. The research methodology by Crossan and Apaydin (2010) in their study (literature review on organizational innovation) was limited to peer-reviewed journals with the highest impact factors. Another bibliometric study on sustainable design systems by Zhu, Yan, LV (2023) used the WOS database and BibliometrixR package to analyze the data. Both these approaches are applied in this study to consolidate it.

Tab. 2 - Profile of the selected databases, Source: authors own research

No.	Database name	Type	Description
1	Web of Science	Citation database	Scientific citation indexing service for citation search of papers from peer-reviewed journals. Primarily used in bibliometric calculations.
2	Scopus	Citation database	Scientific citation indexing service for citation search of papers from peer-reviewed journals. Primarily used in bibliometric calculations.
3	Emerald	Subject area/ publisher database	Covers c. 250 journals, primarily in management.

During the initial data identification in the databases, the PRISMA framework has been applied to guide the data-gathering process. PRISMA offers several advantages, including the facilitation of

precise research question formulation, the establishment of inclusion and exclusion criteria, and the efficient evaluation of extensive literature databases within predefined time constraints (Page et al., 2021). Effectively, this approach helped to map and identify the most relevant articles. Articles identified in Wos, Scopus, and Emerald-indexed journals are widely regarded as highly reputable citation indexing databases, and academic institutions frequently utilize these due to their provision of comprehensive citation data (Li et al., 2018).

The PRISMA flow-chart of this study:

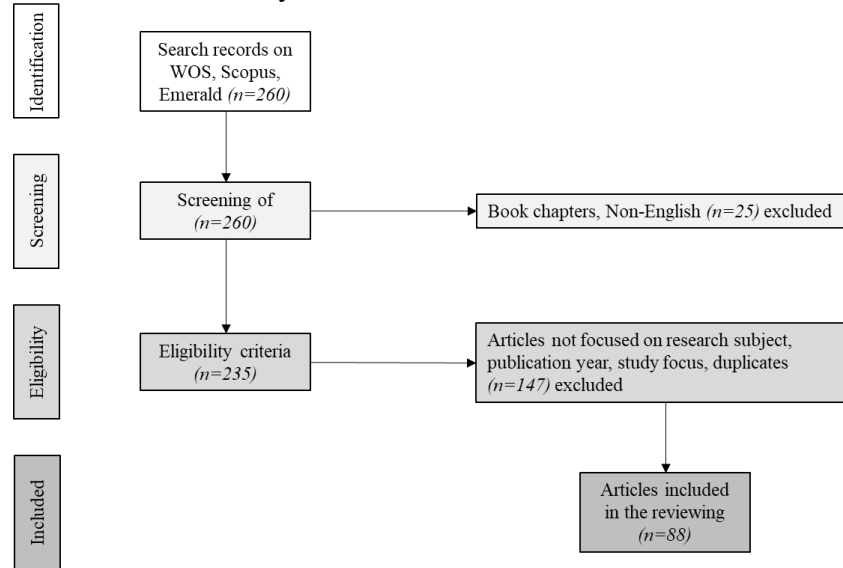


Fig. 1 - Modified PRISMA flow-chart, Source: <http://www.prisma-statement.org/>

The article selection criteria have the following eligibility indicators: 1. Peer-reviewed journal articles of mature and comprehensive reports 2. Articles that are published in the English language 3. Articles that are developed around business economics research area 4. Articles only focused on ethical consumption in the intersection of the I-B gap among gen-z and 5. Articles that are published between 2001 and 2024(See Table 1).

Tab 3 - Inclusion and Exclusion criterion, source: authors own research

Criterion	Eligibility	Exclusion
Article class	Journal articles, Case study	Book chapter, Conference paper
Language	English	Other languages
Research subject area	Business economics, Social Science, Business management accounting, economics, Econometrics, Finance	Other
Focus of study	Ethical consumption, I-B gap, Gen-Z, Consumer behavior	Other
Year of publication	2001 to 2024	Published before 2001

Watson (2015) outlined that web-based searches may result in irrelevant findings and un-identifying the most relevant ones. Therefore, central to this study, the study's research subject area and focus have been pre-determined to control the variability in including research articles. Keywords or search strings were developed for the search process. Database-wise search terms and search strings are tabled here:

Tab. 4 - Database, topic/search words, number of inclusion in the study source: authors own research

Database	Year	Topic/search words	No. of inclusion
Web of Science	2025	((intention-behavior gap OR intention-behavior gap OR I-B gap OR i-b gap) AND (ethical consumption OR ethical consumerism) AND (Gen-Z OR gen-z OR generation z))	34
Scopus	2025	("intention-behavior gap" OR "intention-behavior gap" OR "I-B gap" OR "i-b gap") AND("ethical consumption" OR "ethical consumerism")AND("Gen- Z" OR "gen-z" OR "generation z")	42
Emerald	2025	("intention-behavior gap" OR "intention-behavior gap" OR "I-B gap" OR "i-b gap") AND("ethical consumption" OR "ethical consumerism") AND("Gen-Z" OR "gen-z" OR "generation z")	59

At the final inclusion stage, all qualified articles, according to the pre-designed criteria, are matrixed as BibTex database using Rstudio. This is to remove duplicates in the included articles from the databases. After removing duplicates, 88 articles are being forwarded in the analysis section. These 88 articles were analyzed to generate a report using the generate report function of BibliometrixR software.

4 RESULTS

Bibliometric analysis or the result of the identified article follows the standard prescription by Donthu, Kumar, Mukherjee, Pandey, and Lim (2021). In their study, the authors have suggested a bibliometric analysis toolbox that aligns with the objective of this study. However, in addition to their suggestion, research questions from the thematic clustering analysis have been included in this study (Dey, Hung, Hoc, & Pham, 2022). This additional step provides an opportunity for future studies to replicate the findings from this study as a foundation stone.

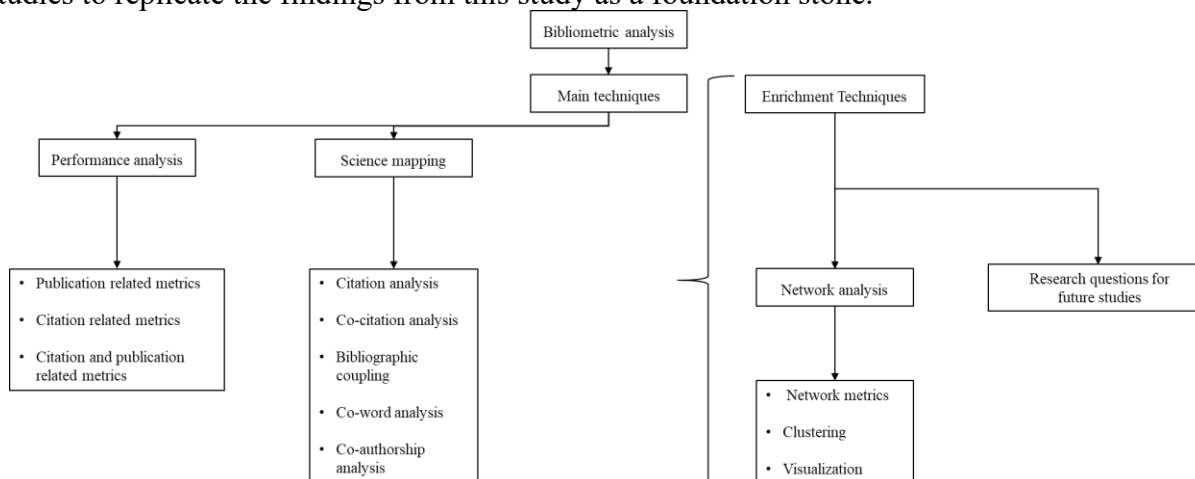


Fig. 2 - Modified bibliometric analysis framework, Source: Donthu et al., 2021

The primary data selection and identified number of papers was done based on this study's research subject area and focus. Rationally, this strategy is more logical because it helped to find and include the most relevant literature in the bibliometric analysis.

4.1 Description of the analyzed publications

All the 88 relevant articles from WOS, Scopus, and Emerald databases are analyzed using BibliometrixR software on the Rstudio interface. The main information for the analysis articles can be found in the following table. The analyzed articles are published in 54 source journals between 2002 to 2025. Within the study focus area, 241 authors and seven single authors have contributed to the studies with an annual growth rate of 10.2% and 38.36% average citation per document and an average document age rate of 3.59. Additionally, 35 keywords plus (ID) and 175 Author keywords were identified in these articles.

Tab. 5 - Main information about the data, source: authors own research

Description	Results
Main information about the data	
Timespan	2002:2025
Sources (Journals, Books, etc)	54
Documents	88
Annual Growth Rate %	10.02

Document Average Age	3.59
Average citations per doc	38.36
References	0
DOCUMENT CONTENTS	
Keywords Plus (ID)	35
Author's Keywords (DE)	175
AUTHORS	
Authors	241
Authors of single-authored docs	7
AUTHORS COLLABORATION	
Single-authored docs	7
Co-Authors per Doc	3.01
International co-authorships %	0

4.2 Performance analysis

The contributions of research constituents to a given field is examined by performance analysis (Cobo, L'opez-Herrera, Herrera-Viedma, & Herrera, 2011; Ramos-Rodríguez & Ruíz-Navarro, 2004).

Annual publication analysis

Donthu et al. (2021) have argued that the number of publications and citations per year/ research constituent is the most prominent measure in bibliometric performance analysis, where publication is the proxy for productivity, and citation is a measure of impact and influence.

Annual publications on ethical consumption and the I-B gap among gen-z have gradually grown over the last two decades (see Table 6). This means academics have become interested in delving into this study area over time. The academic study development of ethical consumption and the intention-behavior (I-B) gap among Generation Z has demonstrated a progressive expansion over the past two decades, as evidenced by the publication trends in Table 5. Early years (2002–2009) exhibited minimal academic output, with only one article published in 2002 and no further contributions until 2010. A sporadic yet discernible increase emerged between 2010 and 2020, with intermittent peaks (e.g., five articles in 2010 and 2020) interspersed with periods of limited activity. However, a pronounced surge in publication frequency occurred from 2021 onward, culminating in a marked escalation during 2023–2024 (19 and 28 articles, respectively), indicative of intensified academic engagement with this research domain.

Tab. 6 - Number of publications per year, source: authors own research

Year	Articles
2002	1
2003	0

2004	0
2005	0
2006	0
2007	0
2008	0
2009	0
2010	5
2011	2
2012	0
2013	0
2014	1
2015	2
2016	1
2017	1
2018	0
2019	1
2020	5
2021	5
2022	7
2023	19
2024	28
2025	9

Tab. 7 - Number of citations per year, source: authors own research

Year	MeanTCperArt	N	MeanTCperYear	CitableYears
2002	72	1	3	24
2010	228	5	14.25	16
2011	300.5	2	20.03	15
2014	73	1	6.08	12
2015	80.5	2	7.32	11
2016	259	1	25.9	10
2017	113	1	12.56	9
2019	26	1	3.71	7

2020	27	5	4.5	6
2021	45	5	9	5
2022	44.43	7	11.11	4
2023	9.89	19	3.3	3
2024	2.46	28	1.23	2
2025	0.33	9	0.33	1

Concurrently, citation metrics (Table 7) reveal a contrasting temporal pattern. While early publications (e.g., 2010–2011) achieved relatively high mean total citations per article (228 and 300.5, respectively), subsequent years exhibited declining citation rates, particularly during 2014–2015, 2017–2019, and 2022–2025. Notably, articles published in 2023 and 2024 recorded substantially lower mean citations per article (9.89 and 2.46, respectively) despite their recent proliferation. This inverse relationship between publication volume and citation frequency aligns with the inherent temporal lag in citation accrual, wherein newer publications require sustained exposure and integration into scholarly discourse to attain measurable impact.

The observed divergence between rising publication rates and diminishing citation metrics may be attributed to the temporal dynamics of academic influence. Early publications benefit from extended citable years (e.g., 24 years for the 2002 article), enabling gradual citation accumulation, whereas recent contributions (e.g., 2023–2024) lack sufficient time to permeate the literature. One possible reason for such a declining trend in reflection of the increasing number of publications over the years is probably because citations of contemporary articles need time to accumulate citations and gain exposure and attention. Furthermore, the exponential growth of articles post-2021 suggests a rapidly evolving field wherein emerging scholarship competes for visibility within a crowded intellectual landscape. This underscores the necessity of longitudinal analysis to contextualize citation trends, as contemporary research outputs may exhibit delayed recognition of scholarly impact (Tables 6 & 7).

Source, citation, and publication-related metric analysis

The dissemination of research on ethical consumption and the Gen Z intention-behavior (I-B) gap is concentrated within a select group of academic journals, as evidenced in Tables 8 and 9. The Journal of Business Ethics and the Journal of Retailing and Consumer Services jointly lead the field, each publishing eight articles (cumulative frequency: 16). These are classified within Zone 1, denoting their prominence as core outlets for this research domain. Young Consumers ranks third (6 articles), highlighting the interdisciplinary intersection of ethics, retail dynamics, and youth consumer behavior. Journals in Zone 2 (e.g., Australasian Marketing Journal, European Journal of Marketing) contribute modestly, with 1–2 article frequencies reflecting fragmented engagement across niche subfields.

Tab. 8 - Most relevant journals and number of publications, source: authors own research

SO	Rank	Freq	cumFreq	Zone
JOURNAL OF BUSINESS ETHICS	1	8	8	Zone 1
JOURNAL OF RETAILING AND CONSUMER SERVICES	2	8	16	Zone 1

YOUNG CONSUMERS	3	6	22	Zone 1
JOURNAL OF CONSUMER MARKETING	4	3	25	Zone 1
JOURNAL OF FASHION MARKETING AND MANAGEMENT	5	3	28	Zone 1
JOURNAL OF MACROMARKETING	6	3	31	Zone 1
AUSTRALASIAN MARKETING JOURNAL	7	2	33	Zone 2
EUROPEAN JOURNAL OF MARKETING	8	2	35	Zone 2
INTERNATIONAL JOURNAL OF ETHICS AND SYSTEMS	9	2	37	Zone 2
INTERNATIONAL JOURNAL OF MARKET RESEARCH	10	2	39	Zone 2
JOURNAL OF BUSINESS RESEARCH	11	2	41	Zone 2
JOURNAL OF ISLAMIC MARKETING	12	2	43	Zone 2
JOURNAL OF SUSTAINABLE MARKETING	13	2	45	Zone 2
JOURNAL OF SUSTAINABLE TOURISM	14	2	47	Zone 2
TOURISM REVIEW	15	2	49	Zone 2
ASIA MARKETING JOURNAL	16	1	50	Zone 2
ASIA PACIFIC JOURNAL OF MARKETING AND LOGISTICS	17	1	51	Zone 2
ASIAN JOURNAL OF BUSINESS ETHICS	18	1	52	Zone 2
AUSTRALASIAN ACCOUNTING, BUSINESS AND FINANCE JOURNAL	19	1	53	Zone 2

Tab. 9 - Source local impact by h-index, source: authors own research

Source	h_ind ex	g_ind ex	m_ind ex	TC	NP	PY_start
JOURNAL OF BUSINESS ETHICS	8	8	0.3333 3333	1931	8	2002
JOURNAL OF RETAILING AND CONSUMER SERVICES	6	8	1	258	8	2020
YOUNG CONSUMERS	3	6	0.75	159	6	2022
AUSTRALASIAN MARKETING JOURNAL	2	2	0.125	54	2	2010
INTERNATIONAL JOURNAL OF MARKET RESEARCH	2	2	0.1818 1818	35	2	2015

JOURNAL OF FASHION MARKETING AND MANAGEMENT	2	3	0.5	53	3	2022
JOURNAL OF ISLAMIC MARKETING	2	2	0.6666 6667	15	2	2023
JOURNAL OF MACROMARKETING	2	3	0.5	48	3	2022
JOURNAL OF SUSTAINABLE MARKETING	2	2	0.6666 6667	4	2	2023
ASIA PACIFIC JOURNAL OF MARKETING AND LOGISTICS	1	1	0.3333 3333	29	1	2023
AUSTRALASIAN ACCOUNTING, BUSINESS AND FINANCE JOURNAL	1	1	0.2	15	1	2021
EUROPEAN JOURNAL OF MARKETING	1	2	0.5	25	2	2024
GLOBAL BUSINESS AND FINANCE REVIEW	1	1	0.3333 3333	1	1	2023
INDIAN JOURNAL OF MARKETING	1	1	0.5	1	1	2024
INTERNATIONAL ADVANCES IN ECONOMIC RESEARCH	1	1	0.0666 6667	78	1	2011
INTERNATIONAL JOURNAL OF CONSUMER STUDIES	1	1	0.0833 3333	73	1	2014
INTERNATIONAL JOURNAL OF ETHICS AND SYSTEMS	1	2	0.25	6	2	2022
INTERNATIONAL JOURNAL OF NONPROFIT AND VOLUNTARY SECTOR MARKETING	1	1	0.1428 5714	26	1	2019
INTERNATIONAL REVIEW ON PUBLIC AND NONPROFIT MARKETING	1	1	0.5	3	1	2024

The Journal of Business Ethics demonstrates unparalleled influence, evidenced by its h-index of 8, total citations (TC: 1,931), and sustained productivity since 2002 (Table 9). This longevity contrasts with emerging sources such as the Journal of Retailing and Consumer Services (h-index: 6; TC: 258), which, despite a shorter publication timeline (2020–2025), achieves a higher m-index (1.0 vs. 0.33), signaling rapid contemporary impact. Similarly, Young Consumers (h-index: 3; TC: 159), though recent (2022–2025), exhibits strong annual citation momentum (m-index: 0.75), aligning with heightened interest in Gen Z consumer studies.

4.3 Science mapping

Science mapping examines the relationships between research constituents (Baker, Kumar, & Pandey, 2021; Cobo et al., 2011; Ramos-Rodrigue & Ruiz-Navarro, 2004). Science mapping helps to map the structure of scientific research and its dynamics.

Most relevant authors, global and local citation impact analysis

Tables 11, 12, 13, and Figure 6 show the analysis of the most relevant authors, the number of publications produced by the authors, and the author's global and local impact by total citation index.

Kaur J emerges as the most prolific author (3 articles, fractionalized count: 0.95), followed by Chatterjee R, Dlamini S, and El-Bassiouny N (2 articles each) (Table 10). Fractionalized authorship metrics reveal collaborative dynamics: Fukukawa K's fractionalized count (1.5 for two articles) indicates frequent co-authorship, whereas Kaur J's lower fractionalization (0.95 for three articles) suggests primary authorship dominance.

Tab. 10 - Most relevant authors, source: authors own research

Authors	Articles	Articles Fractionalized
KAUR J	3	0.95
CHATTERJEE R	2	0.45
DLAMINI S	2	0.58333333
EL-BASSIOUNY N	2	0.66666667
FUKUKAWA K	2	1.5
GUPTA S	2	0.45
MADINGA N	2	0.58333333
MALHOTRA G	2	0.45
MISHRA S	2	0.45
SANGROYA D	2	0.39285714
SHUKLA Y	2	0.45
ABBAS M	1	0.5
AGGARWAL S	1	0.25
AGU A	1	0.2
AKINTIMEHIN O	1	0.25
AL-AFLAK A	1	0.5
ALI S	1	0.25
ALMA'AMUN S	1	0.2

Tab. 11 - Authors production over time, source: authors own research

Author	year	freq	TC	TCpY
CHATTERJEE R	2023	2	53	17.667
DLAMINI S	2024	2	1	0.5

EL-BASSIOUNY N	2023	1	13	4.333
EL-BASSIOUNY N	2024	1	2	1
FUKUKAWA K	2002	1	72	3
FUKUKAWA K	2010	1	31	1.938
GUPTA S	2022	1	0	0
GUPTA S	2023	1	0	0
KAUR J	2021	1	15	3
KAUR J	2022	1	0	0

Despite Kaur J's productivity, her works exhibit limited citation traction (2021–2022 publications: TC: 15 and 0) (Table 11). Conversely, foundational authors like Fukukawa K achieve sustained citation accrual (2002 article: TC: 72; 2010 article: TC: 31) despite lower contemporary output. Chatterjee R's 2023 publications (TC: 53; TC/year: 17.67) illustrate rapid early impact, likely due to alignment with emergent Gen Z research priorities.

Tab. 12 - Most globally cited document, source: authors own research

Paper	Total Citations	TC Year	per TC
CARRINGTON M J, 2010, JOURNAL OF BUSINESS ETHICS	814	50.88	3.57
BRAY J, (2011). JOURNAL OF BUSINESS ETHICS	523	34.87	1.74
HASSAN L M, 2016, JOURNAL OF BUSINESS ETHICS	259	25.90	1.00
ECKHARDT G M, 2010, JOURNAL OF CONSUMER BEHAVIOUR	229	14.31	1.00
LU L, 2015, JOURNAL OF BUSINESS ETHICS	139	12.64	1.73
ALI S, 2021, J OPEN INNOV: TECHNOL MARK COMPLEX	139	27.80	3.09
DJAFAROVA E, 2022, YOUNG CONSUM	135	33.75	3.04
BUERKE A, 2017, REVIEW OF MANAGERIAL SCIENCE	113	12.56	1.00
PATEL J D, 2020, JOURNAL OF RETAILING AND CONSUMER SERVICES	100	16.67	3.70
JOHNSTONE L, 2022, J RETAIL CONSUM SERV	82	20.50	1.85

Seminal works anchor global citation metrics (Table 12). Carrington M.J.'s 2010 article (Journal of Business Ethics) dominates with 814 TC (50.88 TC/year; normalized TC: 3.57), establishing it as a methodological cornerstone. Bray J (2011; TC: 523) and Hassan L.M. (2016; TC: 259) further exemplify the enduring impact of early ethical consumption frameworks. Contemporary contributions, such as Ali S (2021; TC: 139; normalized TC: 3.09) and Djafarova E (2022; TC: 135; TC/year: 33.75), demonstrate the rising influence of open innovation and digital consumer behavior studies.

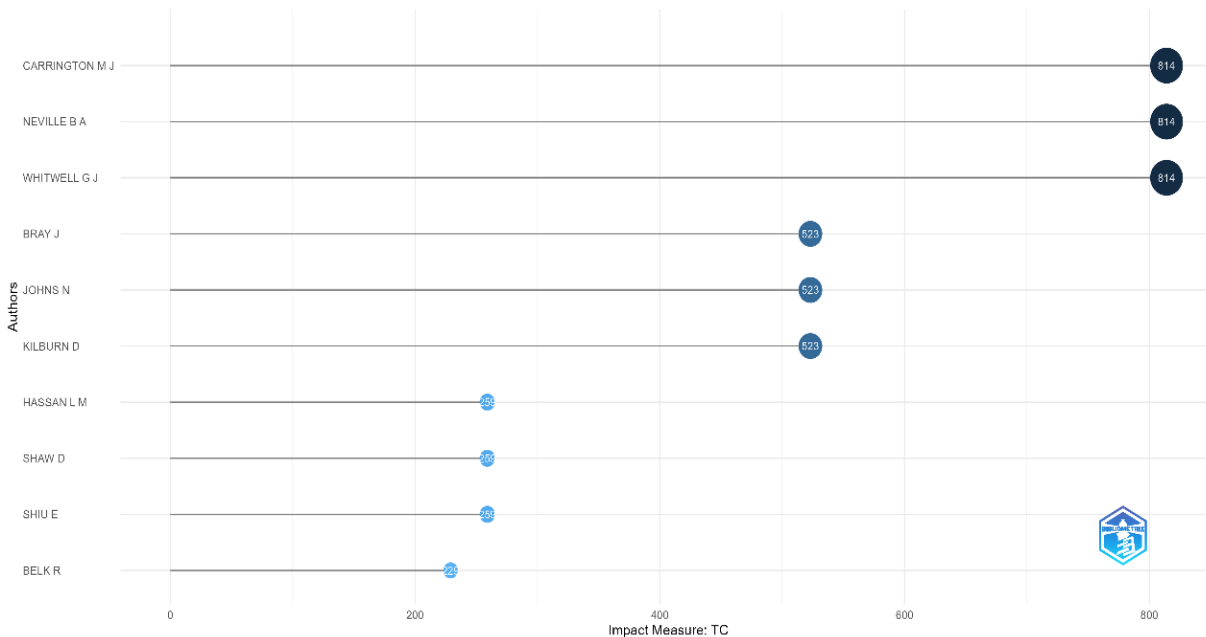


Fig. 3 - Authors local impact by TC index, source: authors own research

Figure 3 highlights divergent citation hierarchies. While Carrington M.J. (TC: 814) dominates global and local citation indices, regionally active authors like Kaur J and Chatterjee R. exhibit attenuated global influence. This suggests localized citation clusters may prioritize context-specific applicability over theoretical novelty, whereas globally cited works transcend regional boundaries through methodological or conceptual innovation.

Cooperation network analysis

The collaborative dynamics underpinning research on ethical consumption and the Gen Z intention-behavior (I-B) gap reveal distinct geographical, institutional, and interpersonal networks, as illustrated in Figures 7 & 8 and Tables 14 & 15.

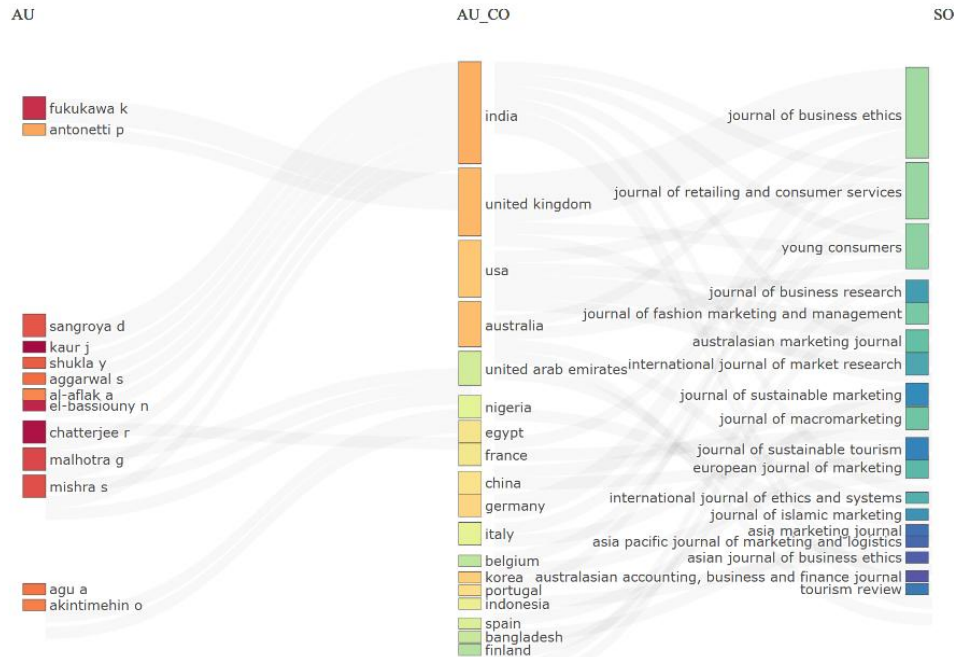


Fig. 4 - three field plot diagram of Author, Author country, and Sources, source: authors own research

Figure 4 (three-field plot) delineates the interplay between authors, their countries of origin, and publication sources. Indian scholars dominate the authorship landscape, with contributors such as Kaur J and Chatterjee R. publishing predominantly in Young Consumers and the Australasian Marketing Journal. Conversely, UK-based authors, including Fukukawa K and Antonetti P, are closely affiliated with the Journal of Business Ethics, a longstanding influence in ethical consumption research (Tables 14 & 15). This geographical stratification underscores regional preferences for specific publication outlets, potentially reflecting editorial priorities or institutional affiliations.

Collaboration networks between authors

Tab. 13 - Collaboration networks between authors, source: authors own research

Node	Cluster	Betweenness	Closeness	PageRank
Kaur j	1	12	0.037	0.065
Gupta s	1	0	0.036	0.05
Shukla y	1	30	0.043	0.057
alma'amun s	1	0	0.034	0.031
arshad m	1	0	0.034	0.031
Bhardwaj n	1	0	0.026	0.019
Bulsara h	1	0	0.038	0.027
Chatterjee r	2	0	0.03	0.054
Malhotra g	2	0	0.03	0.054

Mishra s	2	0	0.03	0.054
dlamini s	3	5.5	0.037	0.053
Madinga n	3	5.5	0.037	0.053
Aspeling d	3	0	0.026	0.03
Sangroya d	4	0	1	0.05
Ashaduzzaman m	4	0	1	0.05
Aggarwal s	5	0	1	0.05
Arora u	5	0	1	0.05
Chang a	6	0	1	0.05
Chang h	6	0	1	0.05

Table 13 maps collaboration clusters using network metrics (betweenness, closeness, PageRank), identifying six distinct clusters:

Cluster 1 (Kaur J, Gupta S, Shukla Y): Exhibits moderate betweenness (12–30) and closeness (0.034–0.043), signaling a loosely interconnected group with limited brokerage roles in the broader network.

Cluster 2 (Chatterjee R, Malhotra G, Mishra S): Characterized by low betweenness (0) and PageRank (0.054), indicative of tightly knit but isolated collaborations.

Cluster 3 (Dlamini S, Madinga N): Demonstrates intermediate betweenness (5.5) and PageRank (0.053), suggesting emerging influence as bridging nodes.

Clusters 4–6 (sangroya, ashaduzzaman, Aggarwal, Arora, Chang, Chang): Peripheral groups with minimal network centrality, reflecting nascent or ad hoc collaborations.

The fragmentation of collaboration clusters underscores the absence of a unified intellectual front. While Cluster 1's moderate betweenness implies partial integration into the broader network, the prevalence of low-centrality clusters highlights a field dominated by small, siloed research groups rather than interdisciplinary or international coalitions.

Keyword analysis

A lexical (keywords) analysis of 88 articles on ethical consumption and the Generation Z (Gen Z) intention-behavior (I-B) gap reveals distinct thematic priorities and conceptual frameworks within the field, as quantified in Table 16 and visualized in Figure 9.

Tab. 14 - Frequency of words and occurrence, source: authors own research

Words	Occurrences
ethical consumption	6
sustainable fashion	5
attitude	4
generation z	4

sustainability	3
sustainable consumption	3
theory of planned behavior	3
theory of planned behaviour	3
augmented reality	2
consumer behavior	2
corporate social responsibility	2
environmental concern	2
fast fashion	2
gender	2
green purchase intention	2
organic food	2
pls-sem	2
purchase intention	2
social norms	2
trust	2
values	2
(un)planned behaviour	1
action self-efficacy	1
actual behavioural control	1
anticipated warm glow	1
attitude-behavior inconsistency	1
attitude-behavior gap	1

The term ethical consumption (6 occurrences) emerges as the most frequent keyword, anchoring the discourse, followed by sustainable fashion (5), attitude (4), and generation z (4). These terms collectively highlight the intersection of sustainability-driven consumer practices (e.g., sustainable consumption, green purchase intention) and psychological determinants of behavior, particularly within the Gen Z demographic. The prominence of sustainable and fast fashion (2) underscores the textile industry's centrality in ethical debates, reflecting broader societal concerns about environmental externalities and fast fashion's ecological footprint. The recurrence of the theory of planned behavior (TPB) and its variant spelling (3 occurrences each) signals the framework's dominance in modeling behavioral intentions, particularly in bridging the I-B gap. This aligns with explicit references to attitude-behavior inconsistency (1) and attitude-behavior gap (1), which directly interrogate the disjunction between ethical intent and action. Methodologically, including PLS-SEM (2) highlights the field's reliance on partial least squares structural equation modeling to analyze latent variables in consumer decision-making.

Lower-frequency terms (<3 occurrences) delineate niche or emergent subthemes. Augmented reality (2) and corporate social responsibility (2) reflect the growing interest in digital interfaces and organizational ethics as drivers of ethical consumption. Terms such as anticipated warm glow (1) and action self-efficacy (1) suggest nascent integration of prosocial motivation and agency theories, while organic food (2) and environmental concern (2) denote sector-specific explorations. However, the absence of terms like cultural values, circular economy, or digital activism reveals underexplored intersections between ethical consumption and macro-level socioeconomic or technological systems.



Fig. 5 - Word cloud of word occurrence. Source: own research

The word cloud visualization (Figure 5) reinforces this thematic hierarchy, with sustainable fashion, ethical consumption, and Gen Z dominating the lexical landscape. These trends collectively emphasize the field's focus on sustainability imperatives, generational specificity, and theoretical Consolidation around TPB.

The keyword distribution (Figure 9) and frequency metrics (Table 16) collectively emphasize three research trajectories:

Sustainability Imperatives: Prioritizing environmental and ethical consumption models, particularly in fashion and retail.

Generational Specificity: Explicit focus on Gen Z as a unique demographic cohort, necessitating age-tailored behavioral analyses.

Theoretical Consolidation: Dependence on established frameworks (TPB) alongside exploratory forays into understudied psychological mechanisms (e.g., warm glow).

Network analysis

Built on the core techniques of bibliometric analysis, this section presents the add-ons that can augmented to enrich the outcomes of the analysis techniques applied in this bibliometric study (Donthu et al., 2021).

Document coupling thematic cluster analysis

A bibliometric analysis of document coupling, visualized in Figures 10 and 11 and quantified in Tables 18 and 19, identifies two distinct thematic clusters within research on ethical consumption and the Gen Z intention-behavior (I-B) gap. These clusters reflect divergent intellectual priorities,

methodological approaches, and contextual applications, delineating the field's conceptual boundaries and interdisciplinary intersections.

Tab. 15 - Labelled research themes and the frequencies, source: authors own research

label	group	freq	centrality	impact
ethical consumption	1	56	1.0595847	1
sustainable fashion				
sustainability				
theory of planned behavior	2	31	1.31171796	1
consumer behavior				
organic food				

Cluster 1 (Ethical Consumption, Sustainable Fashion, and Sustainability; frequency: 56; centrality: 1.06) dominates the corpus, emphasizing macro-level sustainability frameworks and industry-specific challenges, particularly in fast fashion and circular economies. Foundational works like Bray J (2011) and Buerke A (2017) established ethical decision-making frameworks, while contemporary studies (e.g., Brand B, 2025) extend these to Gen Z's retail engagement. Despite its thematic breadth, the cluster's moderate centrality reflects diffuse conceptual linkages, indicative of a broad yet loosely integrated agenda.

In contrast, Cluster 2 (Theory of Planned Behavior [TPB], Consumer Behavior, and Organic Food; frequency: 31; centrality: 1.31) exhibits tighter intellectual cohesion, anchored in Ajzen's TPB and its application to micro-level behavioral modeling. Seminal works like Fukukawa K (2002) and recent studies (e.g., Agu A, 2023) dissect cognitive antecedents of organic food consumption, bridging behavioral psychology with agri-ethical practices. The cluster's elevated centrality underscores its role as a conceptual bridge, integrating niche applications (e.g., organic food) with universal behavioral theories.

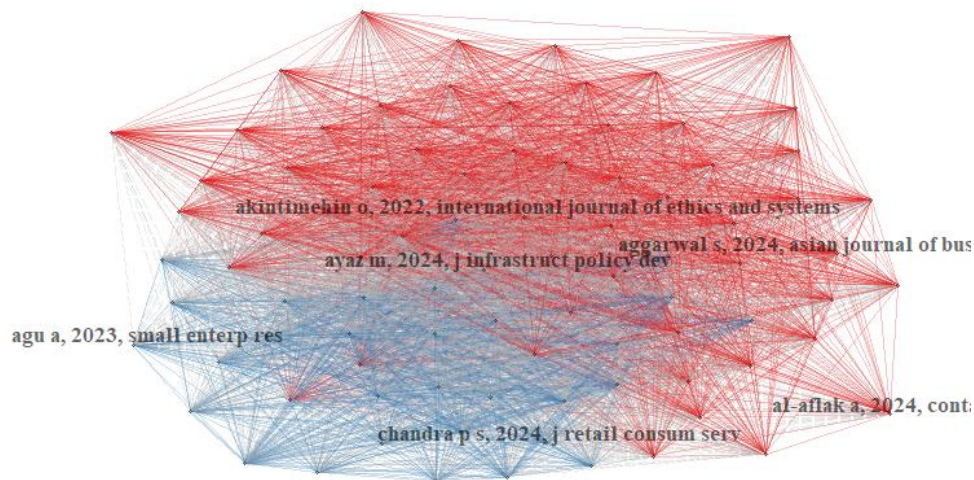


Fig. 6 - Coupling network of documents. Source: own research

Network dynamics (Figure 6) reveal asymmetric citation influence. The red section indicates Cluster 1, and the blue is Cluster 2. Cluster 1 labels the ethical consumption domination with 56%

frequency and 1.05 centrality, whereas cluster 2 represents the domination of TPB with 31% frequency and 1.31 centrality rate.

Thematic map and evolution analysis

Figure 7 presents the most relevant sources of publications. According to the development degree (density) and relevance degree (centrality), sustainability and consumer behavior are the basic themes of the study.

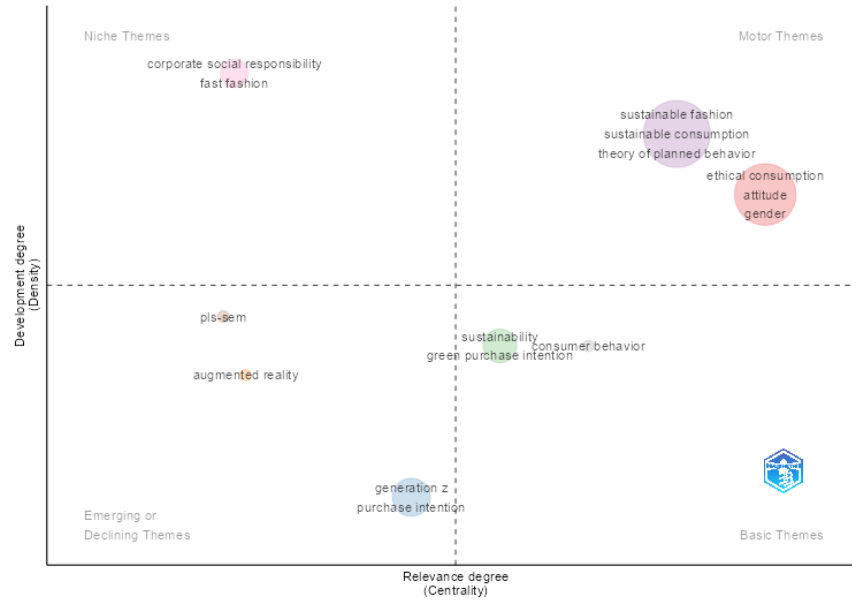


Fig. 7 - Thematic evolution. Source: own research

These themes are potentially not well developed and hence offer future research avenues. The highly developed and relevant themes can be found in the quadrant of motor themes. Sustainable fashion, consumption, TPB, and ethical consumption gender are the most established and important research areas. CSR and fast fashion are the niche themes well established in the analyzed publication; however, they are very specialized within a focus area of a field of study. Pls-sem as an analytical technique and augmented reality as a theme are not well-developed and central in the analyzed articles. These themes are gradually developing and gaining traction; however, they are not very central in terms of relevance.

Tab. 16 - Clustered thematic evolution, source: authors own research

CL1	CL2	Words	Inc_W eighted	Inc_i ndex	Occ	Stabil ity
behavior--2002- 2023	behavior-- 2024-2025	consumer;behavior	0.4117 6471	0.166 6666 7	9	0.05
behavior--2002- 2023	green-- 2024-2025	role	0.1470 5882	0.166 6666 7	7	0.033 3333 3

consumption-- 2002-2023	behavior-- 2024-2025	ethical;sustainable;consum ers;study;fashion;attitude	0.4062 5	0.066 6666 7	17	0.031 25
consumption-- 2002-2023	evidence-- 2024-2025	evidence	1	1	2	0.055 5555 6
consumption-- 2002-2023	ewom-- 2024-2025	gap	0.2222 2222	0.25	6	0.047 6190 5
consumption-- 2002-2023	green-- 2024-2025	consumption;intention;fact ors	0.1578 9474	0.055 5555 6	27	0.023 8095 2
control--2002- 2023	green-- 2024-2025	intentions	0.25	0.25	2	0.035 7142 9
food--2002-2023	green-- 2024-2025	food;products;millennials	0.8181 8182	0.333 3333 3	4	0.037 0370 4
generation-- 2002-2023	behavior-- 2024-2025	generation	0.3333 3333	0.25	4	0.055 5555 6
generation-- 2002-2023	green-- 2024-2025	organic	0.25	0.25	3	0.035 7142 9
purchase--2002- 2023	green-- 2024-2025	purchase;green	0.3437 5	0.090 9090 9	6	0.028 5714 3
purchase--2002- 2023	understandi ng--2024- 2025	understanding	0.4	0.5	2	0.083 3333 3
theory--2002- 2023	behavior-- 2024-2025	theory;planned	0.75	0.333 3333 3	4	0.058 8235 3

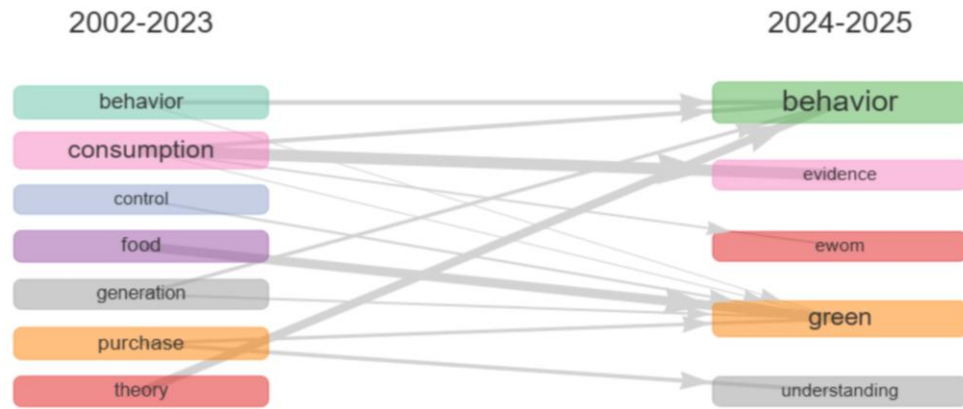


Fig. 8 - Visual representation of thematic evolution. Source: own research

The thematic evolution chart provided maps of the progression of research themes (clusters) from 2002-2023 to their projected connections or transformations in 2024-2025. This analysis reveals how academic focus areas are anticipated to evolve, merge, or diverge, emphasizing keyword shifts, conceptual overlaps, and emerging interdisciplinary trends. The interpretation of results in Table 16 reveals a significant pivot toward sustainability ("green" themes) as the dominant trajectory across research clusters. The "behavior" cluster evolves to emphasize consumer behavior in sustainability contexts, marked by keywords like "ethical" and "sustainable," though its low stability (0.05) signals rapid adaptation rather than continuity. Consumption studies diverge into two key paths: a robust, evidence-driven approach (perfect link strength to "evidence") and an emerging focus on sustainable consumption (high keyword co-occurrence but weak thematic overlap), highlighting unresolved questions about consumer motivations. Notably, food research powerfully merges with green themes (connection strength 0.82), driven by millennials' influence on eco-friendly product trends. At the same time, purchase behavior is increasingly tied to environmental consciousness, though its moderate link strength (0.34) suggests lingering barriers to green adoption.

The Theory of Planned Behavior remains central, bridging theoretical and behavioral clusters (strength 0.75), underscoring its utility in predicting sustainable actions. Simultaneously, generational shifts emerge as a cross-cutting theme, with studies focusing on younger cohorts' preferences for organic products and green lifestyles. Despite these trends, the pervasive low stability values (≤ 0.05 for most clusters) indicate a field undergoing rapid transformation, risking fragmentation. Key niches like eWOM (electronic word-of-mouth) and ethical fashion appear nascent but influential, urging interdisciplinary collaboration to consolidate insights and address sustainability's multifaceted challenges.

5 DISCUSSION

The bibliometric analysis of 88 articles on ethical consumption and the intention-behavior (I-B) gap among Generation Z reveals a dynamically evolving field characterized by exponential growth, thematic diversification, and regional disparities in scholarly influence. This discussion synthesizes key findings, contextualizes them within existing literature, and delineates implications for future research and practice.

5.1 Research Output and Temporal Dynamics

The study period (2002–2025) underscores a paradigm shift in academic engagement with ethical consumption. Early publications (2002–2010) were sparse, reflecting nascent interest in the I-B gap. However, a pronounced surge occurred post-2021, with 2023–2024 contributing 47 articles (53% of total output). This aligns with global discourse on sustainability, digital-native consumer behavior, and Gen Z's role in driving market transitions. Despite this growth, citation metrics exhibit a temporal lag: older publications (e.g., Carrington et al., 2010; Bray et al., 2011) dominate citations (TC: 814 and 523, respectively), while recent works (2023–2025) show limited impact (mean TC: 9.89–2.46). This pattern mirrors Donthu et al.'s (2021) assertion that citation accrual requires prolonged exposure, particularly in fast-growing fields where newer studies compete for visibility. The inverse relationship between publication volume and citation frequency highlights the need for longitudinal assessments to evaluate the enduring impact of contemporary research.

5.2 Geographical Disparities in Productivity and Impact

India emerged as the most prolific contributor (11 articles, 32.4% of output), yet its research exhibited attenuated global citation influence. In contrast, nations like the USA, Pakistan, and Sweden achieved disproportionate citation prominence despite modest output (1–5 articles). This discrepancy suggests that India's regional focus or methodological approaches may limit global resonance, whereas smaller contributors likely prioritized theoretical innovation or international collaboration. For instance, Pakistan's sole article (Ali et al., 2021) garnered 139 citations (normalized TC: 3.09), underscoring the impact of open innovation frameworks. Ling et al. (2023) posit that citation metrics reflect integration into global discourse, emphasizing the need for cross-border collaborations to amplify visibility. The dominance of single-country publications (SCPs) further corroborates this, as limited international partnerships may hinder methodological diversity and contextual generalizability.

5.3 Journal Influence and Author Contributions

The Journal of Business Ethics (h-index: 8; TC: 1,931) and Journal of Retailing and Consumer Services (m-index: 1.0) emerged as core outlets, reflecting their foundational and contemporary relevance. While the former has shaped ethical consumption frameworks since 2002, the latter's rapid rise post-2020 aligns with applied studies on retail dynamics and Gen Z. Author productivity metrics revealed a dichotomy: Kaur J (3 articles) led in output but had minimal citations (TC: 15), whereas foundational authors like Fukukawa K (2002, TC: 72) sustained long-term impact. This underscores the tension between productivity and influence, where seminal works anchor theoretical paradigms, while contemporary studies may require time to permeate scholarly dialogue.

5.4 Thematic Clusters and Conceptual Evolution

Document coupling and keyword analyses identified two dominant clusters:

Ethical Consumption and Sustainability (56 articles): Focused on macro-level challenges like sustainable fashion, circular economies, and Gen Z's retail engagement.

Theory of Planned Behavior (TPB) and Behavioral Modeling (31 articles): Explored cognitive antecedents of ethical decisions, particularly in organic food consumption.

The TPB cluster exhibited higher centrality (1.31 vs. 1.06), signaling its role as a conceptual bridge between niche applications and universal theories. Keyword trends further revealed a shift from abstract ethics (e.g., “ethically,” 2010–2020) to applied sustainability (“green,” “fashion,” post-2021). Emerging terms like “augmented reality” and “PLS-SEM” denote technological and methodological advancements, though their low centrality suggests underexplored potential.

5.5 Collaboration Networks and Fragmentation

Co-authorship analysis revealed fragmented networks dominated by regional clusters (e.g., India’s Kaur J and Chatterjee R; South Korea’s Soongsil University). Six collaboration clusters were identified, with limited cross-cluster linkages (e.g., Cluster 1’s betweenness: 12–30). This insularity contrasts with fields like climate science, where global consortia drive innovation. The lack of international co-authorships (0%) and low m-indexes (≤ 0.75) for most journals highlight missed opportunities for interdisciplinary synergy. Emich et al. (2020) argue that co-word analysis reveals thematic relationships. However, the bifurcation between sustainability and TPB clusters suggests a need for integrative frameworks linking behavioral theories to sectoral transitions.

6 CONCLUSION

This bibliometric review systematically examined the research landscape on ethical consumption and the intention-behavior (I-B) gap among Generation Z, analyzing 88 articles to map the field's intellectual structure, temporal evolution, and global scholarly dynamics. The study employed robust bibliometric methodologies, including co-word analysis, citation network mapping, and thematic clustering, to synthesize trends, identify gaps, and propose pathways for future inquiry. The findings underscore the field's rapid growth, thematic diversification, and persistent challenges, offering a foundation for advancing scholarly and practical efforts to address sustainability and ethical consumption in the Gen Z era.

The analysis revealed a marked acceleration in research output post-2021, with over half of the publications emerging between 2023 and 2025. This Surge aligns with global imperatives to address sustainability crises and the rising influence of Gen Z as a demographic that is reshaping consumption norms. However, citation metrics highlighted a temporal dissonance: foundational studies from the early 2010s, such as Carrington et al. (2010) and Bray et al. (2011), continued to dominate citation networks, while recent contributions faced visibility challenges inherent to fast-evolving fields. Geographically, India emerged as the most prolific contributor, yet its research exhibited limited global citation impact compared to smaller but methodologically innovative studies from nations like Pakistan and Sweden. This discrepancy underscores the complex interplay between regional research prioritization and global academic influence, suggesting that productivity alone does not guarantee scholarly resonance.

Thematic analyses identified two dominant clusters: one centered on macro-level sustainability challenges, such as sustainable fashion and circular economies, and another focused on micro-level behavioral frameworks, particularly the Theory of Planned Behavior (TPB). While the former dominated in volume, the latter demonstrated greater conceptual centrality, reflecting TPB's enduring utility in modeling cognitive drivers of ethical decision-making. Keyword evolution traced a conceptual shift from abstract ethical theorization in the 2010s to applied, sector-specific investigations post-2021, emphasizing "green consumption" and "fast fashion." This progression signals the field's responsiveness to real-world sustainability challenges but also

reveals underexplored intersections, such as the role of cultural values or digital activism in bridging the I-B gap.

Collaboration networks remained regionally fragmented, dominated by single-country publications and insular institutional clusters. This contrasts sharply with interdisciplinary fields like climate science, where global consortia drive innovation, and highlights missed opportunities for cross-border methodological synergy. The near absence of international co-authorships (0%) further exacerbates this fragmentation, limiting the diversity of contextual and theoretical perspectives.

The study's theoretical contributions lie in its systematic Consolidation of fragmented literature, clarifying how behavioral psychology and sustainability science intersect or diverge in addressing the I-B gap. By delineating TPB's centrality alongside its under-integration with systemic frameworks, the review calls for hybrid models that contextualize individual agency within structural barriers, such as economic inequities or infrastructural limitations. Practically, the prominence of terms like "sustainable fashion" and "green purchase intention" underscores the urgency of industry and policy interventions, including transparent supply chains, eco-labeling initiatives, and Gen Z-targeted educational campaigns. For academic journals, the dominance of outlets like the *Journal of Business Ethics* signals opportunities to champion interdisciplinary special issues, particularly on emerging themes like digital interfaces in ethical consumption or postcolonial critiques of sustainability.

Methodologically, the field's reliance on PLS-SEM and self-reported surveys, while valuable for modeling latent variables, risks oversimplifying the I-B gap's complexity. Future studies could adopt mixed-methods approaches integrating ethnography, longitudinal tracking, and experimental designs to capture dynamic behavioral shifts and contextual nuances. The low stability of thematic clusters (e.g., "behavior" stability: 0.05) further underscores the need for real-time data to track Gen Z's evolving ethical priorities, particularly in crisis contexts like pandemics or climate emergencies.

Limitations of this review include its reliance on three major databases (WOS, Scopus, Emerald), which may exclude regionally influential journals, and its focus on English-language articles, potentially overlooking critical non-Anglophone perspectives. Additionally, projected data for 2025 introduce uncertainties that future updates must address.

Looking ahead, four priorities emerge for advancing the field. First, interdisciplinary integration is critical to bridge the divide between behavioral theories and systemic sustainability frameworks. For instance, research could explore how platform economies (e.g., clothing rental apps) mediate Gen Z's attitudes toward fast fashion within circular economy paradigms. Second, technological innovations such as augmented reality tools for ethical sourcing transparency or blockchain applications for supply chain accountability warrant rigorous investigation as potential bridges for the I-B gap. Third, comparative, cross-cultural studies are essential to unpack how collectivist versus individualist societal norms shape ethical consumption patterns, particularly in underrepresented regions like Africa and Latin America. Finally, crisis-driven contexts such as climate emergencies or geopolitical instability demand attention to understanding how external shocks amplify or diminish Gen Z's ethical engagement, especially in digital-native consumption ecosystems.

In conclusion, this review not only maps the current state of research but also charts a course for its evolution. As Generation Z redefines global consumption ethics, the field must transcend

disciplinary silos, embrace technological and methodological innovations, and prioritize inclusive, culturally nuanced inquiries. Bridging the I-B gap is not merely an academic endeavor but a societal imperative that demands collaborative, actionable scholarship to foster equitable and sustainable futures. By addressing these challenges, researchers, policymakers, and industries can transform fragmented insights into a cohesive paradigm capable of navigating the complexities of 21st-century ethical consumption.

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THE STRENGTHENING EFFECT OF THE INNOVATIVE ENVIRONMENT ON TOURISM PERFORMANCE

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Abstract

The economic growth of industries is conditioned by their innovativeness. Tourism, as a representative of production with low knowledge intensity, can still benefit from the synergistic effects of cooperation within the innovation environment. The promotion of innovations in the tourism industry is driven by changing customer needs, competitive pressure, and companies' sustainable ambitions. The primary goal of this article is to analyze the relationship between investments in R&D and labor productivity in the tourism industry. A complementary objective is to assess the broader impact of innovations on performance within the sector. To achieve these goals, we used correlation analysis of selected indicators across a sample of 31 countries and panel regression analysis involving four selected countries, totaling 32 observations and four cross-sectional units. The indicators include R&D expenditures and labor productivity metrics, observed over the reference period 2013–2020. The results clearly confirm that R&D spending positively influences labor productivity in tourism. Hence, the economic growth of the tourism industry depends on the quality of the innovation environment. Critical prerequisites are the ability of tourism entities to recognize the need for change and to harness synergistic effects from collaboration in innovation. An effective tool for increasing innovation adoption in tourism is the implementation of an open innovation platform.

Keywords: labor productivity, R&D, innovations, panel regression, EU countries

1 INTRODUCTION

Although tourism is often classified as a low-knowledge-intensive sector, this does not imply a low potential for innovation. On the contrary, the increasing sophistication of customer demand, the availability of advanced technologies, and the intensifying market competition provide tourism enterprises with opportunities to enhance their competitiveness through innovation. In this context, it becomes important to examine how the broader innovation environment of an economy—particularly national investments in research and development (R&D)—can influence performance outcomes in the tourism industry.

In general, countries with strong innovation systems tend to achieve higher rates of economic growth and productivity (Romer, 1990). For example, a study by the Organization for Economic Co-operation and Development (OECD) found that a 1% increase in R&D spending can lead to a 0.13% increase in GDP growth (OECD, 2005). Does this also apply to tourism?

The significant share of tourism in the global GDP justifies the importance of research in this area. In this sense, it is essential to be interested in the various aspects that can affect this sector. One of these aspects is the macroeconomic level of education and research and development in individual countries, as these are the main components of countries' innovative activities (Gavurova, 2021). Innovations are thus attributed a positive role in the development of tourism. Blake and Sinclair (2006) confirmed the impact of innovations on labor productivity in the tourism industry of Great

Britain. Authors Santos et al. (2020) investigated labor productivity growth in Portuguese firms based on capital, firm size, innovation and firm competitiveness. The growth of investments in research and development significantly and positively affects the growth of labor productivity. The impact of research and development is a more significant factor in the growth of labor productivity than the growth of capital, which confirms the importance of investments in research and development (Heshmati, 2011). The importance of the sophistication of human performance in the tourism industry for the growth of labor productivity is investigated by a study by the authors Stauvermann and Kumar (2017).

Recent studies confirm that R&D investment plays a crucial role in boosting productivity and economic growth. A positive link between R&D expenditure and GDP growth has been demonstrated across countries, including in Israel and the South Caucasus (Gulaliyev et al., 2024). Public R&D spending in Europe has also shown strong returns on productivity, particularly in agriculture (Vollaro et al., 2021), and evidence from advanced economies suggests public R&D has greater impact than private R&D (Ciaffi et al., 2024).

However, the effectiveness of R&D varies widely. While Estonia benefits from R&D-driven productivity, neighboring Baltic states do not show similar results (Zienkiewicz et al., 2023). Meta-analyses show that R&D–growth links are well-documented in high-tech sectors but underexplored in services such as tourism (Shahid et al., 2024). This represents a key research gap our study aims to address.

Despite the growing role of innovation in shaping the competitiveness of tourism, the macroeconomic dimension of the innovation environment—particularly national R&D investment—remains underexplored in tourism research. Most existing studies either focus on firm-level innovation strategies or on productivity in manufacturing and high-tech sectors. However, emerging evidence suggests that R&D expenditures can positively influence labor productivity even in service-based industries, including tourism. For example, studies by (Santos et al., 2020) and (Blake & Sinclair, 2006) have shown a measurable impact of innovation on productivity in the tourism sector.

Nonetheless, there is a lack of research that explicitly connects national-level R&D spending to labor productivity in tourism, especially within Central European countries, where tourism holds economic significance, but innovation readiness varies widely. Our study addresses this gap by analyzing the relationship between R&D investment and labor productivity in tourism across selected European countries, with a focused sample including the Slovak Republic, Czech Republic, Austria, and Norway.

To provide structure and improve the clarity of the research, we formulate the following research question:

RQ1: Does spending on R&D affect labor productivity in the tourism industry?

H₀: There is no dependence between R&D investment and labor productivity in the tourism industry.

H₁: There is a dependency between R&D investment and labor productivity in the tourism industry.

By investigating this question, the paper contributes to a better understanding of how innovation inputs at the macroeconomic level influence sectoral performance in tourism, with implications for innovation policy and sustainable competitiveness in service economies.

2 LITERATURE REVIEW

Innovation in the tourism sector refers to the implementation of new or significantly improved products, processes, marketing methods, or organizational structures that enhance a firm's competitiveness (Cardoso et al., 2024). In the context of this research, three main types of innovation are considered:

- Digital innovation, such as mobile apps, virtual and augmented reality, AI-driven personalization, and IoT applications (Paliy, 2024).
- Sustainable innovation, including eco-friendly accommodations, renewable energy use, and green supply chains (Ismailov et al., 2024).
- Service innovation, involving experience-based tourism, product personalization, or new business models such as open tourism and co-creation platforms (Dolynska et al., 2023).

These innovations have been shown to improve customer satisfaction, increase productivity, and strengthen long-term competitiveness in tourism enterprises (Levchenko, 2022). However, much of the existing literature remains focused on micro-level innovation practices, such as individual firm adoption or digital service improvements.

What remains underexplored is the macro-level influence of national innovation environments—particularly public R&D spending—on tourism performance. Tourism SMEs, which dominate the sector, often lack internal innovation capacity but may benefit from operating in highly innovative economies (Gabor et al., 2023). Despite this potential, few studies have empirically investigated how country-level R&D expenditure correlates with labor productivity in the tourism sector.

This gap becomes especially relevant in Central Europe, where tourism is economically significant, but innovation capacity is uneven across countries. Addressing this relationship is essential to understand how macroeconomic inputs can enhance service-sector productivity and contribute to sustainable development in tourism.

The cross-sectionality and multiplier effects of the tourism industry are starting points for considerations about the importance of entering the industry. The production of tourism services is characterized by a low degree of knowledge intensity. However, the competitive success of tourism products is conditioned using sophisticated technologies in various areas. These are primarily information and communication technologies, digital technologies, environmentally sustainable technologies, and in the case of medical tourism, also technologies associated with regeneration and treatment. Tourism thus generates demand for inputs of technologically and knowledge-advanced quality.

The effects of the innovative environment on tourism performance

The innovation environment is manifested in its three components: innovation potential, innovation culture, innovation performance (Kubičková & Benešová, 2022). R&D spending has a decisive influence on its quality. The R&D expenditure indicator is therefore one of the possible expressions of the maturity level of the innovative environment. Tourism, as an industry with a low degree of knowledge intensity, represented mainly by small and medium-sized enterprises with limited own innovation resources, can use synergistic effects from an innovation-stimulating environment, primarily based on the action of open innovation (Pikkemaat & Peters, 2016, Brunswicker, 2016). Authors Egger et al. (2016) recognize a new business model of open tourism, which opens its structures and integrates external resources into internal processes. This is the

principle that opens the space for connectivity and sharing of effects from the co-director. Regional tourism development faces the challenge of looking for opportunities for non-traditional forms of innovation and connectivity through the sharing of social capital (Annamalah et al., 2023, Del Vecchio et al., 2018). It is generally recognized that the use of open innovation systems in tourism is fully consistent with its sustainable development (Corte et al., 2019). The need for interdisciplinary solutions as responses to the pandemic situation associated with the disease COVID-19 and to the limited production of tourism services only strengthened the effectiveness of open innovation in the tourism environment (Pillmayer et al., 2021).

The innovatively advanced environment of the economy creates favorable conditions for ensuring the required inputs into the tourism industry in terms of its sustainable development. Therefore, it is essential to be interested in the various aspects that can affect this sector. One of these aspects is the macroeconomic level of education and research and development in individual countries, as these are the main components of countries' innovative activities (Gavurova, 2021).

Several studies have been devoted to the relationship between innovations and tourism performance. The results document the positive impact of the use of information and communication technologies on client satisfaction, sales volume and work productivity (Platon, 2017). The capacity of a tourist destination can be increased by investing in innovation. This is confirmed by the model of the authors Albaladejo and Garcia (2015), in which investments in R&D create sustainability of income in the tourism industry in the long term. Tourism revenue is growing as fast as innovation. If we invest in tourism innovation, tourism arrivals grow (Albaladejo & Martínez-García, 2015). The authors Hall and Williams (2008) associate innovation with the possibility of business prosperity and staying in the market. A study in North American countries showed that constant innovation brings hotels a competitive advantage and attracts more new customers (Victorino et. al., 2005).

Author Domi et al. (2019) investigated the innovativeness and impact of innovations in small and medium-sized enterprises in Albania. The results of their study confirmed the findings of Grisseman et al. (2013), Atuahene-Gima (1996) and De Jong et al. (2003), who concluded that the more employees and managers are open to new ideas and change, the more innovation will take place in small and medium-sized enterprises. The results of the study in Albania confirmed that if managers and owners are open to change and innovation, more innovations are introduced in small and medium-sized enterprises.

Author Sardak et al. (2016) identified five key areas of deployment of global innovation trends that are part of the tourism sector: tourism growth; application of qualitatively new solutions of a scientific, methodological and application nature; the growing influence of tourism in society; the existence of a synergistic effect in the tourism industry as a result of combining the efforts of subjects at all levels of management; the changing role of internal and external factors that support the development of innovative tourism.

In the past, several authors have devoted themselves to innovations in the tourism industry and what kind of innovations businesses in the tourism industry have. The author Hall (2009) in his study in proved that accommodation and food businesses in Australia and New Zealand are comparatively innovative than other businesses in the economies of these countries. On the other hand, Evangelista (2000) claims that less than 20% of Italian accommodation and catering facilities are innovating, while in other services more than 30% of businesses are innovating. Later, this author stated in his study that small and medium-sized and less than half of service sector

enterprises experience an impact of innovation on employment. These are enterprises in industries that have a strong scientific and technological base. The negative impact of innovations on employment is, on the contrary, found in large companies, capital-intensive industries and in all financial industries (banking, insurance and other financial services) (Evangelista, 2002). A negative impact can occur because increased innovation reduces the demand for human performance, which is reflected due to employment, which can decrease as a result.

Recent studies show that innovation has changed rapidly in recent decades and is not the same as it was at the end of the 20th century. For example, innovations in information technology offer new opportunities. The tourism industry is influenced by innovations with environmental, sociocultural, psychological and economic impact (Gossling, 2017). Several authors have stated that innovation has a very positive impact on tourism. The author Milicevic (2020) investigated the relationship between tourism income and the development of ICT services. The result confirmed that ICT services have a positive impact on tourism revenues, while the next variable examined was tourist arrivals. This study confirmed that innovations in tourism bring a competitive advantage to companies that have innovations in tourism services (Gavurova, 2021).

Productivity in tourism as a performance indicator

The maturity of the innovative environment is a determining factor of productivity in the tourism industry. The authors Joppe and Li (2016) state that "North American and European countries lead the world tourism industry in terms of productivity growth". The mentioned authors recognize labor productivity as the most important indicator of productivity evaluation in the tourism industry. They argue the critical importance of human capital for the provision of tourism experiences (Joppe and Li, 2016).

Labor productivity is key in determining potential growth in living standards, as a higher level of per capita income will bring more output to be produced by labor (Sharpe, 2000). Low labor productivity causes many negative impacts on the inhabitants of the country where low labor productivity is recorded. The result is low incomes, high corruption and a large gap between income levels (Ivanov, 2021).

The use of input indicators to express labor productivity can be different. Some authors state that the labor productivity of the tourism industry is determined by the ratio of the gross product (GDP) and the number of employees (Drakh et. al., 2021; Conference Board of Canada, 2009), respectively. GDP and the volume of work expressed in hours (Joppe, 2016). Another author measured labor productivity as the ratio of the volume of production to the expended live labor (Joppe, 2016). The Greek Ministry of Tourism states that the quality, price of labor and its productivity determine the unit expense of labor, so the average volume of employer expenses per employee (Joppe, 2016).

A holistic approach to expressing productivity emphasizes customer satisfaction and sustainability. The methodology of this approach combines cost of goods sold and labor expenditures with revenue and profit, including variables such as guest and employee satisfaction. This American approach emphasized customer satisfaction and sustainability (Ryenolds & Biel, 2007). Cahuc and Debonneuil (2004) also confirm the presence of the aspect of service quality in the methodology of expressing productivity in the tourism industry. They compared service productivity in France and the United States of America for the HORECA sector. They reported that the improvement in the quality of services brought about an increase in labor productivity in the US and was twice as high as in France.

3 METHODOLOGY

The subject of our research was the relationship between labor productivity and investments in research and development in the countries of the European Union. The main goal of our research was to identify the relationship between investments in R&D and labor productivity in the tourism industry.

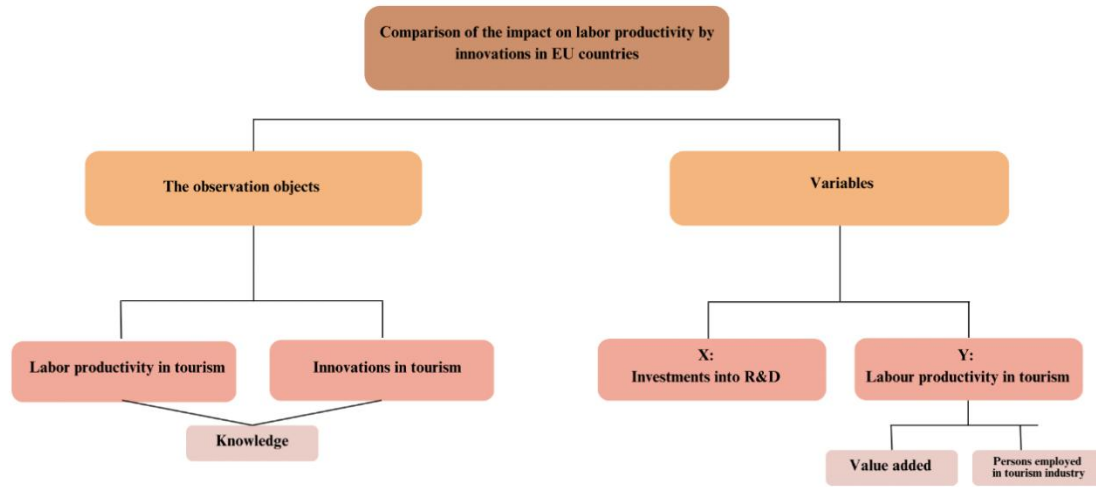


Fig. 1 - Schematic presentation of research methodology. Source: own research

RQ1: Does spending on R&D affect labor productivity in the tourism industry?

H₀: There is no dependence between R&D investment and labor productivity in the tourism industry.

H₁: There is a dependency between R&D investment and labor productivity in the tourism industry.

To fulfill the main goal of the work, several scientific methods were used - primarily mathematical-statistical methods for testing a data set in the Gretl software. The main data source for our research was Eurostat, mainly due to the complexity of the data. Relevant indicators were total investments in R&D in 31 countries and labor productivity in tourism. We identified labor productivity in the tourism industry as the share of added value and the number of employees in the tourism industry. Tourism is represented by sections NACE I - Accommodation and catering services, N - Travel agency and travel agencies, sections R - Arts, entertainment and recreation. To assess the suitability of parametric testing, we first verified the normality of the residuals using the Shapiro-Wilk test, which is recommended for small- to medium-sized samples due to its sensitivity and power (Razali & Wah, 2011). This test evaluates whether the data distribution significantly deviates from normality; a high p-value supports normality, while a low p-value rejects it. A panel regression was performed on the panel data of 4 countries using the GRETl program. Panel regression was performed based on 32 observations, which reflected 4 cross-sectional units (Czech Republic, Austria, Slovak Republic and Norway) over a period of 8 years (2013-2020). We applied a panel regression model using the pooled ordinary least squares (OLS) approach, which is appropriate when individual effects across cross-sectional units are assumed constant (Wooldridge, 2010). The model is expressed as:

$$y_{it} = \alpha + \beta_1 x_{it1} + \beta_2 x_{it2} + \dots + \beta_k x_{itk} + u_{it} \quad (1)$$

Where the index i denotes the cross-sectional dimension $i=1, \dots, n$, the index t the time dimension $t=1, \dots, T$, variables X_1 to X_k are explanatory variables not including the unit vector and variables Z_1 to Z_q represent individual effects - diversity, by which an individual or an entire group can be distinguished from other entities - a possible vector of units is included here. Individual effects do not change over time.

4 RESULTS

The starting data for the implementation of the research were the values of investments in R&D and the achieved labor productivity in the tourism industry in the countries of the European Union for the period of 2013-2020. Labor productivity is expressed as a share of added value per employee in tourism, tourism is represented by sections NACE I - Accommodation and catering services, N - Travel agencies and travel agencies, and sections R - Arts, entertainment and recreation.

Table 1 presents the R&D investment values that serve as the independent variable in the model, while Table 2 shows the tourism labor productivity values, used as the dependent variable in the regression analysis.

Tab. 1 - Investments in research and development in EU countries (2013-2020) in millions EUR. Source: Eurostat, 2024

Country	2013	2014	2015	2016	2017	2018	2019	2020	2021
Belgium	9 156,953	9 551,244	10 118,2	10 852,674	11 867,981	13 158,259	15 109,898	15 425,429	16 151,868
Bulgaria	266,736	339,927	434,838	375,434	388,707	423,818	512,39	523,464	549,136
Czechia	2 996,666	3 090,662	3 250,243	2 963,274	3 433,337	4 006,462	4 348,346	4 285,863	4 755,475
Denmark	7 685,904	7 744,272	8 340,596	8 756,111	8 641,546	8 967,155	9 107,7	9 255,319	9 470,62
Germany	79 729,508	84 246,766	88 781,819	92 173,556	99 553,616	104 669,045	110 025,41	106 582,971	112 850
Estonia	326,045	286,736	302,82	270,34	304,32	365,64	452,97	480,89	550,962
Ireland	2 813,14	2 967,2	3 108,7	3 175,1	3 727,603	3 812,432	4 370,61	4 595,286	4 501,544
Greece	1 465,67	1 488,74	1 703,82	1 754,18	2 038,43	2 179,31	2 337,66	2 494,2	2 635,232
Spain	13 011,798	12 820,756	13 172	13 260	14 063	14 946	15 572	15 768	17 249,25
France	47 362,045	47 918,737	48 959,451	49 650,92	50 513,598	51 913,8	53 427,81	53 229,762	55 317,06
Croatia	354,684	339,857	374,809	402,357	423,517	501,756	600,754	626,587	725,121
Italy	20 983,1	21 781,275	22 157	23 171,612	23 793,65	25 232,243	26 259,661	25 028,257	26 516,918
Cyprus	87,469	89,521	85,286	98,815	110,214	133,097	164,435	184,764	208
Latvia	139,766	162,8	152,2	110,4	137,9	186,2	195,2	208,23	232,2
Lithuania	332,426	376,827	389,67	327,612	378,906	426,306	485,998	564,868	622,354
Luxembourg	605,731	630,3	678	712,1	720,7	704,5	737,8	688	739,439
Hungary	1 415,099	1 428,824	1 510,935	1 371,667	1 672,945	2 051,375	2 158,621	2 196,412	2 531,109
Malta	59,055	60,539	71,491	58,702	65,928	74,626	80,05	86,205	94,99
Netherlands	14 240	14 595	14 808	15 235	16 081	16 554	17 760	18 494	19 316
Austria	9 571,282	10 275,18	10 499,146	11 145,02	11 289,781	11 912	12 441,232	12 199,02	12 951,77
Poland	3 436,284	3 864,016	4 316,508	4 112,349	4 834,038	6 018,489	7 046,915	7 292,84	8 252,87
Portugal	2 258,471	2 232,249	2 234,37	2 388,467	2 585,1	2 769,072	2 991,864	3 236,212	3 564,918
Romania	557,769	575,12	782,142	818,444	944,906	1 024,77	1 067,442	1 026,09	1 141,236
Slovenia	935,006	890,232	853,067	811,953	802,291	892,724	990,698	1 007,493	1 117
Slovakia	610,876	669,632	927,272	640,835	748,955	750,947	776,59	838,927	918,35
Finland	6 684,1	6 512,1	6 070,9	5 926,1	6 173,2	6 437,7	6 715,1	6 932,7	7 491,102
Sweden	14 406,172	13 611,914	14 662,533	15 141,358	16 142,23	15 631,342	16 154,347	16 769,514	18 033,107
Iceland	205,335	260,85	344,556	396,732	456,79	444,915	515,793	470,257	600,609
Norway	6 500,596	6 447,728	6 727,586	6 818,16	7 416,769	7 582,923	7 799,17	7 245,337	8 031,052
Switzerland	-	-	19 255,903	-	18 932,77	-	20 572,036	-	-
United Kingdom	33 998,705	37 960,055	43 573,987	40 426,602	39 704,118	41 903,357	44 364,32	-	-

Tab. 2 - Labor productivity in tourism in EU countries (2013-2020) in millions EUR Source: Eurostat, 2024

Country	2012	2013	2014	2015	2016	2017	2018	2019	2020
Czechia		0,01315	0,01302	0,013674	0,01442	0,01694	0,01777	0,01849	0,01194
Spain	0,02469	0,02500							
Croatia	0,01317	0,01648	0,01586	0,01689	0,01883	0,01837	0,02023	0,01878	
Lithuania	0,00665	0,00730	0,00855	0,00967	0,01010	0,01243	0,01276		
Hungary		0,00784	0,01039		0,01296	0,01467	0,01621	0,01588	0,00754
Malta					0,02547		0,02915		
Austria	0,03599	0,03611	0,03628	0,03759	0,04042	0,04187	0,04267	0,04467	0,04333
Slovakia	0,01763	0,01361	0,01206	0,01342	0,01037	0,01075	0,01134	0,01276	0,00864
Sweden	0,03896	0,03845	0,03788	0,03823	0,03887	0,03924			
Norway		0,05901	0,05086	0,04443	0,04469	0,04319	0,03996	0,04304	0,02972
United Kingdom	0,03608	0,03561	0,04064	0,04527	0,04250	0,04064	0,04122		

As we can see from the data in Tables 1 and 2, the necessary data that we examined in our research were not available in every EU country. For this reason, we chose 3 countries for summary

statistics: the Czech Republic, the Slovak Republic and Austria. Another country that had all the necessary data for our research was Norway, a representative of the region of advanced innovation environment.

In the following section, we present an overview of R&D investments and tourism labor productivity (PP) for the Czech Republic, Slovak Republic, Austria and Norway for the period 2013-2020.

Tab. 3 - Czech Republic, Slovak Republic, Austria and Norway - investments in R&D and tourism labor productivity (PP) (2013-2020) in millions EUR. Source: Eurostat, 2024

YEAR	CZECHIA		SLOVAKIA		AUSTRIA		NORWAY	
	R&D	PP	R&D	PP	R&D	PP	R&D	PP
2013	2 996,666	0,01315	610,876	0,01361	9 571,282	0,03611	6 500,596	0,05901
2014	3 090,662	0,01302	669,632	0,01206	10 275,18	0,03628	6 447,728	0,05086
2015	3 250,243	0,01367	927,272	0,01342	10 499,146	0,03759	6 727,586	0,04443
2016	2 963,274	0,01442	640,835	0,01037	11 145,02	0,04042	6 818,16	0,04469
2017	3 433,337	0,01694	748,955	0,01075	11 289,781	0,04187	7 416,769	0,04319
2018	4 006,462	0,01777	750,947	0,01134	11 912	0,04267	7 582,923	0,03996
2019	4 348,346	0,01849	776,59	0,01276	12 441,232	0,04467	7 799,17	0,04304
2020	4 285,863	0,01194	838,927	0,00864	12 199,02	0,04333	7 245,337	0,02972

For a better illustration, we will use the following figure to present the development of investment in R&D as well as the development of tourism labor productivity in the Czech Republic, the Slovak Republic, Austria and Norway for the period 2013-2020.

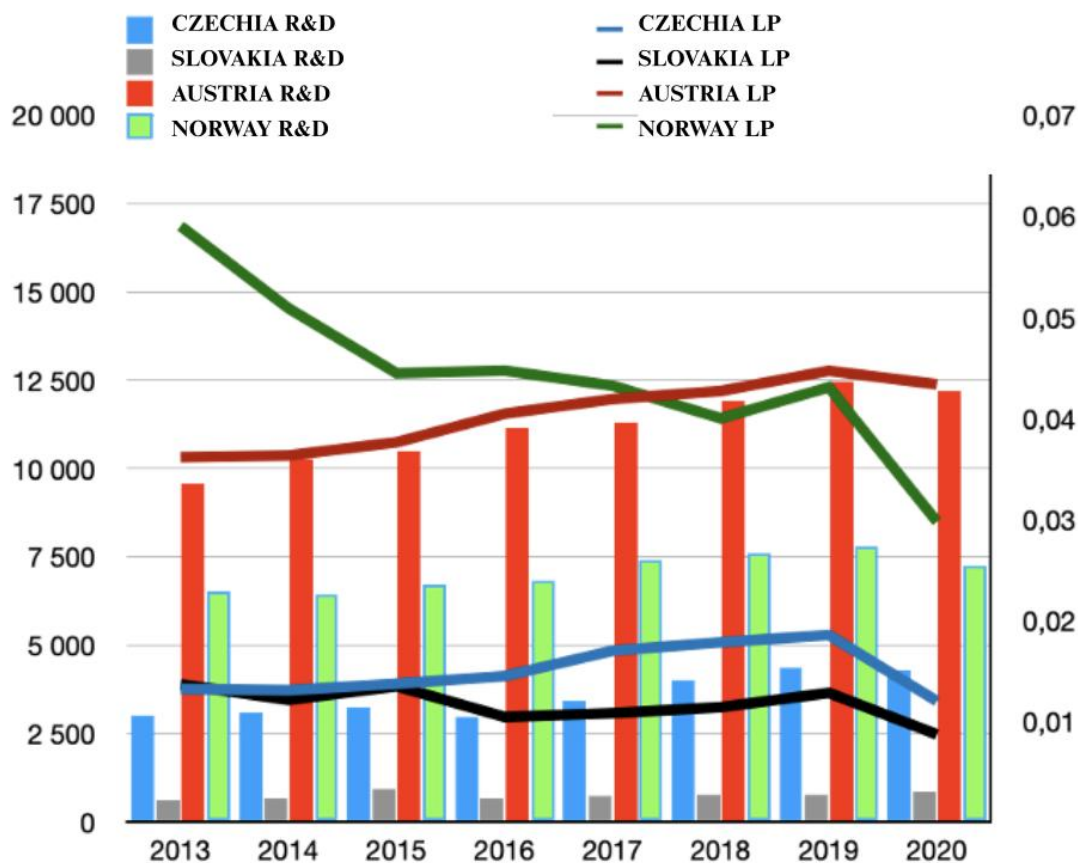


Fig. 2 - Czech Republic, Slovak Republic, Austria and Norway - investments in R&D and tourism labor productivity (PP) (2013-2020). Source: own research

The value of tourism labor productivity (PP) does not reflect the development of investment in R&D during the monitored years on figure number 2. From the above figure, it is not possible to assess whether there is a dependence between labor productivity and investments in R&D. The decline in tourism labor productivity of the Czech Republic in 2020 is significant. The development of investment in R&D as well as the development of tourism labor productivity in Austria in the years 2013-2020 point to almost the same dynamics of tourism labor productivity (PP) and investment in R&D as in the Czech Republic. The development of investment in R&D as well as the development of tourism labor productivity in the Slovak Republic for the period 2013-2020 shows independent dynamics between the indicators. The independent relationship of these two variables is further investigated using panel regression. In the case of Norway, a sharp drop in tourism labor productivity can be noted, like what happened in the Slovak Republic and the Czech Republic.

To assess the distribution and variability of the independent variable used in the analysis, Table 4 presents descriptive statistics for R&D investment (RD) across the observed countries and years.

Tab. 4 - Summary statistics for the RD (investment in R&D) variable. Source: own research

Mean	Median	Minimum	Maximum
5631,6	5398,0	610,88	12441,
Std. Dev.	C.V.	Skewness	Ex. kurtosis
4010,7	0,71218	0,24529	-1,2472
5% Perc.	95% Perc.	IQ range	Missing obs.
630,35	12284,	7692,0	0

Table 4 shows that the mean R&D investment was approximately 5,631.6 million EUR, with a median of 5,398 million EUR. The minimum investment observed was 610.88 million EUR, and the maximum was 12,441 million EUR, indicating a substantial range between less and more innovation-driven countries. The standard deviation is high (4,010.7), with a coefficient of variation (C.V.) of 0.71, reflecting significant relative variability in R&D spending. The skewness value of 0.25 indicates slight right skew, and excess kurtosis of -1.25 suggests a flatter distribution than the normal curve. Again, no missing observations were found, and the interquartile range (7,692) highlights wide dispersion among the central 50% of values. These statistics demonstrate large disparities in innovation investment across EU countries and support the relevance of exploring its effect on labor productivity in tourism.

In this step, we determined the distribution of the investigated data, and for this we used the test of normality of the distribution of residuals. A histogram of the data distribution was created for each country and R&D investment. A histogram of the distribution of R&D investment data is shown below in Figure 3.

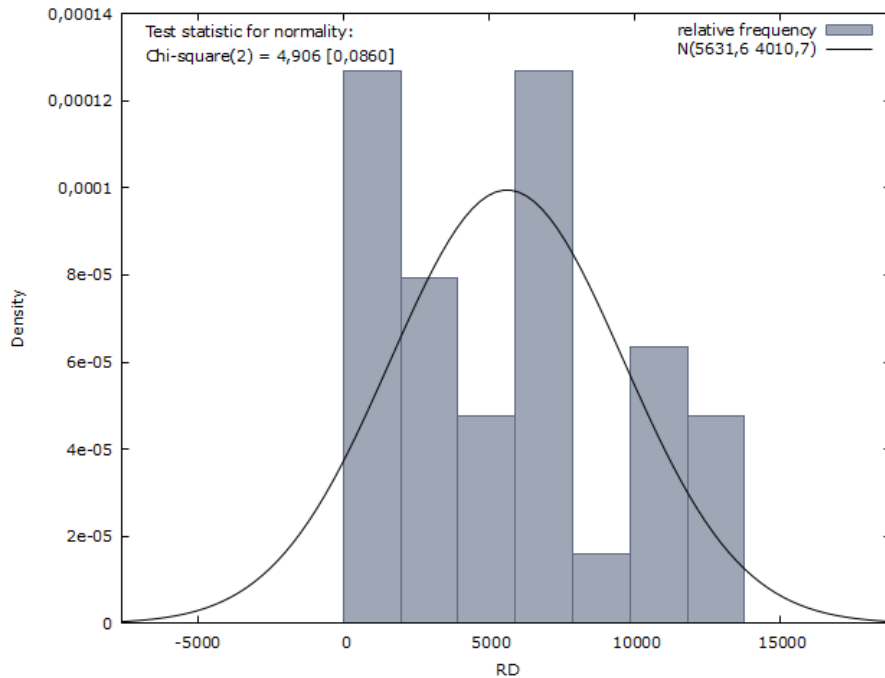


Fig. 3 - Histogram of the normality of the distribution of residuals of investments in research and development (RD) (2013-2020). Source: own research

Figure number 3 shows that the data is not normally distributed. This finding tells us that some countries have different investments in research and development and thus the standard deviation mentioned above is higher than in the case of a normal distribution.

To better understand the distribution of tourism labor productivity across countries and years, we provide descriptive statistics for the dependent variable (PP) in Table 5.

Tab. 5 - Summary statistics for the variable PP (tourism labor productivity). Source: own research

Mean	Median	Minimum	Maximum
0,027819	0,024106	0,0086442	0,059008
Std. Dev.	C.V.	Skewness	Ex. kurtosis
0,015567	0,55958	0,22456	-1,5074
5% Perc.	95% Perc.	IQ range	Missing obs.
0,0097647	0,053710	0,029895	0

Table 5 summarizes the key characteristics of tourism labor productivity (PP). The mean value is 0.0278, while the median is slightly lower at 0.0241, indicating a mildly right-skewed distribution. The standard deviation of 0.0156 reflects moderate variability, and the coefficient of variation (C.V.) of 0.56 suggests relative dispersion around the mean. The minimum and maximum values show the range of productivity levels across observations (0.0086 to 0.0590). The skewness value

of 0.22 confirms slight asymmetry, and excess kurtosis of -1.51 indicates a distribution flatter than the normal distribution. No missing observations were recorded. These statistics confirm the diversity of productivity levels in EU countries' tourism sectors and support the relevance of further analysis using regression techniques.

In the next step, we determined whether the investigated data were of a normal distribution, and for this we used the test of normality of the distribution of residuals. A histogram of data distribution was created for each country and tourism labor productivity. A histogram of the distribution of tourism labor productivity data is shown below in Figure 4.

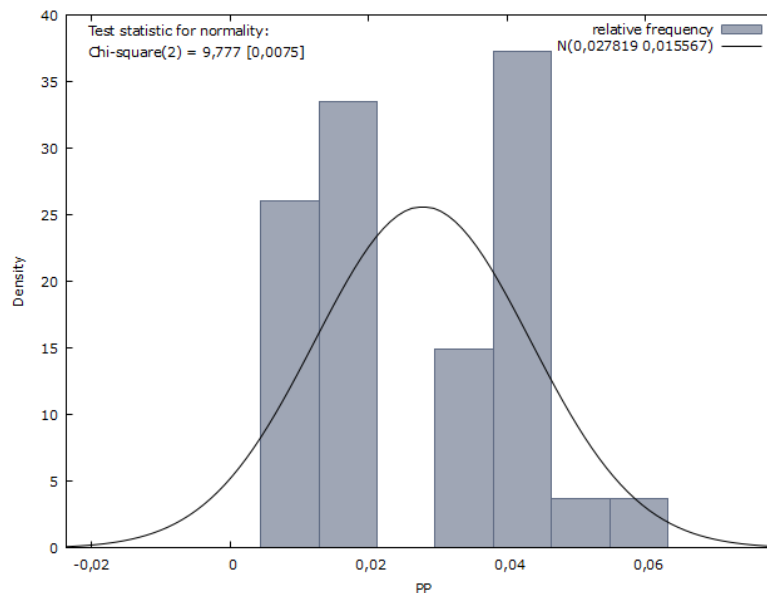


Fig. 4 - Histogram of the normality of the distribution of labor productivity residuals (PP) (2013-2020). Source: own research

It is clear from the above figure that the data are not normally distributed, which means that some countries have different labor productivity in the tourism industry and thus the standard deviation mentioned above is higher than with a normal distribution.

A panel regression was performed using GRET software on data from four countries: the Czech Republic, Austria, Slovak Republic, and Norway. The dataset includes 32 observations, reflecting 4 cross-sectional units over 8 years (2013–2020).

We refer to the resulting specification as Table 6, which is a pooled ordinary least squares (OLS) regression model. This model assumes a common intercept across countries and time, meaning it treats the panel data as one combined dataset without accounting for fixed or random effects. This choice is appropriate when the goal is to test for a general relationship and when individual effects across countries are not assumed to significantly vary, which aligns with the structure of our data and our primary research question.

Tab. 6 - Pooled OLS using 32 observations. Source: own research

Including 4 cross-sectional units; Time series length = 8 years; Dependent variable: PP (tourism labor productivity)

	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-ratio</i>	<i>p-value</i>	
const	0,00972500	0,00273425	3,557	0,0013	***
RD	3,21290e-06	3,97576e-07	8,081	<0,0001	***
Mean dependent var	0,027819	S.D. dependent var		0,015567	
Sum squared resid	0,002365	S.E. of regression		0,008878	
R-squared	0,685224	Adjusted R-squared		0,674732	
F(1, 30)	65,30602	P-value(F)		5,08e-09	
Log-likelihood	106,8000	Akaike criterion		-209,6000	
Schwarz criterion	-206,6685	Hannan-Quinn		-208,6283	
rho	0,797856	Durbin-Watson		0,097780	

The constant is statistically significant ($p=0.0013$), as is the value of R&D investments ($p<0.0001$). R-squared (0.685), points to a positive relationship between investment in R&D and calculated tourism labor productivity. If R&D investments increased by one unit (million EUR), tourism labor productivity would increase by 0.00000321290.

The following figure illustrates the linear relationship between R&D investments and labor productivity in the tourism sector across all countries included in the analysis.

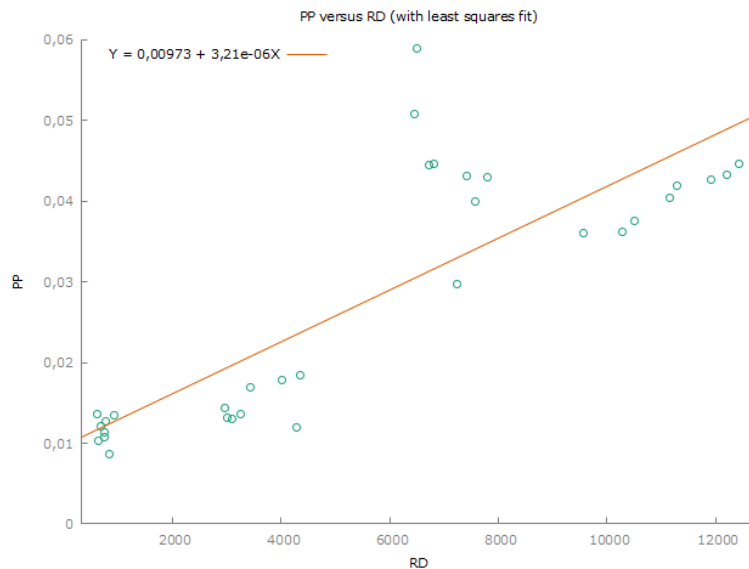


Fig. 5 - Regression line between investment in research and development and labor productivity in tourism in EU countries (2013-2020). Source: own research

The figure above shows all the countries studied and the direct linear dependence of labor productivity in the tourism industry on investments in research and development. As we can see, most countries confirm that the dependence of labor productivity in the tourism industry exists, only a few countries exclude this statement. However, we can conclude that the dependence between labor productivity in the tourism industry and investments in research and development exists, but at the same time it can be concluded that there is a certain clustering in the data (clustering - it makes more sense in English), so there is a high probability that our results another factor also affects it. This figure shows us that there is a potential indication of a linear relationship between the tourism labor productivity variable and R&D investment and another factor affecting labor productivity, and therefore more work needs to be devoted to this research and should be studied more deeply.

5 DISCUSSION

The findings of our study confirm a positive and statistically significant relationship between national investments in R&D and labor productivity in the tourism sector, which aligns with the conclusions of several previous authors. For instance, Heshmati (2011) highlighted that growth in R&D investment significantly contributes to labor productivity gains, particularly in service sectors. Similarly, Joppe and Li (2016) emphasized that North American and European countries lead globally in productivity growth within tourism, a trend our results reinforce within the European context.

What differentiates our study is the macro-level focus on innovation—specifically national-level R&D spending—and its sector-specific effect on tourism labor productivity. While many earlier studies examined innovation within individual firms or regions, our research draws on panel data across multiple EU countries and applies econometric modeling to uncover a broader structural pattern. This complements the microeconomic findings of authors such as Victorino et al. (2005) and Hall (2009) but brings a new perspective by linking macroeconomic innovation policies to tourism sector performance.

Another contribution of this study is its regional focus on Central Europe, including countries like Slovakia and the Czech Republic, which are often underrepresented in tourism innovation research. The panel regression results indicate that even in countries with lower absolute R&D investment, there is a measurable return in terms of increased productivity in tourism, suggesting that R&D intensity matters regardless of scale.

This analysis was based on data from 2013 to 2020 due to the unavailability of fully compiled financial data for subsequent years. As newer datasets become available, especially post-pandemic figures for 2021 and 2022, future research should extend this model to assess whether the observed relationship holds under shifting global and economic conditions.

6 CONCLUSION

This study confirms a statistically significant and positive relationship between research and development (R&D) investment and labor productivity in the tourism industry across EU countries. Based on the results of the panel regression analysis, we rejected the null hypothesis and confirmed the alternative: R&D investment influences tourism labor productivity. This directly

answers our research question (RQ1) and contributes new empirical evidence to the macro-level relationship between innovation policy and sector-specific performance in tourism.

Our findings demonstrate that countries with stronger investment in R&D create more favorable innovation environments, which tourism enterprises can leverage—even as a low-knowledge-intensity sector. Through mechanisms like open innovation platforms, tourism businesses can participate in innovation ecosystems by cooperating with partners, adopting new technologies, and sharing knowledge. These collaborative efforts not only support sector growth but also foster long-term resilience and competitiveness.

This research contributes to the field by providing a macroeconomic perspective on tourism innovation, with a focus on understudied Central European countries. It also underlines the importance of human capital—specifically the qualification and digital readiness of tourism workers—as a prerequisite for effective innovation adoption.

Future research should build on these findings by incorporating post-2020 data and examining additional variables that may influence productivity, such as digital infrastructure, education level, or firm-level innovation strategies. This would deepen understanding of the innovation–productivity nexus in tourism and guide effective policymaking in innovation-driven economic development.

Acknowledgement

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MODELING COST- AND VALUE-ORIENTED INFORMATION FLOWS IN MANUFACTURING ENTERPRISES

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Abstract

The aim of this article is to assess the cost-effectiveness of working with production data across management layers (line–plant–group) and to show how the costs of data collection, transfer, storage, and processing can be quantified in normal operations. A quantitatively oriented case study was conducted in the automotive industry, in which monthly operating costs were derived for the reference data flow by individual layers based on internal operating data and publicly available price lists and statistics. The relationships for calculating costs are based on the principles of total cost of ownership and activity-based costing, as well as a multi-level view of information flow; the text provides precise formulations of the relationships used and their breakdown into layers. The main result is the demonstration of differences in estimated costs between layers; the hypothesis that layer costs differ was confirmed in the case study. The question of the existence of a formal tool for systematic cost assessment (first hypothesis) was assessed only indicatively in the context of the case study based on available organizational artifacts. The study showed that without quantifying the evaluated components, waste occurs in the form of duplicate transfers and excessive retention, which increases the operating costs of information systems. The proposed approach is transferable and allows for the comparison of data work scenarios across layers or extension to other domains.

Keywords: *information flows, cost modeling, value contribution, information quality, Industry 4.0, automotive*

1 INTRODUCTION

The scope of digitization, the advent of cyber-physical systems, and the principles of Industry 4.0 are leading to exponential growth in the volume and speed of data and, at the same time, to an increase in the operating costs associated with information systems: collection, transmission, storage, processing, management, and cybersecurity. Given that information is both a production resource and a risk carrier, it is desirable that it be treated as a measurable and manageable process with transparent metrics. Without a quantitative understanding of information flows, there is a risk of excessive data retention, redundant transfers, inefficient architectures, and difficulty in justifying the costs of IT (information technology) and OT (operational technology). Measurable evaluation enables rational retention policies, setting service level agreements (SLAs), total cost of ownership (TCO) management, and ongoing optimization between cost burden and value contribution for decision-making.

Value Stream Mapping (VSM) has been widely used as a classic tool for optimizing production processes, with the aim of highlighting waste and reducing lead times by mapping the current state and designing the future state. In the traditional approach, attention was focused primarily on material flows and capacity constraints, while the information dimension—data quality, availability, and cost—was only marginally addressed. This work builds on the principles of VSM

and argues for their extension to the domain of information flows so that cost and value impacts can also be assessed in the digital environment.

In the last decade, the impact of digitization on the volume and dynamics of information flows in manufacturing companies has been significantly strengthened. At the same time, it has been observed that traditional value stream mapping does not adequately capture the economic consequences of data links or the qualitative requirements for information. A research gap has been identified in the absence of a formalized, quantitatively comprehensible tool for evaluating the effectiveness of information flows across management levels.

In response to this gap, two research questions were defined: (1) How do manufacturing companies map the operating costs of information flows? (2) How do the operating costs of information flows change across the different layers of complex information flows in manufacturing companies? Based on these questions, two hypotheses were formulated: H1 – manufacturing companies do not have a formalized tool for systematically evaluating the operating costs of information flows; H2 – the operating costs of information flows associated with specific information vary significantly between the individual layers of complex information flows. Emphasis is placed in particular on the second question and hypothesis H2, while H1 is assessed indicatively in a single case study.

The aim of the article is to present a replicable methodological framework that will enable a quantitative assessment of the costs and benefits of information with regard to information quality criteria. The framework links the information flow cost model with a value perspective and information quality thresholds and is applied to a case study in the automotive industry. As part of the verification, a quantitative comparison of operating costs between information flow layers was performed; the results of this comparison are used to test the second hypothesis, while the first hypothesis is evaluated based on existing management artifacts as an indicative conclusion.

The article shows that the debate on digitization must be supplemented by a simple question: how much does specific data cost and what benefits does it bring to decision-making at individual levels—on the line, in the plant, and at the group level? A method is proposed for quantifying the costs of data collection, transmission, storage, and processing in normal operation and comparing these costs with their actual benefits in practice. This approach makes it possible to quickly identify unnecessary duplication, excessive storage, and data transfers without added value, which increase the operating costs of information systems in manufacturing. The result is a set of practical steps and decision-making rules that can be used to determine which data should be collected, stored, and for how long in order to support decision-making while reducing waste.

2 LITERATURE REVIEW

The extension of VSM to the digital domain was described in (Hartmann et al., 2018), where the methodology was extended to include aspects of information logistics. The need for digitization and automation of mapping was summarized in a review paper (Horsthofer-Rauch et al., 2022). Automated frameworks for Industry 4.0 were formalized in (Wang et al., 2021). Logistically oriented guidelines for practice, using data-driven indicators, were presented in (Mühlbauer et al., 2022). Approaches emphasizing information quality and its operationalization in coordination processes were analyzed in (Busert & Fay, 2021). Current trends include the integration of process mining (Horsthofer-Rauch et al., 2024) and digital twins of value streams (Müller et al., 2022; Frick & Metternich, 2024; Reslan et al., 2025), thereby supporting real-time evaluation of flows and impacts on value.

2.1 Cost models of information flows

Following classical economic and IT approaches, models have been identified that enable the capture and quantification of information flow costs between multiple entities or layers. These models provide a framework for distinguishing between transmission, storage, management, and calculation costs and for aggregating them in multi-level architectures. (Nguyen, Behdani, & Bloemhof, 2018; Coetzer & Vlok, 2019).

The multi-tier cost model assumes that each entity/layer bears its own costs for data transmission, storage, and management; the total costs are obtained by summing across all entities and allow for comparison of variants based on the number and arrangement of layers. (Coase, 1937; Williamson, 1979; Coetzer & Vlok, 2019).

$$TC = \sum_{i=1}^n (C_{transfer,i} + C_{storage,i} + C_{management,i}) \quad (1)$$

Where:

- TC is the total cost,
- $C_{transfer,i}$ is the cost of transferring data to the i-th entity,
- $C_{storage,i}$ is the cost of storing data at the i-th entity,
- $C_{management,i}$ is the cost of data management at the i-th entity,
- n is the number of subjects.

In a cloud environment, the costs of storage, transfer, and computation for individual entities (user, provider, third party) are considered; the total costs of the cloud are the sum of these components across entities. (Makhlouf, 2020; Ellram, 1993).

$$C_{cloud} = \sum_{i=1}^n (C_{storage,i} + C_{transfer,i} + C_{compute,i}) \quad (2)$$

Where:

- C_{cloud} is the total cost of the cloud,
- $C_{storage,i}$ is the cost of storing data at the i-th entity,
- $C_{transfer,i}$ is the cost of transferring data to the i-th entity,
- $C_{compute,i}$ is the cost of computing power at the i-th entity
- n is the number of subjects.

Note on deriving the relationship for cloud costs: the formulation used is based on linear aggregation of cost components based on the principles of total cost of ownership and activity-based costing, i.e., a breakdown into storage, transfer, and computation for individual entities and their sum. This is not an ad hoc proposal, but an adaptation of established cost frameworks to the cloud service environment, as discussed in the literature on TCO and ABC and in economic reflections on the cloud (Ellram, 1993; SpringerPlus, 2013; Makhlouf, 2020).

The network cost model describes data transfer between nodes as a flow in a network; costs are then a function of edges (relationships between nodes), taking into account both transfer and traffic management. (Sifaleras, 2013).

$$TC = \sum_{(i,j) \in E} (C_{transfer,ij} + C_{management,ij}) \quad (3)$$

The above formulations are used in this article as a theoretical basis for the line-plant-group layers, where the sums refer to specific components and activities of the information flow in a given layer and are used to compare the cost intensity between layers. (Horsthofer-Rauch, Schumann, Milde, Vernim, & Reinhart, 2022).

A summary of the research conducted showed that digital transformation in manufacturing plants is not feasible without a deeper understanding of information flows. A need was identified for tools that link process modeling, data metrics, and lean management principles.

It was found that although the general principles of information logistics (transfer, storage, distribution) are described, there is no comprehensive approach to:

- quantifying the value of information in relation to decision-making processes at individual levels of the enterprise,
- structural modeling of operating costs associated with information flow across layers,
- determining information waste (transfer, storage, or management of information without real benefit to decision-making or quality).

The research reveals a significant research gap: insufficient methodological and systemic support for the analysis, measurement, and optimization of information flows in manufacturing plants in the context of digital transformation. The gaps are particularly evident in:

- insufficient integration of information logistics with value chains (there is no standardized framework for mapping and evaluating information flows, including their efficiency, redundancy, utilization, and benefits)
- the absence of quantification of costs associated with information flows (there are no clear metrics/KPIs for the costs of collecting, transmitting, storing, and managing information and for the ratio of information value to burden – Information-to-Waste Ratio),
- ad hoc or technocratic information management without regard to lean and value stream principles (leading to redundancy, unnecessary retention without value, and absence of selective treatment based on value and life cycle),
- the lack of a methodology for visualizing information flow, including the value of information at each stage.

Based on these findings, there is scope for research that:

- create a mapping tool that takes into account information logistics and related waste,
- creates a mapping and evaluation tool for individual phases of the information process (collection, transfer, storage, processing, decision-making),
- defines indicators of information logistics efficiency,
- quantifies the cost-benefit ratio of information,
- supports the improvement of business processes by eliminating information waste.

In this article, the first step is to focus on the operating costs of information flows in individual layers (line–plant–group). Quantifying these costs is seen as a necessary basis for subsequently expanding the value perspective and visualizing information flows in future work.

2.2 Determinants of data transfer and storage costs

The cost intensity of data transfer and storage is associated in the literature with network and operational parameters. Latency and variability of transmission paths (Paxson, 1999), security overhead and risk management (Rittinghouse & Ransome, 2017), the nature of the transmitted content, including data-intensive formats such as video or process records (Chen, Mao, & Liu, 2017), and the nature of the transmitted content, including data-intensive formats such as video or process records (Chen, Mao, & Liu, 2017), are important factors. Ransome, 2017), the nature of the transmitted content, including data-intensive formats such as video or streaming records (Chen, Mao, & Liu, 2014), and structural trends in digitization affecting unit costs and scaling (McKinsey, 2023).

3 METHODOLOGY

3.1 Research design

The study was designed as a quantitatively oriented case study in a manufacturing company in the automotive industry. The unit of analysis was the information flow related to tightening parameters on the assembly line and its passage through the layers line–plant–group. The aim of the methodology was to verify differences in operating costs between layers (primarily testing hypothesis H2) and to assess whether a formalized tool for systematic evaluation of these costs exists in the organization (indicative assessment H1 in one multi-level automotive company).

3.2 Setting and data

The analysis environment was an assembly line with a record of tightening parameters, higher-level plant systems, and the group's central platforms. The data came from operational records (PLC/MES/QMS or equivalent), integration layers, and repositories. The analysis worked with aggregated metrics from normal operations without personal data; the scope and frequency of processing corresponded to the operational practice of the company.

3.3 Measurement and metrics

Additional definition of metrics: for each data flow, volume indicators (number of records, message size, frequency) and corresponding unit rates for transmission, storage, calculation, and management were determined in each layer. Estimates were constructed from internal operational data from the case study and verified against publicly available price lists and wage statistics listed in the bibliography. Where alternative technically equivalent options existed, rates and volumes were parameterized to be comparable across layers.

Cost metrics were defined for activities including collection, transmission, storage, processing, and management/security. For each layer, monthly operating costs were quantified as the sum of the individual components. The theoretical basis was provided by multi-layer cost and network flow models and their summation across entities and edges (see equations (1)–(3)); the symbols $C_{transfer}$, $C_{storage}$, $C_{compute}$, and $C_{management}$ were used consistently across layers.

Unit rates (e.g., price per transferred volume, per unit of stored capacity, per computing time, per operational management) were primarily taken from internal price lists or operational records obtained in the case study and related to the volumes and frequency of the given data flow. If internal rates were not available, public cloud storage price lists and public wage/statistical sources

were used for specific determinations; see the References section for links. The result for each layer was a monthly cost indicator.

Clarification of the procedure: the flow was mapped from the source on the line to the central storage, identifying specific components (sensors/PLCs, intermediate layers, storage, analytical nodes) and their links. For each link, volume and frequency parameters were quantified and unit rates were assigned. The monthly costs were calculated by layer according to equations (1)–(3)

3.4 Scenario construction

Representative data processing scenarios reflecting normal operating practice (e.g., different retention periods, record granularity, method of replication between layers) were evaluated. The scenario parameters were based on information quality requirements and operational and regulatory constraints. The costs were calculated by layer for each scenario.

3.5 Analysis procedure

The analysis procedure included: (i) mapping the flow and inventory of components and activities in the layers, (ii) parameterization of unit rates and volume/metric quantities, (iii) calculation of monthly costs by layer, and (iv) comparison of cost indicators between layers. The primary objective was to assess whether there were differences in estimated monthly costs between layers in line with hypothesis H2.

4 RESULTS

4.1 Cost of data transmission and storage in the information flow

Given the focus of this article on selected operating costs associated with data transmission and storage, these costs are discussed in more detail in the following section.

Data transmission costs (see Fig. 1) can be influenced by a number of factors and vary significantly depending on the environment, technology used, and method of transmission. The main components and factors influencing costs include:

- **Bandwidth** – Bandwidth costs are typically charged based on the amount of data transferred over a given period (month). Internet and cloud service providers charge different rates depending on the region and type of service. The price per GB may vary; for example, Amazon Web Services (AWS) charges approximately \$0.09/GB for transfers outside AWS. Furthermore, it was based on unit rates and sources listed in section 3.3; see References.
- **Transfer speed and latency** – higher transfer speeds usually require more expensive infrastructure (optical networks, high-speed wireless) and minimizing latency requires investment in reliable networks, which increases costs. It was also based on unit rates and sources listed in section 3.3; see References.
- **Security and encryption** – ensuring transmission security includes the costs of encryption, VPNs, and other measures; implementing protection against attacks (e.g., DDoS) may further increase overall costs. Based on unit rates and sources listed in Section 3.3; see References.

- Cloud services – providers (AWS, Google Cloud, Microsoft Azure) charge for data transfer between data centers and outbound transfers; interregional transfers tend to be more expensive than intra-regional transfers.
- Type and size of data – larger files require more resources; some formats (e.g., video, 3D models) increase bandwidth requirements. This was also based on unit rates and sources listed in Section 3.3; see References.
- Type of transmission technology – fixed connections (e.g., fiber optics) tend to have lower unit costs than mobile networks (4G/5G); satellite and wireless transmissions tend to be more expensive, especially in remote locations. This was also based on unit rates and sources listed in Section 3.3; see References.

In practice, costs may also be affected by volume discounts, the choice of transmission technology, or regional price differences.

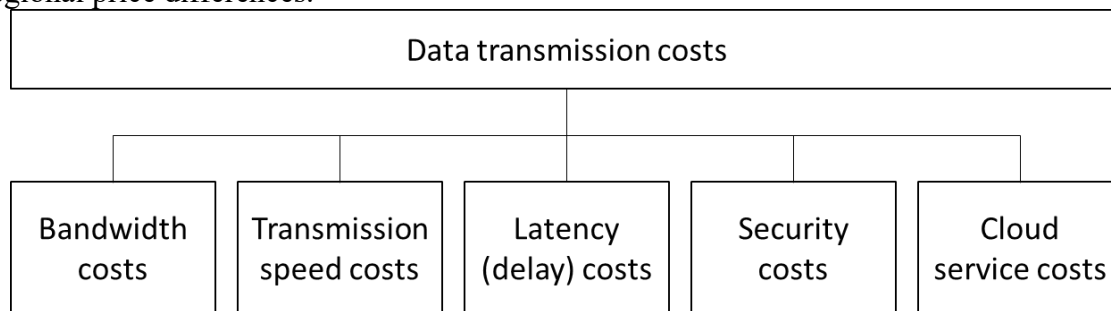


Fig. 1 – Fundamental data transmission costs. Source: own research

Cloud costs are a significant item in information logistics (see Fig. 2). Their modeling includes several components that determine the total costs, in particular: It was also based on unit rates and sources listed in Section 3.3; see References.

- Computing power – costs of virtual machines (CPU, RAM) and operating hours.
- Storage – costs of block, object, and file storage, including backup and recovery.
- Data transfer – costs for interregional transfers and transfers between the cloud and external devices.
- Network – costs for VPN, load balancers, and other network services.
- Security – costs for encryption, monitoring, and auditing.

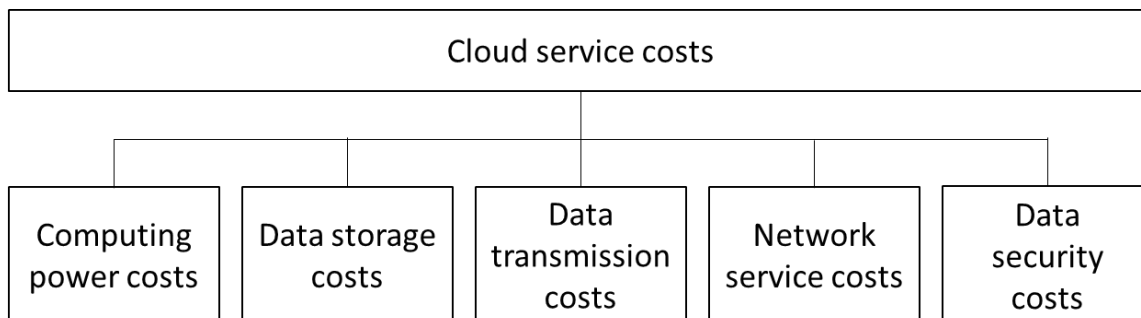


Fig. 2 – Fundamental costs of cloud services. Source: own research

For illustration purposes, the monthly costs of cloud services can be expressed as follows:

$$\begin{aligned}
 \text{Total Monthly Costs} = & \sum_{i=1}^n (\text{Number of hours used}_i \times \text{Hourly rate}_i) \\
 & + \sum_{j=1}^m (\text{Amount of stored data}_j \times \text{Price per GB/month}_j) \\
 & + \sum_{k=1}^p (\text{Transferred data}_k \times \text{Price per GB}_k) \\
 & + \text{Other service costs}
 \end{aligned} \tag{4}$$

Where:

- n is the number of types of compute instances.
- m is the number of storage types.
- p is the number of network service types.
- Other service costs are costs associated with other specific cloud services (e.g. databases, analytics tools).

Example: The use of the following cloud services for one workplace is considered:

- virtual server: 1 server, 730 hours/month, price 1 CZK/hour
- block storage: 500 GB, \$2/GB/month
- transferred data: 100 GB, \$0.0005/GB

The partial costs are as follows:

- computing power: 1 server $\times$ 730 hours $\times$ \$1/hour = \$730/month
- storage: 500 GB $\times$ \$2/GB/month = \$1000/month
- transfer/data services: 100 GB $\times$ \$0.008/GB = \$0.16/month

The total monthly cost of cloud services for 1 workstation is:

$$\$730/\text{month} + \$1,000/\text{month} + \$20/\text{month} = \$1,750/\text{month}.$$

4.2 Operating cost model in a manufacturing company

For practical application, we chose to model selected operating costs associated with the information flow of tightening torques and angles from a single tightening station on an assembly line in the automotive industry. The aim was to determine the expected course of operating costs for data transmission and storage in a flow passing through three layers — see Fig. 3.

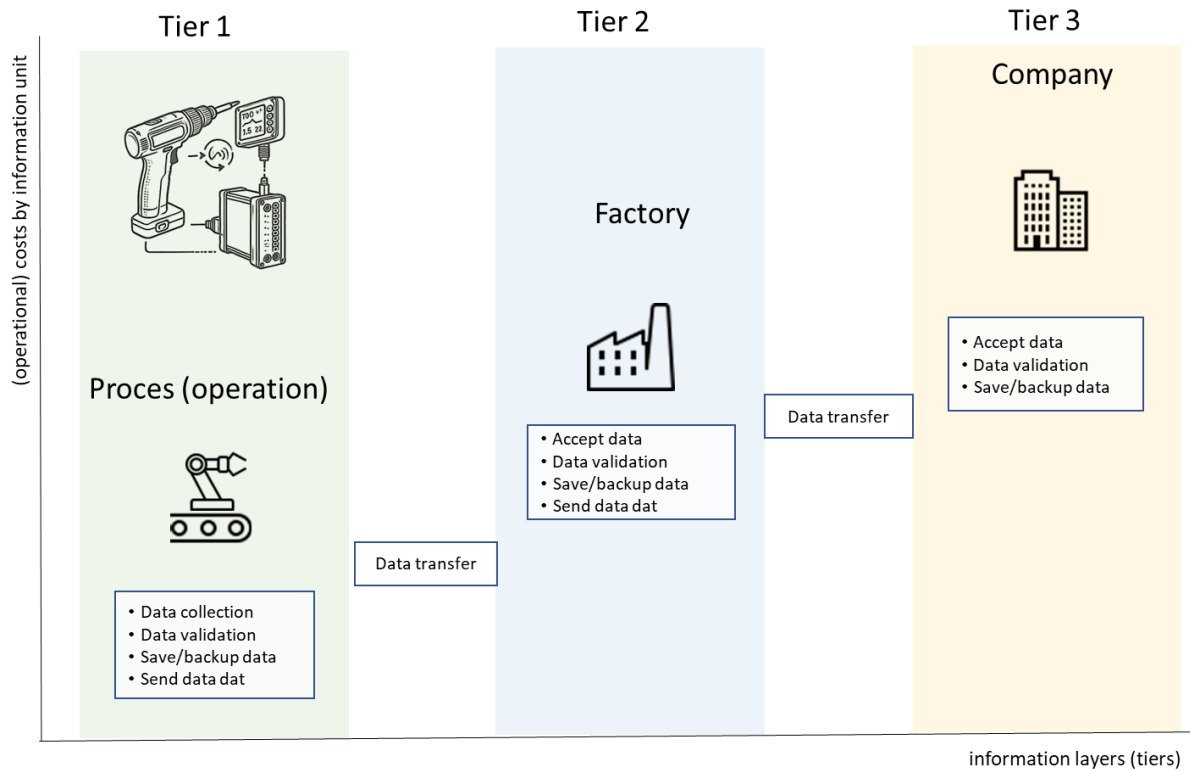


Fig. 3 – Growth of operational costs in information flow through multiple information layers Source: own research

The assembly process consists of the following steps (only aspects related to tightening data are listed):

- Based on call-offs, specific orders and parameters are sent from the production control system to the line; tightening programs (torque/angle, tolerance) are transferred via a defined interface from the MES to the PLC — usually as a set of programs with a reference to the specific program for the given product/operation.
- The PLC line stores this information in its operating memory so that the appropriate program can be called up for each operation and transferred to the electric tightening tool (EC). The transfer between the PLC and EC takes place via the Profinet bus.
- The connection is tightened by the operator or an automatic station; the result is evaluated directly in the EC of the tightening tool by comparison with the permitted values and an OK/NOK indication. The values (torque/angle) are stored in the PLC or persistently on the RFID chip of the pallet so that the output control can decide on the conformity of the product. The information is transferred from the tightening device to the PLC, and/or from the PLC to the RFID reader via the Profinet bus. Within the line, the data is only kept for the time necessary for production (a few minutes).
- The line is then able to autonomously decide on the result of the assembly (within the scope of the monitored connections). Were it not for legislative requirements for storage, it would be possible to forget the values after completion of assembly. In automotive manufacturing, however, the necessary data must be stored in higher-level systems (not only the result and

values, but also the date/time, model, unique product identifiers, and connections) via a defined interface from the PLC to the connection database (SCADA, OT→IT platforms).

- The connection database accepts the information and, upon confirmation of qualified storage, provides feedback to the PLC that the data can be released on the line. The database is operated at the plant level (quality/audit) and allows basic tightening data to be traced for the period specified by legislation (several years). Modern EC tighteners also allow the complete tightening process (curves) to be stored, which represents diagnostic data with a multiple increase in volume. For statistical evaluation, the data is transferred to a data lake; the curves can also be used for autonomous detection of deviations. The frequency of use is lower, and the storage period is long.
- The availability and operation of the data lake can be limited to the needs of the plant; if necessary, data is promoted to the corporate level via an integration interface and API platform from the plant's on-premise environment to the corporate cloud. The enterprise data lake enables the aggregation of findings across plants and the calculation of statistics; the frequency of use is lowest, and the storage period is long.

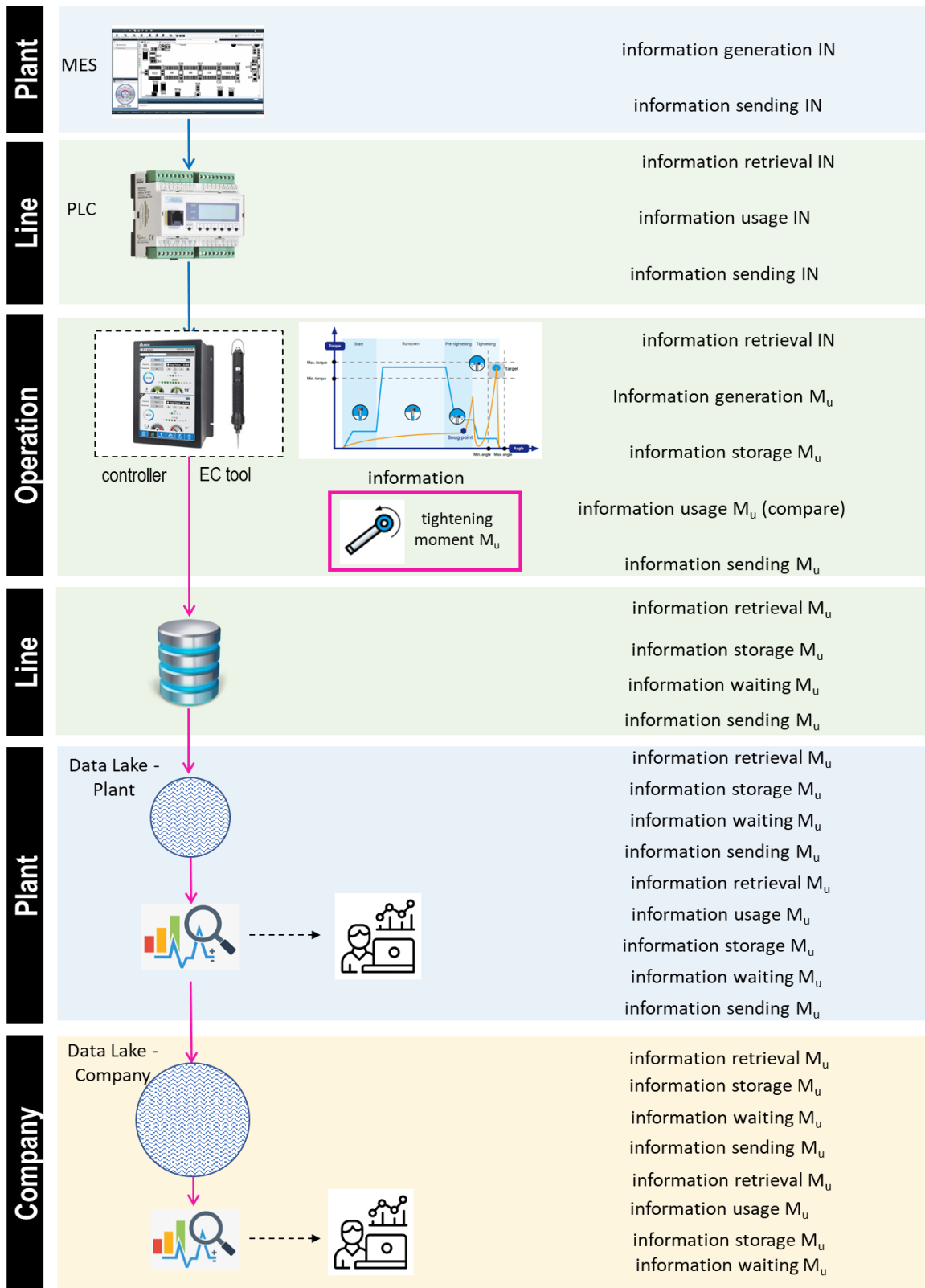


Fig. 4 – Data flow. Tightening torque information. Source: own research

The acquisition costs of the HW/SW solution were not taken into account in this section, as they are considered constant within the layers.

To estimate operating costs, the article focuses on the cost of storing 1 GB of data per month [GBm], using the average monthly price of major cloud providers of CZK 0.47/GB, plus transaction costs (CZK 1.64/10,000 writes and CZK 0.14/10,000 reads). It is assumed that on-premise storage on the plant's disk arrays may be cheaper to operate. The cost of storage operation and support is approximated by the proportion of IT operator work spent on managing "one" database per month [FTE/m], with wages based on Q4/2023. The operation of communication platforms ensuring data transfer between layers is considered similarly. For network connectivity itself, the use of guaranteed bandwidth (MB/s) is assumed, with a transition to a higher bandwidth at a higher price necessary as volumes grow. It was also based on unit rates and sources listed in section 3.3; see References.

The illustrative example assumes an average of ~20 connections per product, production of ~14,000 products/month, and an indicative volume (1) of basic data of ~0.8 KB per connection for a specific connection, i.e., a total monthly volume of ~0.21 GB.

The volume (2) of extended data for a single record is 1.1 KB (including basic data), i.e. ~0.29 GB per month. The volume (3) of complete data including curves is 35 KB (including extended data), i.e. ~9.35 GB per month. For simplicity, the number of transactions is assumed to be 280,000 entries and the same number of reads at the plant level; at the enterprise level, four times the number of reads compared to entries is assumed, i.e., 1,120,000 transactions.

The total operating costs of the TC for a given information flow are therefore determined as the sum of the costs of transmission, storage, and management of support tools as follows

$$TC = \sum_{i=1}^n (C_{transfer,i} + C_{storage,i} + C_{management,i}) \quad (5)$$

for each layer separately; the cost of a higher layer is also given by the sum of the costs of the previous layers.

Tab. 1 – Unit operating costs taken into account for each information layer. Source: own research

Layer (tier)	Type cargo	Cost of operation, support	Unit load (estimate)	Cost per month (estimate in CZK)
(1) Line	TC transfer	OT network layer operation 1GB/s	1000 CZK/m	1000
	TC storage	Storage in PLC (4 days)	0.042 GB/m	0.2
	TC management	Support for data collection and storage in PLC, security on the line	0.01 FTE/m	830
(2) Race	TC transfer	Network layer OT > IT 10GB/s	1000 CZK/m	1000
	TC transfer	Data transfer to storage (in/out transactions)	280/280 ktr/m	50
	TC management	Communication platform (keeware)	0.01 FTE/m	830
	TC management	API management and integration platform, security	0.01 FTE/m	830
	TC storage	Storage in the database/datalake of the plant (6 months)	56 GB/m	26
	TC management	Support system to display tightening reports	0.02 FTE/m	1660

	TC management	Incident management platform and watch centre	0.01 FTE/m	830
(3) Company	TC transfer	Internet connection bandwidth (to the cloud) 1GB/s	1000 CZK/m	1000
	TC transfer	Data transfer to storage (in/out transactions)	280/1120 ktr/m	107
	TC management	Group API management and integration platform	0.01 FTEm	830
	TC storage	Storage in object storage/datalake (36 months)	336 GBm	158
	TC management	Cloud reporting platform support	0.02 FTEm	1660
	TC management	Group incident management and servicedesk	0.01 FTEm	830

Total operating costs increase with increasing layer; in the illustrative case of tightening data collection, the dependence is not linear (see the following graph).

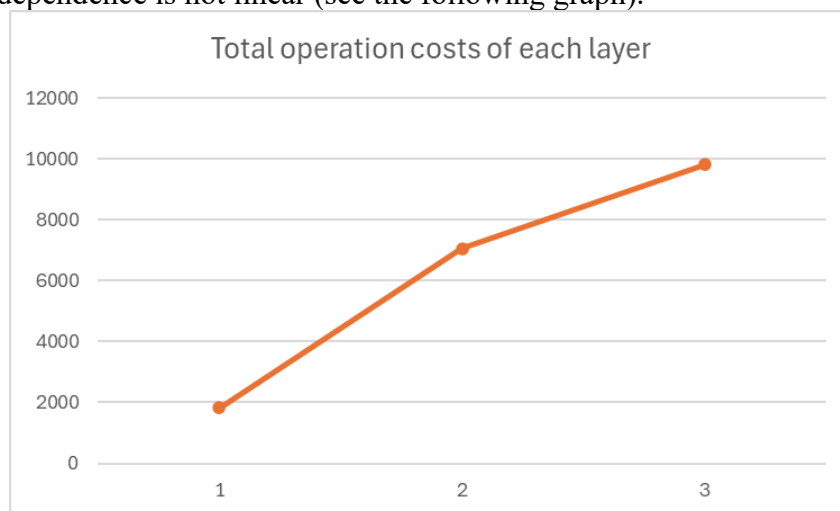


Fig. 5 - Total operating costs of the information flow of each layer. Source: own research

5 DISCUSSION

The results were interpreted as indicating that monthly operating costs for data processing increase as the same information is transferred and stored in higher management layers. This supported hypothesis H2. The existence of a uniform and formal tool for evaluating these costs was only indirectly documented in the analyzed company; therefore, H1 is evaluated as indicative in this study. Supporting calculations and outputs are presented in Chapter 4, and methodological steps are presented in Section 3.3.

The most important practical conclusion is that the information flow should first be mapped and, for each piece of information, it should be determined where it is actually needed for decision-making. Data should primarily be collected and stored at the level where decisions are made (line, plant, or group). Every unnecessary transfer to a higher layer and every storage without a clear purpose increases the costs of transfer, storage, and management.

The case study revealed simple rules: (i) if information is only needed for local quality control, it should be stored at the line or plant level, and only aggregated findings should be sent to higher

layers; (ii) replication to multiple repositories should be limited to justified purposes (audit, legislation, shared reports); (iii) retention periods should be set according to purpose and legal requirements, not "just in case." This prevents duplication, excessive retention, and unnecessary interregional transfers.

A simple procedure has proven effective for planning and managing costs: determine the volume and frequency for each flow, assign unit rates for transfer, storage, and management, and sum the costs by layer according to relationships (1)–(3). The monthly costs obtained in this way allow for a comparison of options (different granularity, shorter/longer retention, different transfer routes) and quick identification of areas where costs are incurred without corresponding benefits for decision-making.

The study is limited to one company and works with estimates of unit rates based on a combination of internal data and publicly available sources. The conclusions should therefore not be generalized mechanically, but the proposed approach is easily transferable and can be used in other companies. Further research should verify the behavior in other industries and when rules for transfer and retention change (before/after intervention), possibly in combination with tools for accurate flow mapping.

6 CONCLUSION

The article focused on the cost-effectiveness of working with production data across the line-plant-group layers. Based on a quantitatively oriented case study, a computational framework was used in which monthly operating costs were determined as the sum of the costs of transfer, storage, calculation, and management for each layer according to relationships (1)–(3).

The research question RQ1 ("How do manufacturing companies map operating costs for information flows?") was answered by finding that no uniform, formally implemented tool for systematic evaluation of these costs was identified in the analyzed company. Mapping was carried out using partial internal procedures; therefore, hypothesis H1 was assessed only indicatively.

Research question RQ2 ("How do operating costs for information flows vary across layers?") showed that estimated monthly costs vary across layers and generally increase with increasing layer. The dependence was not found to be linear, which corresponds to the accumulation of administrative and integration overhead costs and possible data replication; hypothesis H2 was supported.

From a practical point of view, it is recommended that information flows be systematically mapped and that a layer be determined for each piece of information where it is actually needed for decision-making. Data should primarily be collected and stored at the lowest relevant layer; replication to higher layers should only be carried out for justified reasons (audit, legislation, shared analysis). Retention periods should be set according to purpose and legal requirements. For cost planning, it is advisable to maintain a catalog of unit rates and review it regularly.

The study shows that even in normal operations, information flow costs can be quantified by layer using a simple, replicable process, and that decisions on data location, retention, and replication based on purpose of use lead to a reduction in unnecessary costs. In further research, the framework will be tested on a multi-case set and in different industries.

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GENERATIVE INTELLIGENCE AND THE TRADITIONAL SEARCH

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Abstract

This paper investigates user behavior and preferences regarding the use of generative artificial intelligence (AI) tools such as ChatGPT, Gemini, and Claude in comparison with traditional search engines (Google, Bing, Seznam). The primary aim of the study was to evaluate the extent to which users employ generative AI as their main information-searching tool, determine whether higher utilization of generative AI correlates with decreased interaction with traditional search engines, assess the perceived time efficiency benefits provided by generative AI, and identify potential demographic differences gender and age influencing AI usage. The empirical research was conducted through a quantitative survey involving 206 respondents. Data were collected using a structured questionnaire, which measured frequency of AI usage, perceived answer quality, preference for AI-generated recommendations, changes in traditional search engine interactions, and perceived time-saving efficiency. Statistical analysis methods included descriptive statistics, Pearson correlation analysis, linear regression modeling, independent-samples t-tests, and one-way ANOVA. Findings indicate a moderate to high level of generative AI usage among respondents, significant correlations between higher AI usage and reduced clicks on traditional search engine results, and notable improvements in perceived time efficiency. Demographic analyses revealed no statistically significant differences based gender and age. This study contributes to the ongoing discourse about AI-driven changes in information-seeking behavior and offers practical implications for AI developers and educators.

Keywords: *Generative AI, Search Engines and AI, User Digital Preferences, Information Behavior*

1 INTRODUCTION

Recently, the field of artificial intelligence (AI) has seen dramatic developments, with one of the most prominent innovations being generative AI models such as ChatGPT, Gemini, and Claude. The aforementioned models represent a new way for users to interact with the digital environment, as they are able to generate realistic answers to questions, provide product and service recommendations, as well as efficiently summarize complex information from available data (Huang et al., 2022). The popularity of the aforementioned models in their various versions is largely based on their superior ability to retrieve information through search engines such as Google, Bing, Seznam, etc., due to their ability to generate personalized and contextually rich answers (Chen et al., 2024).

Generative AI models use deep learning algorithms to recognize patterns and generate answers with a high degree of accuracy and relevance (Banh & Strobel, 2023). However, there is an ongoing debate in the marketing sphere as to whether the use of generative AI actually leads to higher information retrieval efficiency, and whether it can gradually replace traditional search engines (Kshetri et al., 2024). Brown et al. (2024) point to the potential benefits of generative AI, including time savings, higher user satisfaction and increased convenience in information retrieval, but they also highlight the potential risks associated with the reliability of the answers generated and users' overconfidence in these tools. In light of these trends, there is a need to explore how

users perceive and actually use generative AI compared to traditional search methods. There are numerous studies on artificial intelligence, but few of them focus on a practical comparison of user behavior between generative artificial intelligence and traditional search engines in a home environment. The aim of this article is to compare user behavior when using generative artificial intelligence with traditional search engines and to identify differences in behavior.

2 LITERATURE REVIEW

AI is one of the most significant innovations of our time, impacting both economic and social factors, and its influence is increasing. According to Nasr and El-Deeb (2025), said technology allows computers to mimic human cognitive abilities such as learning, problem solving, planning, reasoning, and even creating new information. Deep learning technology, which is based on neural networks, plays an important role in AI. That algorithm achieves significant results in various fields including natural language processing (NLP), image analysis, or autonomous systems (Berahmand et al., 2024). As defined by Kanbach et al. (2024), there is currently a particularly intense development in the field of generative artificial intelligence, which is capable of not only passively analyzing existing data, but also actively generating new information, texts, images and even videos with a high degree of realism and accuracy. Generative models represent a significant shift in the relationship between users and information technology. Compared to traditional web search engines that provide links to existing web pages, generative AI directly generates answers to user queries, significantly changing the way people interact with information (Zhou & Li, 2024). Hersh (2024) points out that generative models not only have the potential to increase the efficiency of information retrieval, but also to reduce information overload, which is associated with having to navigate through a large number of traditional search results, forcing the user to create the answer themselves.

Another aspect that is important to mention is just evaluating the time efficiency of generative AI compared to traditional search methods. Campbell (2023) states that users using generative AI achieve significant time savings due to the system offering answers directly instead of extensive lists of web pages. On the other hand, it is also important to note the downside of the fundamental pitfall of AI that users do not always verify the correctness of the answers generated and may in fact receive misleading and distorted information (Chang & Van Swol, 2023). The aforementioned fact is also confirmed by Pak et al. (2024) and adds the phenomenon of trustworthiness of generative AI, where despite the solid quality of the answers, potentially AI can also generate incorrect or misleading information, leading to the need for increased vigilance on the part of users. As defined by Amer and Elboghhdady, (2024) there is currently a change in user behaviour where users are less likely to click on links in internet search engines and rely more on instant answers generated through AI, which may be affecting the overall quality and diversity of information received. Another important phenomenon is the impact of generative AI on consumer behaviour. Specifically, generative AI has the potential to fundamentally change the way consumers search for products or services by providing personalized recommendations instead of the traditional comparison of different sources (Mogaji & Jain, 2024). Zhu et al. (2024) define that users of generative AI have the potential to be more prone to accept recommendations without further validation, which can lead to a closed-loop effect in which AI recommendations become progressively amplified and limit access to a wider range of alternative products and services (Zhu et al., 2024). Another aspect that enters into the clarification of the topic is that AI can also be influenced by demographic factors such as age, gender or education. Seok et al. (2025) suggest

that, younger age groups tend to use generative AI more actively, while older users may be more skeptical or less trusting of new technologies. Similarly, gender differences in the use of AI are defined by Strzelecki and ElArabawy, (2024), and it is a matter of controversy whether there are significant differences between men and women in the acceptance and frequency of use of generative models. It is also important to mention several risks and ethical challenges that AI faces. In particular, there are issues of privacy, data security and transparency of the processes by which AI generates answers. Dorta-González et al. (2024) also draw attention to the high need for regulations, which they defend by minimizing the risks, and they endorse laws related to the topic as well as the AI Act from the European Union (Regulation (EU) 2024/1689, 2024). In general, there is considerable room for exploration Stark, (2023) highlights the need for an interdisciplinary approach in the further development of AI to ensure that technologies serve society while respecting ethical principles.

Further exploration should focus on further refining generative AI models, increasing their transparency, as well as exploring the social impacts on human behaviour and society as a whole. Within the domestic region, the extent to which generative AI is being used and whether there is a marked impact of specialised characteristics in the form of demographic data has not yet been clarified. Based on the theoretical background, the following research questions emerged:

RQ1: To what extent do respondents use generative AI as their main tool for information retrieval?

RQ2: Is the higher frequency of use of generative AI related to a decline in user interaction with traditional search engines?

RQ3: Does the use of generative AI reduce the time required to retrieve information compared to traditional search engines?

RQ4: Are there gender and age demographic differences in the rate of use of generative AI?

3 METHODOLOGY

The present paper was conducted as a quantitative survey to further investigate the way users use generative artificial intelligence (AI), to analyze their preferences in relation to traditional Internet search engines and to verify whether there are significant differences in the use of the said technology based on demographic specifics. The research sample consisted of 206 respondents, of which 105 were female, representing 51.2% of the research population, and 101 were male, representing 48.8% of the population. The age composition of the sample was diversified, with the largest age group consisting of respondents aged between 45 and 60 years with 72 respondents (35.0%), followed by the age group aged between 29 and 44 years with 51 respondents (24.8%), followed by the 61 to 79 age group with 41 respondents (19.9%), the 18 to 28 age group with 27 respondents (13.1%) and the smallest group was the over 79 age group with 15 respondents (7.3%) of the research sample. The respondents were approached through the CAWI method , through random sampling. A custom questionnaire was developed for the research using the Google Forms platform.

The questionnaire contained five items measured using a five-point Likert scale, which were aimed at ascertaining the frequency of use of generative AI, the perceived quality of answers provided by AI, respondents' preferences for AI-generated recommendations over traditional search engine

results, the impact of generative AI on the click-through rate of links in traditional search engines, and the perception of the time-efficiency of generative AI in information retrieval. In addition, the questionnaire included questions regarding the demographic characteristics of the participants, specifically their gender and age. Analyses of the collected data were performed in the software Jamovi (version 2.6). In the first step, descriptive statistical analysis was performed, which involved finding the means, medians, standard deviations and ranges of the variables, thus creating a basic description of the research sample under study. This was followed by a correlation analysis using Pearson's correlation coefficient:

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2} \sqrt{\sum(y_i - \bar{y})^2}} \quad (1)$$

x_i is the value of the first variable for the i -th respondent

y_i is the value of the second variable for the i -th respondent

$\bar{x}$ is the mean value of the variable x

$\bar{y}$ is the mean value of the variable y

n is the number of respondents

The above coefficients were used to assess the strength and direction of the relationships between the variables under study, specifically between the frequency of use of generative AI, the decline in clicks on traditional search engine links, and the perception of time efficiency. Linear regression analysis was applied to confirm the predictive relationships

$$y = \beta_0 + \beta_1 x + \varepsilon \quad (2)$$

where y is the dependent variable,

x is the independent variable,

β_0 is a constant,

β_1 : regression coefficient,

ε is the error,

while two main models were analyzed. The first model tested the extent to which higher use of generative AI is associated with a decrease in interaction with traditional search engines, and the second model focused on examining the relationship between the frequency of AI use and perceptions of time savings in information retrieval. The proposed regression models were validated against statistical significance criteria at a p -value of less than 0.05. In the next part of the analyses, differences in the use of generative AI between demographic groups were verified. A t -test for two independent samples was used to detect potential gender differences

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \quad (3)$$

where x_1, x_2 - means of both groups

s_1^2, s_2^2 - variances of both groups

n_1, n_2 - number of respondents in each group

which allows to compare the average values of the frequency of AI use between men and women. One-factor ANOVA (Welch's test) was used to compare the age groups,

$$F = \frac{\sum \frac{(\bar{x}_i - \bar{x})^2}{g-1}}{\sum \frac{s_i^2}{n_i} / (N - g)} \quad (4)$$

where $\bar{x}_i$ is the mean of the i -th group,

$\bar{x}$ is the overall mean,

s_i^2 is the variance of the i -th group,

n_i is the number of respondents in the i -th group,

g is the number of groups,

N is the total number of respondents

due to the fact that the different age categories exhibited inequalities of variances. Before the main analyses were performed, normality was checked using Gaussian distribution.

4 RESULTS

Analyses were conducted to examine the use of generative artificial intelligence in the context of information retrieval. The first step in the analyses was the descriptive analysis of the collected data. In the descriptive analysis, central tendencies, data variability, and distribution of responses were assessed. The complete results (Table 1) are presented in the following table.

Tab. 1 - Descriptive characteristics of the variables studied. Source: own research

Variable	Mean	Median	Modus	Standard deviation	Variance	Min.	Max.
Frequency of use of AI	3,07	3,00	5	1,50	2,25	1	5
Quality of answers ai	3,13	3,00	3	1,26	1,59	1	5
AI preference	2,43	2,00	1	1,27	1,61	1	5
Fewer clicks on links	2,85	3,00	3	1,38	1,90	1	5
AI time efficiency	3,32	4,00	5	1,48	2,19	1	5

The defined research question RQ1 with the formulation to what extent respondents use generative AI as their main search tool was evaluated using descriptive analysis as follows. Respondents indicated the frequency of use of generative AI on a 5-point scale, where the mean was 3.07 (SD = 1.50), the median was 3, and the most frequent response was a mode of 5, indicating that despite the overall mean, there is a significant group of users who use generative AI very extensively. The minimum and maximum values were 1 and 5, respectively, with a variance of 2.26. The results indicate relatively high variability in the extent of AI use among respondents. Respondents rated

their use of generative AI relatively positively. The highest rated area was time efficiency ($m = 3.32$), with a modal score of 5, indicating a significant degree of satisfaction on the part of some respondents. In contrast, the lowest rated area was preference for AI over traditional search engines ($m = 2.43$, $\text{modus} = 1$). This indicates some distrust of respondents towards generative AI fully replacing traditional search methods. Correlation analysis was used to identify relationships between variables. The results of this analysis (Table 2) are summarized in the table below.

Tab. 2 - Pearson correlations between the variables studied. Source: own research

Variable (1)	Variable (2)	Pearson's r	Significance (p)
Use of AI	Fewer clicks	0,519	< 0,001
Use of AI	Saving time	0,595	< 0,001
Fewer clicks	Saving time	0,651	< 0,001

Correlation analysis shows that there is a significant positive relationship between the intensity of generative AI use and the decrease in interaction with traditional search engines, as well as between AI use and perceived time efficiency. The following is the result of research question RQ2, which was defined as whether higher use of generative AI is associated with fewer clicks on links in traditional search engines. That question was investigated through correlation and regression analysis. The Pearson correlation coefficient between the variables of AI usage and fewer clicks reached a value of $r = 0.519$ ($p < 0.001$), indicating a strong, positive, and highly significant correlation. Regression analysis confirmed that the intensity of AI use significantly predicted the rate of decline in interactions with traditional search engines ($\beta = 0.699$; $t = 10.38$; $p < 0.001$). The overall regression model explained approximately 34.6% of the variability ($R^2 = 0.346$), indicating a significant effect of AI usage frequency on users' traditional information-seeking behavior. In the next step, the relationships between variables were analyzed using regression analysis. The regression model tested the predictive ability of the intensity of generative AI use in relation to the decrease in interaction with traditional search engines (less clicks variable). The results (Table 3) are presented in the table below.

Tab. 3 - Regression model predicting the decline in clicks based on the use of AI. Source: own research

Predictor	B (estimate)	Se	T	P	R ²
Intercept	1,374	0,184	7,45	<0,001	0,346
You can use	0,699	0,067	10,38	<0,001	

Research question RQ3 was analyzed to define whether the use of generative AI reduces the time required to retrieve information. When examining the time efficiency of AI, respondents reported that AI saves their time at an average level of 3.32 ($SD = 1.48$), with the highest possible value of 5 being the most common, indicating a high level of perceived time efficiency of generative AI among the majority of respondents. Correlation analysis showed a strong relationship between AI use and time efficiency ($r = 0.595$; $p < 0.001$). The regression model further confirmed a significant prediction of time efficiency by the intensity of AI use ($\beta = 0.585$; $t = 10.57$; $p < 0.001$). The regression model explained up to 35.4% of the variability in perceived time efficiency ($R^2 = 0.354$). The results are presented (Table 4) in the table below.

Tab. 4 - Regression model predicting time efficiency based on AI usage

Predictor	B (estimate)	Se	T	P	R ²
Intercept	1,519	0,189	8,02	<0,001	0,354
Usage	0,585	0,055	10,57	<0,001	

The following is the outcome part of the defined research question RQ4, which asks whether there are demographic differences in the use of generative AI. The examination of demographic differences was conducted using t-test and ANOVA analysis. The t-test results showed no significant difference between males and females in the intensity of generative AI use ($t(204) = 0.233$; $p = 0.816$). Similarly, a one-factor ANOVA (Welch's test) did not confirm significant differences between the age groups of respondents ($F(4,20.1) = 2.409$; $p = 0.083$). Taken together, the above results define that demographic characteristics do not have a statistically significant effect on the frequency of generative AI use among the surveyed respondents, suggesting the versatility of this technology across different user groups. T-test and ANOVA showed no significant differences between males and females ($t = 0.233$; $p = 0.816$), nor between age groups (Welch's test: $f = 2.409$; $p = 0.083$). Suggesting the universality of AI use across demographic groups. The end result is that respondents use generative AI moderately to moderately as a primary search tool. More intensive use of AI leads to a decrease in the use of traditional search engines and contributes significantly to time savings. Conversely, demographic factors are shown to be irrelevant in the context of the intensity of AI use, confirming the versatility and broad acceptability of this technology.

5 DISCUSSION

The results of the research conducted provide new insights into user behaviour and the use of generative AI. The first research question addressed the extent to which respondents use generative AI as their main tool for information retrieval. The results show that the use of generative AI is quite moderate, with mean values at the middle level of the scale. The above results are in line with a trend that shows an overall gradual increase in the use of generative models such as ChatGPT, Gemini or Claude among Internet users, although the mentioned technology has not yet become a universal standard for all users (Bordas et al., 2024).

The aforementioned usage rates can potentially be influenced by various factors such as technological literacy, personal preferences, or the availability of alternative search tools (Jia et al., 2023). In the second research question, we tested the relationship between the intensity of use of generative AI and the decrease in clicks on traditional search engine links. The present results confirmed the existence of a significant, positive relationship, suggesting that users who make more intensive use of generative AI are less likely to use traditional search engine links. These results are consistent with the initial claim of Epstein et al. (2022), who suggest that with the advent of more advanced technologies that provide answers directly without the need to click on additional resources, changes in user behaviour are occurring. At the same time, the above results support arguments about changing behavioural patterns of Internet users who prefer immediate answers to searching for additional sources of information (Molnar & Golman, 2024). In the third research question, the investigation focused on verifying whether the use of generative AI indeed leads to time savings in information retrieval compared to traditional search engines. The findings of the investigation indicate a significant correlation between the frequency of AI use and perceptions of time efficiency. This complements the assumption made by Gupta and Mukherjee, (2025) that generative AI can eliminate or significantly reduce the time users spend browsing multiple links in traditional search engines. The above findings correspond with preliminary results of Gill et al. (2024), who defined that it is potentially possible that users value AI precisely for its ability to provide directly targeted answers without the need for extensive searching of individual links. The fourth research question explored the existence of gender differences in the use of

generative AI. The results of the t-test showed that there were no significant differences between males and females, suggesting that both genders have similar preferences and frequency of use of AI technologies. Similarly, ANOVA analysis showed no significant differences between age groups, a finding given that previous research by Heponiemi et al. (2022) suggested that younger users are more likely to make more intensive use of advanced digital tools. The above result may suggest that generative AI has been able to effectively reach a wider range of age groups and is not limited to younger or more technologically savvy users as previously discussed by Chan and Lee, (2023). On the other hand, another aspect associated with the increase in the use of generative AI needs to be mentioned and that is the credibility of the information generated. We complement the investigation of Nauta et al. (2023) by suggesting that although users value the speed and convenience of the answers they receive, they may also underestimate the need to critically evaluate their answers. The results indirectly confirm the concern by showing that AI users click less on traditional links, which may lead to less diversity in the sources and information they consume, thus building on Bauer et al.'s, (2023).

A related area is the impact of AI on consumer decision making. Our results showed relatively lower preference ratings for AI recommendations, which may be due precisely to consumers' distrust or less receptive behaviour towards recommendations from automated systems. The finding is interesting because Gao and Liu, (2023) pointed out that consumers often blindly trust personalized recommendations offered by AI. The present investigation also contains some limitations, this is mainly due to the quantitative nature of the data collection and the structured questionnaire, where the investigation mainly focused on measurable behavioural patterns, which offers scope for future addition of deeper qualitative insights. Respondent participation was based on a voluntary basis and therefore the moderate context of the sampling frame can be taken into account when interpreting the results. Finally, although basic demographic variables such as age and gender were included in the analysis, further research may enrich the interpretation by including a broader range of factors such as technological experience, professional orientation, or personality traits of users. Furthermore, in terms of future research, it would be useful to pay attention not only to users' attitudes and preferences themselves, but also to explore in depth their behaviour in specific situations in the digital environment. Future investigations could track whether trust in AI varies depending on the type of information that is generated and whether time efficiency actually leads to better decisions or to superficiality in the perception of information.

6 CONCLUSION

The results obtained provide significant results and also contribute to a better understanding of how AI is changing users' patterns of information-seeking behaviour in digital environments. As a result, the first research question clarified the essence of the matter, namely that respondents use generative artificial intelligence to a lesser extent and that there is also a large group of intensive users, with moderate use being noticeable. The second research question showed that higher use of artificial intelligence is significantly associated with fewer clicks in search engines. The third research question clarified that generative artificial intelligence provides perceived time savings compared to traditional search. On the other hand, the fourth research question found no significant differences between genders or age groups. The study is limited by sample size, data obtained from respondents' self-reports, and reliance on quantitative methods. From a practical perspective, the results of the investigation suggest that developers and operators of generative AI should, in particular, pay attention to ensuring greater transparency, reliability and trustworthiness of the

information provided. For educators and information literacy practitioners, it is important to focus on educating users in the critical evaluation of AI-generated content. In conclusion, the present investigation contributes to a deeper understanding of the current state of the use of generative AI. Future research is highly desirable, especially focusing on the qualitative aspects of users' interaction with AI and more rigorously exploring the implications of this technology on decision-making and behaviour in digital environments. Future research could also include qualitative approaches and a wider range of demographic and behavioural variables.

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CYBERSECURITY DISCLOSURE AND FIRM PERFORMANCE: THE HIDDEN POWER OF BOARDS IN EUROPEAN UNION FIRMS

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Abstract

As the European Union (EU) is accelerating digital transformation and facing increasingly complex cybersecurity risks, cybersecurity disclosure (CSD) has become an essential requirement in modern corporate governance. However, the decision to disclose CSD is not only influenced by legal requirements but also depends on the leadership characteristics and board structure of the enterprise. Despite the increasing attention to this topic, previous studies have largely lacked an integrated approach. This study aims to analyze the impact of CEO tenure and board characteristics (gender diversity, independence) on the level of CSD disclosure and test the mediating role of CSD in the relationship with corporate financial performance (ROA). Data were collected from 40 EU-listed companies over the period 2016-2022. The empirical analysis was conducted using three regression methods, including OLS, GLS, and GMM, to control for endogeneity and bidirectional causality. The results show that long CEO tenure and a high proportion of independent directors have negative effects on the level of CSD disclosure, while the gender variable does not show a statistically significant impact. Moreover, CSD has a positive and significant impact on ROA, thereby confirming the important mediating role in connecting governance structure with performance. The study contributes to corporate governance theory by integrating agency theory and superordinate theory into a model explaining CSD disclosure behavior, and provides useful empirical evidence for policymakers in designing board structures and developing regulations to promote cybersecurity transparency in Europe.

JEL Classification: G32, G34, L25

Keywords: *Cybersecurity disclosure, CEO tenure, Board independence, Gender diversity, Firm performance.*

1 INTRODUCTION

In the context of increasingly complex, persistent, and unpredictable digital threats, cybersecurity disclosure (CSD) has become an indispensable component of modern corporate governance. This is particularly true in the European Union (EU), where legal frameworks such as the Cybersecurity Act, the Cyber Resilience Act (Mueck et al., 2025), and the General Data Protection Regulation (GDPR) (Bertolaccini et al., 2023; Sharf, 2016) have required businesses to increase transparency, control, and resilience to digital risks. However, the disclosure of cybersecurity-related information is not simply a result of legal requirements but is also strongly influenced by the characteristics of business leaders and internal governance structures. Recent studies have shown that CEOs with longer tenures tend to disclose less information, reflecting a conservative or complacent management strategy (Khan et al., 2021; Muttakin & Khan, 2023; Trinh et al., 2025). In contrast, boards with at least three female directors significantly improve the quality and level of CSD disclosure (Elnahass et al., 2024; Radu & Smaili, 2022). At the same time, the presence

of independent directors enhances monitoring capacity and promotes information transparency through their role as a check and reduces information asymmetry (Alodat et al., 2023; Smaili et al., 2023). Although these factors have been studied individually, most previous studies have not fully integrated them to clarify the mediating role of CSD in the relationship between governance characteristics and firm performance. In particular, in the European context where the legal framework is relatively tight but disclosure practices are still uneven, quantitative studies testing the overall model are still limited.

From this gap, the study raises the main question: How do CEO tenure, gender diversity, and independence on the board affect the level of cybersecurity disclosure, and does CSD play a mediating role in influencing firm performance?

To answer this question, the study aims at three main objectives:

- (i) providing empirical evidence on the role of CSD as an effective governance tool in the context of digital risks;
- (ii) expand understanding of the relationship between CEO tenure, board independence, and cybersecurity disclosure behavior;
- (iii) highlight the role of gender diversity in improving information transparency.

The contributions of the study are reflected in three closely linked aspects. Academically, the study integrates two important theoretical foundations, Upper Echelons Theory and Agency Theory, to build a multi-level theoretical model in which cybersecurity disclosure (CSD) is considered a meaningful intermediary variable, connecting governance structure with corporate financial performance. This approach is relatively new and has not been deeply exploited in previous studies, especially in the European research context. Practically, the study provides practical policy implications to enhance corporate monitoring capacity through designing appropriate board structures, while supporting policy makers in developing regulations that encourage gender diversity and enhance independence in governance towards a more transparent and accountable disclosure environment. Methodologically, the study applies a combination of three popular and suitable regression methods for panel data, namely OLS, GLS, and especially GMM, on a data sample of 40 large companies in Europe during the period 2016-2022. The use of GMM allows effective control of endogeneity problems and bidirectional causal relationships between variables, thereby improving the reliability and consistency of the estimates, contributing to strengthening the interpolation value and applicability of the research results in practice.

The paper is structured in six sections: Section 1 introduces; Section 2 presents the theoretical basis and develops hypotheses; Section 3 describes the data and research methods; Section 4 presents the results of the analysis and discussion; and Section 5 provides conclusions, policy implications, and future research directions.

2 BACKGROUND THEORY AND HYPOTHESIS DEVELOPMENT

2.1 Background theories

According to Agency Theory of Jensen et al. (1976), information asymmetry between shareholders and managers is a major cause of agency costs, especially in highly specialized areas such as cybersecurity. In this context, managers with information advantages can selectively disclose information to protect the organization's image or avoid negative market reactions (Linder & Foss,

2015; Morse et al., 2017). Therefore, independent monitoring mechanisms, especially the presence of independent board members, are considered important tools to reduce opportunistic behavior and promote transparency in cybersecurity disclosure (Mazumder & Hossain, 2023; Smaili et al., 2023). However, most studies have focused on the monitoring structure while paying little attention to the behavioral motivations and personal characteristics of managers that may significantly influence disclosure strategies. Filling this gap, the Upper Echelons Theory of Hambrick & Mason (1984) emphasizes that observable characteristics of top leaders, such as tenure or gender, can reflect values, experience, and strategic vision. This, in turn, influences decision-making behaviour, including CSD disclosure. Based on this, Trinh et al. (2025) and Muttakin & Khan (2023) demonstrate that CEOs with longer tenures tend to disclose less information, due to complacency or a shift to a defensive risk management strategy. (Khan et al., 2021) also found an inverted U-shaped relationship, indicating that disclosure levels peak mid-term and decline thereafter. While it has been argued that long tenures help accumulate organizational knowledge and improve decision quality, empirical evidence suggests that this positive effect is inconsistent and limited in practice. This is a notable gap, especially in European markets where cybersecurity transparency is increasing.

In addition, within the framework of the upper echelons theory, leadership gender is also considered a significant driver of disclosure behavior. Specifically, the presence of women on boards, especially when the threshold of three members is reached, is strongly associated with higher levels of CSD disclosure and a more cautious tone (Elnahass et al., 2024; Radu & Smaili, 2022). Studies from many countries, such as the United States, Canada, Bangladesh, and Indonesia, have confirmed the positive role of gender diversity in cybersecurity information transparency (Kurnia & Ardianto, 2024; Mazumder & Hossain, 2023). However, some regional and industry differences remain unexplained, and comparative research across legal and cultural contexts is limited. This suggests the need to examine the role of gender in CSD under different institutional conditions. Continuing with the governance structure, the proportion of independent directors on the board not only helps to strengthen supervision but also contributes to the formation of specialized cybersecurity subcommittees, thereby improving the systematicity and quality of CSD (Héroux & Fortin, 2020; Kluiters et al., 2023). Unlike board size, which does not show a clear effect, independent directors on the board are considered an important factor in promoting voluntary disclosure. However, current studies mostly stop at the direct relationship, without analyzing the moderating role of this factor in the impact of CSD on corporate financial performance.

Moreover, CSD not only reduces asymmetry but also increases market confidence, thereby improving operational efficiency at both the accounting and market levels (Al Amosh & Khatib, 2023; Frank et al., 2019). Proactive, independently verified disclosure helps firms avoid the contagion effects of negative industry events and enhance their competitive position (Baatwah et al., 2025; Navarro & Sutton, 2025). However, much of the current evidence comes from markets such as Canada, the United States, and the United Kingdom.

2.2 Hypothesis development

Recent studies have found that CEOs with longer tenures tend to disclose less information, which is explained by a gradual decrease in proactive disclosure over time (Trinh et al., 2025). This trend reflects the possibility of complacency or a change in disclosure approach strategy in later stages of tenure. Evidence in Corporate Social and Environmental Disclosure (CS&ED) also confirms

that longer CEO tenures are associated with lower levels of disclosure (Muttakin & Khan, 2023; Ratri et al., 2021). In addition, some studies have found an inverted U-shaped relationship between CEO tenure and disclosure, indicating that disclosure levels tend to increase early in the tenure but decrease as tenure lengthens (Khan et al., 2021; Muttakin & Khan, 2023). The fixed model perspective suggests that CEOs with long tenures may become less flexible and resistant to change, reducing their ability to implement or disclose new cybersecurity strategies (Khan et al., 2021). Firms with long-tenured CEOs typically exhibit lower levels of CSD disclosure, possibly due to an "avoidance" strategy of disclosing potential cybersecurity-related weaknesses (Trinh et al., 2025). At the same time, firm performance following CEO replacement is typically lower if the previous CEO had a long tenure, reflecting long-term consequences for the organization and its ability to adapt to new cybersecurity threats (Muttakin & Khan, 2023). Although it has been argued that veteran CEOs possessing accumulated organizational knowledge can enhance the effectiveness of cybersecurity strategies, empirical evidence suggests that this positive effect is limited and is not often observed in practice (Khan et al., 2021). Thus, from the synthesis of theoretical and empirical evidence, the following hypothesis is proposed:

H1: CEO tenure has a negative effect on cybersecurity disclosure of enterprises.

Gender diversity on boards, especially the presence of female directors, is considered an important factor in promoting information transparency and improving disclosure behaviour in organizations. Several recent studies have shown that female CEOs tend to disclose more information related to cybersecurity than their male counterparts and use a more cautious and conservative tone in their reports (Elnahass et al., 2024). This reflects women's more thorough and sensitive approach to issues of risk and accountability in the digital environment. In particular, the positive effects of gender diversity are only genuinely evident when the board reaches a critical mass threshold of at least three women, thereby creating a substantive rather than a formal influence on cybersecurity disclosure decisions (Elnahass et al., 2024; Radu & Smaili, 2022). Empirical evidence from multiple regions, such as US firms (Elnahass et al., 2024), Canada (Radu & Smaili, 2022), Bangladesh (Mazumder & Hossain, 2023), and Indonesia (Kurnia & Ardianto, 2024), all confirm the positive relationship between women's board representation and cybersecurity disclosure. In addition, gender diversity contributes to improved governance and decision-making. Diverse boards tend to have higher levels of information exchange, leading to more inclusive discussions and better strategic decisions (Shehadeh et al., 2022). When integrated into small task force committees, women's perspectives can have a more visible impact on cybersecurity strategies (Khemakhem et al., 2023). Although there are sectoral and regional differences, such as a positive effect in Indonesian banks but not evident in Indian financial firms (Shukla & Pandey, 2023), the overall evidence strongly supports the role of gender diversity in promoting more transparent and prudent cybersecurity disclosure. From the above arguments and evidence, the study proposes the following hypothesis:

H2: Gender diversity in the board of directors has a positive effect on cybersecurity disclosure of enterprises.

Board independence has long been recognized as a core element of effective governance structures, particularly in monitoring, controlling, and enhancing information transparency. In the context of increasing cyber threats, numerous studies have shown that boards with a higher proportion of independent directors tend to disclose more information related to cybersecurity risks and measures, demonstrating a strong commitment to accountability and reducing information asymmetry (Alodat et al., 2024; Mazumder & Hossain, 2023; Shukla & Pandey, 2023; Smaili et

al., 2023). Independent directors are an effective monitoring mechanism, ensuring management is accountable to the board for cybersecurity strategies. With their independence of interests and ability to challenge, they prioritize full disclosure to protect shareholder interests and maintain corporate reputation (Mazumder & Hossain, 2023; Smaili et al., 2023). The increased presence of independent members has also been shown to help form dedicated cybersecurity committees, thereby strengthening the systematicity and effectiveness of disclosure activities (Héroux & Fortin, 2020). Unlike board size, which did not significantly affect cybersecurity disclosure, the number of independent directors was the decisive factor (Mazumder & Hossain, 2023; Smaili et al., 2023). This reflects the importance of quality and the practical role of governance rather than quantity. In addition, boards with a high proportion of independent directors are also associated with greater levels of voluntary disclosure and reduced information asymmetry between investors and the company, thereby contributing to increased firm value and strengthening digital trust (Kluiters et al., 2023). Based on the theoretical and empirical evidence above, the study proposes the following hypothesis:

H3: The number of independent directors on the board positively affects cybersecurity disclosure of enterprises.

In increasingly complex and increasing cybersecurity threats, CSD has become important in governance strategies and building trust with stakeholders. Recent studies have shown that CSD positively impacts business performance, both at the accounting and market levels. Specifically, transparency in disclosure helps reduce information asymmetry and agency problems, enhancing trust and facilitating investment and business development (Al Amosh & Khatib, 2024). Voluntary cybersecurity disclosure helps companies mitigate the negative contagion effects of breaches at peers and positions themselves as resilient and innovative (Baatwah et al., 2025; Kelton, 2021). This is especially important in a competitive environment as investors increasingly pay attention to digital risk management. Furthermore, strategic disclosure, combined with independent third-party assurance, can significantly enhance the confidence of non-professional investors, especially when the disclosure is consistent with industry expectations (Frank et al., 2019, 2023; Navarro & Sutton, 2025). In addition, studies have shown that effective board governance, especially with independent directors and financial expertise, improves the quality of cybersecurity disclosures and thereby improves corporate performance (Smaili et al., 2023). The presence of a Chief Information Officer (CIO) even helps reduce the negative impact of delayed disclosures, emphasizing the role of proactiveness and transparency in risk communication (Huang & Murthy, 2024). Although there is some evidence of negative short-term effects, mainly when disclosures involve data breaches or are made incompletely, overall analyses suggest that timely, quality disclosures supported by independent assurance tend to improve firm performance in the long term (Al Amosh & Khatib, 2024; Cheng et al., 2022; Tripathi & Mukhopadhyay, 2022).

Based on information transparency theory, agency governance, and consistent empirical evidence, the study proposes the following hypothesis:

H4: Cybersecurity disclosure has a positive impact on firm performance.

3 DATA AND METHODOLOGY

3.1 Data

This study uses secondary data from the annual reports of 40 European-listed companies from 2016 - 2022. The companies were selected from various sectors, such as technology, finance, industry, and services, to ensure the representativeness of the European business sector. The dependent variable in the study is the firm performance (ROA), measured by the ratio of return on total assets as reported in the financial statements. The intermediate variable is cybersecurity disclosure (CSD), measured by the number of keywords related to cybersecurity in the company's annual report. The independent variables include CEO tenure, measured by the Blau index; the proportion of independent directors on the board (IND), measured as a percentage; and board gender diversity (DIV), also measured by the Blau index. In addition, the study uses three control variables: firm size (SIZE) measured by the natural logarithm of total assets; firm age (AGE) measured by the number of years since establishment; and financial leverage (LEV) measured by the ratio of total liabilities to total assets.

3.2 Methodology

To test the relationship between corporate governance characteristics and cybersecurity disclosure (CSD), as well as the impact of CSD on business performance, the study applies a combination of three quantitative regression methods: Ordinary Least Squares (OLS), Generalized Least Squares (GLS), and the System Generalized Method of Moments (SGMM).

First, the OLS method is used as a basic model to estimate the linear relationship between variables. However, OLS assumes that the explanatory variables are exogenous, with no endogenous relationship with the error term. This assumption may not be satisfied in the current research context, when variables such as CEO tenure, the independence of the Board of Directors, or the CSD disclosure behavior itself can both be influenced by and impact the financial performance of the business, leading to endogeneity and a two-way causal relationship. In order to partly overcome the phenomenon of heteroskedasticity and autocorrelation in panel data, the study continues to use the GLS method. This method helps to correct errors in the case of heteroskedasticity and the existence of autocorrelation over time in the panel data series. The use of GLS is suitable for the unbalanced panel data characteristics of the study, in which observations are not uniform over time among enterprises. However, to thoroughly handle the endogeneity problem, as well as the two-way causal relationship between CSD and financial performance, the study applies the SGMM method developed by (Arellano & Bover, 1995; Blundell & Bond, 1998) based on the foundation of (Arellano & Bond, 1991). This method allows the use of lagged endogenous variables as instruments, thereby improving consistency and efficiency in estimation. GMM is particularly suitable for management research and non-financial disclosure, which often face problems such as measurement error, heteroskedasticity, and missing data. Moreover, GMM effectively controls for unobservable fixed factors and minimizes deviations from reverse causality.

The GMM model testing was performed with the support of Stata 17 software. Diagnostic tests include the Hansen test to assess the validity of the instrument and first-order and second-order residual autocorrelation tests (Arellano-Bond AR(1) and AR(2)) to ensure that the model does not violate the assumption of residual independence. To ensure the reliability and stability of the model, the study compared the results between the three methods: OLS, GLS, and GMM. The

combination of multiple methods not only helps to test the stability of the estimates but also enhances the interpolation value, thereby improving the reliability of the policy conclusions drawn from the research results.

4 RESEARCH RESULT

Tab. 1 - Descriptive statistics of variables. Source: own research

Variable	Obs	Mean	Std. Dev.	Min	Max
ROA	280	0.0275	0.0592	-0.7700	0.2300
CSD	280	3.1233	0.8941	0.0000	5.4100
CEO	280	10.6060	2.6985	4.9500	18.1300
DIV	280	0.3964	0.1033	0.0000	0.5000
IND	280	0.3520	0.2473	0.0000	0.8500
LEV	280	0.7264	0.1598	0.3100	1.0200
SIZE	280	11.8524	1.5786	6.4100	14.8000
AGE	280	4.4169	0.7976	2.0800	7.6000

The descriptive statistics table shows that the sample companies' operating efficiency (ROA) is relatively low, with a mean of 0.0275 and a standard deviation of 0.0592, indicating insignificant variation. The average level of cybersecurity disclosure (CSD) is 3.12, but some companies do not disclose, reflecting the heterogeneity in information transparency. The average CEO tenure is 10.61 years, indicating that most CEOs have a relatively long leadership period. Board gender diversity (DIV) has an average of 0.396, approaching the highest level of 0.5, reflecting the relative presence of women. The proportion of independent directors (IND) is at an average of 35.2% but ranges widely from 0% to 85%. Financial leverage (LEV) averages 0.726, reflecting a relatively high level of debt in the capital structure. Firm size (SIZE) has an average log of assets of 11.85, while firm age (AGE) averages 83.06 years (4.42). The variables are highly dispersed, reflecting the diversity in governance and financial characteristics among firms, suitable for further regression analysis.

Tab. 2: Correlation and multicollinearity matrix. Source: own research

	CEO	DIV	IND	LEV	SIZE	AGE	VIF
CEO	1.0000						1.37
DIV	-0.0538	1.0000					1.08
IND	-0.3300**	.2612**	1.0000				1.47
LEV	0.2701**	0.0043	-0.2244*	1.0000			1.54
SIZE	0.3036**	0.0410	-0.0335	0.5441**	1.0000		1.52
AGE	0.2083**	0.1388*	0.2835**	0.0995	0.1265*	1.0000	1.24
Mean VIF							1.37

The correlation table and VIF coefficients show no serious multicollinearity problem among the independent variables in the model. All VIF coefficients are low, ranging from 1.08 to 1.54, with

an average value of 1.37, significantly lower than the warning threshold of 5, indicating that the variables do not have a strong linear relationship that affects the regression results.

The regression results from the three OLS, GLS, and GMM models show significant differences in stability and reliability in identifying factors affecting Cyber Security Disclosure (CSD). In particular, the GMM model demonstrates a significantly superior ability compared to the other two models, thanks to its ability to effectively handle problems such as endogeneity, heteroscedasticity, and lag in panel data. This is reinforced by diagnostic tests such as Arellano-Bond for AR(1) and AR(2) with p-values of 0.012 and 0.259, respectively (H3), ensuring the appropriateness of the instruments. In contrast, the Hansen test shows $p = 0.134$, demonstrating that the instruments used are valid and do not cause redundancy.

Tab. 3 - Regression results of factors affecting CSD. Source: own research

	OLS	GLS	GMM						
	H1	H2	H3	H1	H2	H3	H1	H2	H3
L.CSD							0.415*** [52.96]	0.566*** [14.80]	0.440*** [55.06]
CEO	- 0.0796*** [-3.94]			- 0.0696*** [-4.33]			- 0.0519*** [-3.20]		
DIV		0.292 [0.57]			0.212 [0.63]			-0.197 [-0.81]	
IND			-0.239 [-1.05]			-0.185 [-1.08]			-0.197* [-1.72]
LEV	1.107*** [2.90]	0.922** [2.37]	0.803** [1.99]	1.277*** [5.06]	0.951*** [3.73]	0.757*** [2.69]	0.969*** [14.08]	0.553*** [3.75]	0.651*** [5.39]
SIZE	0.0939** [2.40]	0.0652 [1.65]	0.0695* [1.76]	0.152*** [5.23]	0.135*** [4.70]	0.133*** [4.65]	0.0458** [2.14]	0.018 [0.67]	0.0329* [1.97]
AGE	0.081 [1.24]	0.0305 [0.46]	0.0581 [0.84]	0.0647 [1.28]	0.0188 [0.37]	0.0418 [0.79]	0.114*** [6.14]	0.0105 [0.30]	0.123*** [4.86]
_cons	1.693*** [3.74]	1.430*** [2.93]	1.543*** [3.33]	0.844** [2.53]	0.711* [1.90]	0.927*** [2.66]	0.755*** [6.33]	0.951*** [3.94]	.558*** [4.58]
N	280	280	280	280	280	280	240	240	240
R-sq	0.114	0.065	0.068						
Number of instruments							34	25	34
Number of groups							40	40	40
AR(1)							0.013	0.008	0.012
AR(2)							0.258	0.219	0.259
Hansen test							0.138	0.066	0.134

The regression analysis results from three OLS, GLS, and GMM models have provided consistent empirical evidence, particularly elucidating the role of leadership characteristics and governance structures in shaping cybersecurity disclosure (CSD) behavior. Notably, the relationship between CEO tenure and CSD is clearly established with a statistically significant negative coefficient in all three models, with the strongest effect recorded in GMM ($\beta = -0.0519$). This finding supports hypothesis H1, which states that CEOs with longer tenures are less likely to disclose information about cybersecurity risks. This result reflects a common phenomenon in governance: complacency that accumulates over time or defensive tendencies to protect personal and organizational images from negative information (Khan et al., 2021; Trinh et al., 2025). The above conclusion is fully consistent with the Upper Echelons Theory (Hambrick, 2007), according to which the strategic behavior of managers directly reflects their individual cognitive and experiential characteristics. In this case, veteran CEOs may become less sensitive to new cybersecurity challenges and less willing to implement proactive disclosure strategies, in contrast to newly appointed CEOs who often use CSD as a tool to demonstrate transparency and management capacity (Ratri et al., 2021). This finding not only provides reliable empirical evidence but also opens up a new approach in assessing the "strategic energy cycle" of business leaders.

For hypothesis H3, instead of having a positive impact as expected, the proportion of independent members on the board of directors shows a weak negative effect, significant at the 10% level in the GMM model ($\beta = -0.197$). This finding suggests an important fact: nominal "independence" is not enough to ensure effective oversight if there is a lack of IT-related expertise or deep involvement in the cybersecurity control process (Shukla & Pandey, 2023). On the contrary, when independent members are supported by specialized subcommittees and have appropriate technological platforms, their oversight and transparency promotion roles will be more effective (Héroux & Fortin, 2020). This confirms the importance of "quality" governance rather than just focusing on formal structure.

For hypothesis H2, the empirical results do not provide sufficient evidence to confirm the impact of board gender diversity on cybersecurity disclosure behavior.

In addition to the main variables, some control variables also show stable and significant results. Financial leverage (LEV) consistently shows a significant positive effect, especially in GMM (β from 0.553 to 0.969, $p < 0.01$), indicating that firms that use more debt are more motivated to disclose CSD in order to reduce credit risk and increase creditor confidence. The factors of size (SIZE) and age of the firm (AGE) also have a positive effect; AGE is especially significant in many models ($\beta = 0.114$ - 0.123 , $p < 0.01$), indicating that older, more experienced firms tend to build internal control systems and disclose information more transparently.

Tab. 4 - Regression results of CSD and ROA. Source: own research

	OLS	GLS	GMM
L.ROA			0.227*** [34.60]
CSD	-0.000479 [-0.13]	0.00022 [0.29]	0.0149*** [6.37]
LEV	-0.166*** [-6.83]	-0.104*** [-13.04]	-0.227*** [-37.48]
SIZE	0.00147 [0.60]	-0.00134* [-1.72]	0.00509*** [2.96]
AGE	-0.000336 [-0.08]	-0.00126 [-1.41]	0.00384* [1.79]
_cons	0.134*** [4.58]	0.125*** [16.78]	0.0585** [2.38]
N	280	280	160
R-sq	0.185		
Number of instruments			30
Number of groups			40
Arellano-Bond test for AR(1)			0.029
Arellano-Bond test for AR(2)			0.667
Hansen test			0.137

The results presented in Table 4 show that the impact of Cybersecurity Disclosure (CSD) on corporate performance, measured through ROA, is clear and statistically significant and has considerable practical value. Specifically, the CSD variable has a positive coefficient ($\beta = 0.0149$), thereby reinforcing hypothesis H4 that the higher the level of cybersecurity disclosure, the more improved the corporate performance (ROA). This result not only confirms the positive role of information transparency in digital risk management but also shows that CSD is an important link in the chain of influence from governance structure to financial results.

Compared with the two linear regression models (OLS and GLS), the System GMM method shows more reliable results when controlling well for endogeneity and the two-way causal relationship between CSD and corporate performance. The suitability of the GMM model is confirmed through diagnostic tests: the p-value of the Arellano-Bond AR(2) test is 0.667, and the Hansen test is 0.137, both within the acceptable threshold, ensuring that the model does not encounter the phenomenon of weak or redundant instruments. This strengthens the reliability of the estimates and allows policy conclusions to be drawn with a higher level of precision. The research results are also consistent with much previous empirical evidence. According to Al Amosh & Khatib (2023), CSD contributes to reducing information asymmetry and agency risk, thereby increasing investor confidence and improving both accounting and market indicators. This effect is particularly evident in countries with strong cybersecurity regulatory frameworks, such as GDPR or the European Cybersecurity Act, which require companies to be transparent about their strategies and risks related to the digital space (Bertolaccini et al., 2023; Mueck et

al., 2025). In this context, proactive disclosure not only helps companies avoid negative spillover effects from industry violations (Kelton & Pennington, 2020) but also demonstrates their commitment to accountability and their ability to respond to increasingly sophisticated risks.

In addition to its role as a direct explanatory variable, CSD is also seen as a significant mediator in the relationship between governance structures (such as board independence or diversity) and performance. When a company has a transparent board structure and a clear oversight orientation, it is more likely to develop an effective CSD disclosure strategy; thereby indirectly improving financial performance and building a competitive position in the market (Baatwah et al., 2025; Navarro & Sutton, 2025).

5 CONCLUSION

This study aims to explore the impact of CEO tenure and board characteristics on the level of Cybersecurity Disclosure (CSD) and analyze the mediating role of CSD in the relationship with firm performance (ROA). Using panel data from 40 large European companies over the period 2016–2022 and combining three regression methods (OLS, GLS, and GMM), the study provides strong empirical evidence, especially from the GMM model, which is confirmed by the Hansen and Arellano-Bond test. The results show that (i) long CEO tenure has a significant negative effect on CSD; (ii) there is no statistical evidence to confirm the role of gender diversity in the board; (iii) the proportion of independent directors has a weak negative effect on the level of disclosure; and (iv) CSD has a positive and significant impact on firm performance. In particular, the finding of the mediating role of CSD has clarified the spillover mechanism from governance structure design to financial performance, an important contribution from both academic and practical perspectives.

Contributions of the study

In theory, the study extends and systematically integrates two fundamental theories, Agency Theory and Upper Echelons Theory, into the context of cybersecurity disclosure, a relatively new topic in the field of corporate governance. Specifically, the study plays a bridging role between individual-level factors (such as CEO tenure) and organizational-level factors (such as independence and gender diversity on the board of directors) with non-financial disclosure behavior. Beyond establishing a direct relationship, the study also provides empirical evidence on the mediating role of CSD, helping to clearly explain the mechanism of impact between governance structure and financial performance. This is a theoretical gap that most previous studies have not fully approached or have only stopped at superficial relationships.

In practice, the study provides practical policy implications for administrators and policymakers. In the context of increasing cybersecurity risks, building a transparent, consistent, and proactive CSD disclosure mechanism is not only a risk management measure but also a strategy to build trust with investors and stakeholders. Enterprises with better disclosure systems are likely to improve operational efficiency by reducing agency costs, attracting investment capital, and protecting market value in the long term. The results of the study also show that the design of the Board of Directors should not only stop at formal criteria such as “ratio of independent members” or “presence of women,” but also focus on the nature of substantive participation, relevant expertise, and commitment to effective monitoring in key areas such as cybersecurity in European countries.

In terms of methodology, the study uses a multi-model approach while applying system GMM—a modern technique suitable for handling endogeneity, measurement error, and two-way causality. In addition, measuring CSD through exploiting actual disclosure data from

annual and management reports helps to improve reliability, transparency, and comparability between companies. However, this study still has some limitations. Firstly, the small sample size (40 companies) may affect the ability to generalize the research results to the entire region or different industries. Secondly, measuring cybersecurity disclosures based on keyword counts may not fully reflect the quality and strategic content of the information disclosed. Thirdly, the study only focused on internal factors (governance and CEO) and did not consider external factors such as regulatory pressure, the extent of cyber breaches, or industry characteristics. Therefore, future studies should expand the sample size, improve the measurement method by incorporating qualitative content analysis, and consider institutional and cultural environmental factors.

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CONSUMER TRUST IN ARTIFICIAL INTELLIGENCE: A SYSTEMATIC LITERATURE REVIEW USING PRISMA GUIDELINES

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Abstract

This systematic literature review examines how consumer trust in artificial intelligence (AI) is conceptualized, measured and influenced in marketing contexts. Using PRISMA 2020 guidelines, 64 empirical studies published between 2017 and 2024 in ABS-ranked journals were analyzed. The findings highlight that trust is a key driver of AI adoption, satisfaction and engagement, especially in e-commerce, banking and social media marketing. Most studies define trust through cognitive dimensions such as competence and reliability, while emotional or relational aspects are less frequently addressed. Trust is commonly measured using self-reported Likert scales, with little use of behavioral or longitudinal data. Influencing factors include AI design attributes, user characteristics and contextual elements like brand reputation. The review identifies a lack of unified theoretical models and limited research on affective trust, generative AI and underrepresented user groups, offering clear directions for future research.

Keywords: *consumer trust, Artificial intelligence, systematic literature review, PRISMA, AI adoption, E-commerce, Generative AI introduction*

1 INTRODUCTION

The rapid integration of artificial intelligence (AI) into marketing has transformed how firms engage consumers. More recent work confirms that trust in AI agents directly drives satisfaction, engagement and loyalty across sectors such as banking, retail and hospitality (Sujood & Pancy, 2024; Manser Payne et al., 2018; Rahman et al., 2021).

Despite this wealth of empirical studies, definitions, measures and determinants of AI trust vary widely, with many papers focusing on isolated contexts or single technologies. Such fragmentation impedes the development of unified theory and evidence-based design guidelines. In parallel fields like healthcare, systematic reviews guided by the PRISMA protocol have greatly enhanced transparency and reproducibility in literature synthesis (Liberati et al., 2009; Page et al., 2021).

Objectives. Guided by PRISMA, this paper systematically reviews 64 empirical studies published between 2017 and 2024 in leading, ABS-ranked journals. My research question is:

How is consumer trust in artificial intelligence conceptualized, measured and influenced in marketing-related literature?

Specifically, we will map the various trust definitions and theoretical framings; catalogue the tools and methods used to measure trust; and identify the key design, user and contextual factors that shape trust in AI. By synthesising these elements, we aim to provide an insightful overview and directions for future research and practice.

2 METHODS

This systematic literature review explores how consumer trust in artificial intelligence (AI) is conceptualised, measured and influenced in marketing-related contexts. The review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-

Analyses (PRISMA) 2020 guidelines (Page et al., 2021) and drew methodological inspiration from the approach outlined by Pahlevan-Sharif et al. (2019). More precisely, all articles published between 2017 and 2024 in journals ranked by the Chartered Association of Business Schools Academic Journal Guide (2024) were considered for inclusion.

Based on the review objectives, a protocol was developed prior to the search to guide the literature review process. It included the search terms, database selection, document-type filters and inclusion/exclusion criteria. While this protocol was not registered in a public database, it was adhered to throughout the review. A minor post hoc revision was made to the search strategy by adding exclusion terms (“blockchain,” “encryption,” “COVID,” and “political”) after pilot-testing with a number of unrelated results.

The articles were checked to meet several predefined criteria to ensure relevance and quality. First, the article had to be published between 2017 and 2024, as the technology was only recently developed and presented to consumers. Second, only full-length peer-reviewed articles in English were included. Thus, all other publications, such as readers’ comment, book reviews, editors’ comments, conference proceedings were excluded. The final criterion was that the article had to be based on trust as a central concept in the context of artificial intelligence applied to marketing, advertising, e-commerce or customer experience.

The search was conducted exclusively via the Web of Science database, chosen for its comprehensive coverage of scholarly and peer-reviewed journals in marketing and technology. The search was performed in February 2025 and all metadata and full-text PDFs were retrieved through institutional access. A structured boolean query was used to identify records:

((TI=(trust) OR AB=(trust)) AND (TI=(consumer OR customer) OR AB=(consumer OR customer)) AND TS=("artificial intelligence" OR AI) AND TS=(marketing OR advertising OR e-commerce OR "customer experience")) AND PY=(2017-2024) AND LA=(English) NOT TS=(blockchain OR encryption OR COVID OR political)

The title, abstract, keywords, authors’ names, journal name and publication year of all identified records were exported into an Excel spreadsheet for structured data management. The initial screening of titles and abstracts was conducted by the research author, with ongoing verification and consultation to ensure accuracy. Subsequently, the full texts of the remaining articles were assessed based on the pre-defined criteria. The spreadsheet was used both as a data management and coding tool. No contact with original study authors was needed, as all relevant data were available in the published articles. The Excel file was expanded to include bibliographic details, PRISMA-based checklist items and key content variables (like type of AI technology, measurement and influencing factors of trust). A pilot test was performed on a set of 10 randomly selected articles to validate the coding categories and refine extraction procedures. Given the conceptual and qualitative nature of this systematic review, concerns regarding the applicability of individual studies to the review question were addressed during the full-text screening phase. This review did not involve meta-analysis. The included studies varied in their definitions of trust, methodological frameworks and technological contexts.

3 RESULTS

The initial search in Web of Science with the query mentioned in the methodology part returned 188 records. After removing 1 duplicate, 187 records were screened by title and abstract. Following eligibility filters for document type (article, early access, review, or proceedings paper) and ABS journal inclusion, 97 records remained for full-text assessment. Based on the inclusion criteria, 33 articles were excluded for lacking a focus on trust in AI or being unrelated to marketing contexts. In the end, 64 papers from 35 journals (3 articles were published across

ABS 4* journals, 24 articles appeared in ABS 3 journals, 23 articles came from ABS 2 journals and 14 articles were published in a ABS 1 journal) remained. Figure 1 presents the PRISMA 2020 flow diagram summarising the article selection process.

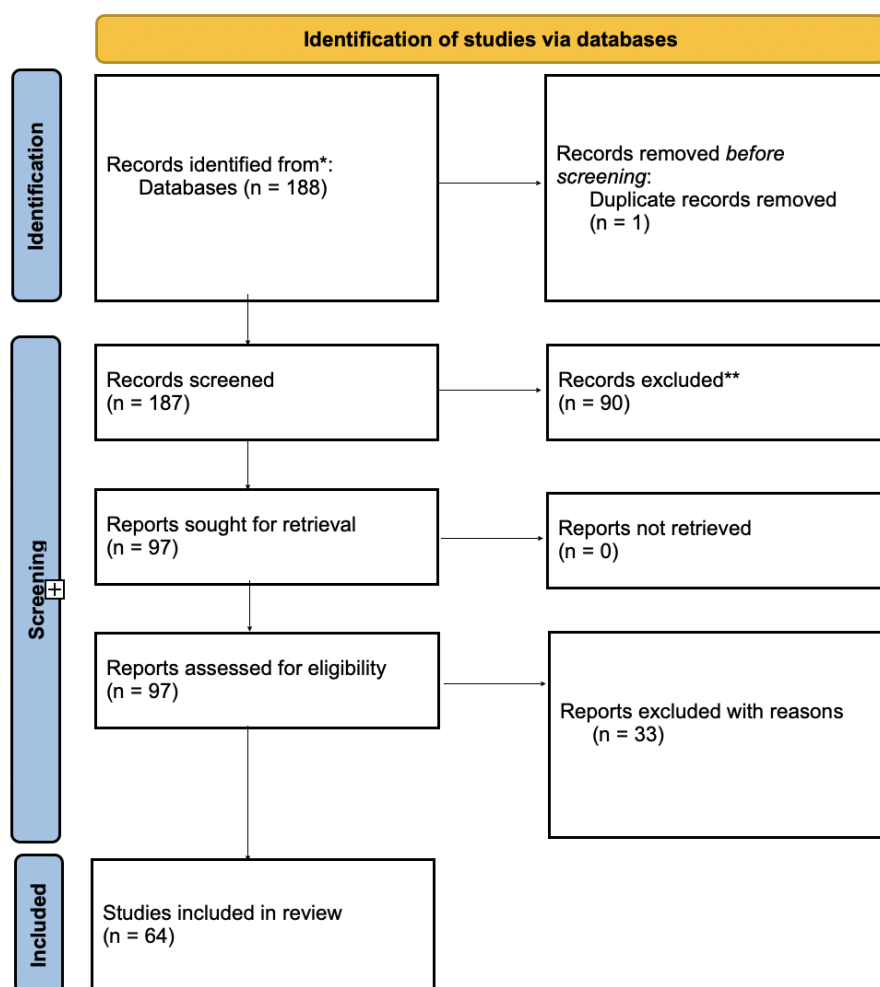


Fig. 1 – PRISMA 2020 flow diagram for systematic reviews. Source: own research

The articles' distribution highlights that ABS 3 journals are leading the discourse, while ABS 4 and 1 journals show lower engagement, possibly due to topical fit or editorial focus. The clustering of articles in ABS 2 and 3 journals suggests a growing academic interest in AI and consumer trust within business and marketing, but still underrepresented in top-tier field journals.

The analysis shows a significant increase in publication volume on the topic of consumer trust in artificial intelligence in recent years. Of the 64 included studies, 62 papers (96.9%) were published between 2021 and 2024, indicating a sharp rise in scholarly interest aligned with the rapid growth and mainstreaming of AI technologies such as chatbots, recommendation engines and voice assistants. Only 2 studies (3.1%) were published before 2021, confirming that this research area has emerged predominantly within the last five years. This temporal concentration likely reflects both the technological development of AI tools and the growing public interest in ethical, social and psychological issues of trusting AI.

For each of the 64 included studies, a structured set of characteristics was extracted to facilitate a comprehensive comparison. Appendix 1 summarises the main characteristics of the studies about consumer trust published in the top marketing journals and other management- and

business-related journals. The data extraction process focused on elements central to the research question: the conceptualisation, measurement and influencing factors of consumer trust in artificial intelligence within marketing contexts.

3.1 Types of Artificial Intelligence

To systematically analyse the scope and function of AI applications studied in the included articles, AI context was categorised into six thematic categories defined in Table 1. The most researched AI systems were chatbots and conversational agents, which appeared in 32 out of 64 studies (50.0%), making them the dominant form of consumer-facing AI analyzed in marketing contexts. These included both text-based chatbots and more advanced avatar-based agents deployed in customer service, e-commerce and mobile applications. The second most studied category was voice assistants and smart speakers, such as Amazon Alexa or Google Assistant, examined in 14 studies (21.9%). These were often assessed in relation to trust in voice-based interactions, anthropomorphism and data privacy. Recommendation systems were the focus of 8 studies (12.5%), predominantly in e-commerce and personalisation contexts. Trust was typically linked to perceived relevance, accuracy and user control. Only 1 study (1.6%) explicitly addressed AI certification and trust governance, indicating this remains an under-explored area within literature. Regarding AI influencers, 7 studies (10.9%) investigated digital personas and their impact on consumer trust, especially on social media platforms. These papers explored concepts like perceived authenticity, human-likeness and social presence. Lastly, 18 studies (28.1%) were classified as mixed or other AI technologies, referring to research that examined multiple AI types simultaneously or used generalised references to AI without a specific application focus. These were often theoretical or exploratory studies situated in experimental or conceptual contexts.

Tab. 1 – Thematic classification of AI technologies used in the reviewed studies. Source: own research

Category	Definition	Example Technologies
Chatbots & Conversational Agents	AI tools that simulate human conversation using text or voice (Chopra, 2019).	Chatbots, virtual assistants, conversational agents
Voice Assistants & Smart Speakers	Voice assistants are speech-based Natural User Interface devices that understand human voice and provide responses through synthesized voice (Chopra, 2019).	Amazon Alexa, Google Assistant, Siri
Recommendation Systems	AI engines that suggest products, services, or content based on user data, machine learning, and artificial intelligence (Yang et al., 2024).	Netflix recommendations, Amazon product suggestions
AI Certification / Trust Governance	Specific subset of audit studies focused on studying algorithmic systems and content”, where the algorithmic system is often tested against a regulatory framework (Blösser & Weihrauch, 2023).	Trust labels, AI ethics seals, governance standards
AI Influencers	Digitally created artificial humans that realistically simulate the characteristics, personalities, and thoughts of real humans (Chan et al., 2023).	Lil Miquela, AI-generated Instagram personalities

Category	Definition	Example Technologies
Other or mixed AI Technologies	Studies that include multiple AI types or refer to AI in broad, conceptual terms without focusing on one specific implementation.	Chatbot + fraud detection

3.2 Types of marketing context

The majority of studies investigated AI technologies within e-commerce and online retail environments, accounting for 21 articles. These studies examined the role of AI in product recommendations, personalised shopping, dynamic pricing and online customer experience optimisation. The next most frequent context was general marketing and consumer behaviour, covered in 15 articles. These studies typically explored trust in AI across multiple sectors, conceptualised trust broadly or focused on consumer-AI relationships without restricting analysis to a specific domain. Influencer and social media marketing was the third most prominent category with 9 studies exploring AI-generated influencers, virtual brand avatars and social media bots. Trust in these contexts was primarily linked to authenticity, emotional engagement and digital identity. Other contexts included hospitality and tourism (6 studies), banking and financial services (5 studies), healthcare (2 studies), voice and conversational marketing (2 studies). This distribution underscores that consumer-facing and commercial environments dominate the academic focus, while trust in AI within sensitive or high-risk sectors like finance and healthcare remains under-explored, despite their growing real-world relevance.

3.3 Trust conceptualisation

The findings of this systematic review reveal that the conceptualisation of consumer trust in artificial intelligence remains fragmented and context-dependent. Although a majority of the studies (47 out of 64; 73.4%) provided a definition or framing of trust, most were concentrated around cognitive trust such as competence, reliability and integrity (Kushwaha et al., 2021; Kim et al., 2024; Minton et al., 2022 ;Liu & Li, 2022, among others).

Only 9 studies (14.1%) explored affective trust, such as emotional attachment or perceived warmth (Karimova & Goby, 2021; Chan et al., 2023, among others) and even fewer integrated multi-dimensional trust models combining cognitive and affective elements (Kyung & Kwon, 2022; Kim et al., 2021). This suggests that emotional and relational aspects of trust are still largely underrepresented in marketing-oriented AI trust literature.

In terms of measurement, nearly all empirical studies (52 out of 64; 81.3%) relied on self-reported Likert scale instruments, often adapted from established models like McKnight et al. (2002) or Gefen et al. (2003) (Manser Payne et al., 2018; Bawack et al., 2021, among others). However, only a small number of studies employed behavioral indicators of trust, such as interaction frequency or choice-based outcomes (Przegalinska et al., 2019; Bawack et al., 2024; Yang et al., 2023), suggesting a methodological gap in capturing trust as a demonstrated behavior rather than a self-perception.

The review also identifies several groups of influencing factors. Most commonly, trust was shaped by technology design attributes, including anthropomorphism, transparency and algorithmic explainability, highlighted in 41 studies (Kushwaha et al., 2021; Yen & Chiang, 2021; Chi et al., 2021; Karimova & Goby, 2021).

User-specific factors, such as prior experience with AI, technological familiarity, or technology readiness - were examined in 23 studies. These factors were shown to influence trust formation,

particularly in applications involving recommendation systems, banking chatbots and virtual assistants (Park et al., 2021; Liu & Li, 2022; Mariani et al., 2023; Rawool et al., 2024). In contrast, only 14 studies addressed contextual or brand-related influences on trust, such as industry domain, perceived brand trustworthiness, or corporate reputation (Kushwaha et al., 2021; Chan et al., 2023; Mariani et al., 2023; Blösser & Weihrauch, 2024; Barari et al., 2024). This imbalance suggests that while interface-level and user-centric attributes are well-explored, the broader socio-cultural and psychological environment in which AI-driven trust develops is frequently overlooked in marketing literature.

3.4 Thematic synthesis of included studies

A large part of recent research consistently shows that consumer trust in AI technologies is a pivotal factor in successful AI-driven marketing outcomes. Across various contexts, higher trust in AI correlates with greater willingness to adopt and use AI-based services, as well as more positive customer experiences. For example, studies in fields from mobile banking to voice commerce find that when consumers trust an AI service, they are significantly more likely to engage with it and continue using it (Manser Payne et al., 2018; Bawack et al., 2021). Trust also frequently mediates the influence of other perceptions (such as perceived risks or benefits) on behavior, underscoring its central role in decision-making (Vimalkumar et al., 2021). Notably, trust is linked not only to initial acceptance but to side outcomes like satisfaction and loyalty. Customers who trust an AI-based service tend to report higher satisfaction and stronger loyalty intentions (Chen et al., 2023; Huang et al., 2024).

Multiple studies have identified key factors that build or undermine consumer trust in AI. On the positive side, an AI system's perceived competence, reliability and usefulness are consistently mentioned as trust drivers (Li et al., 2023; Chang & Park, 2024). Consumers are more willing to trust AI that they find easy to use, compatible with their needs and endorsed by others in their social circle (Mostafa & Kasamani, 2022). Transparency and explainability also increase trust level. When people understand how an algorithm works or believe it operates with integrity, their confidence in the AI grows (Przegalinska et al., 2019). Moreover, the credibility of the AI's provider plays a role. Trust in a familiar brand or reassurance via third-party certifications can transfer to trust in the AI service itself (Li et al., 2023; Blösser & Weihrauch, 2024). Conversely, perceived privacy risks and "creepy" or overly invasive AI behaviors can trigger distrust (Rajaobelina et al., 2021; Barari et al., 2024). In some cases, consumers will refuse or limit use of an AI tool if it makes them uncomfortable or threatens their sense of control over personal data (Vimalkumar et al., 2021; Rajaobelina et al., 2021).

The design and social presence of AI interfaces further influence trust in specific ways. Human-like design elements (anthropomorphism) can sometimes increase user trust by making AI agents seem more relatable or alive (Karimova & Goby, 2021; Yen & Chiang, 2021). For instance, framing a chatbot as a friendly assistant and enabling a conversational, personable tone can foster a sense of relationship, which in turn strengthens trust (Youn & Jin, 2021). However, the literature also warns that anthropomorphism is a double-edged sword. If an AI's human-like avatar or behavior falls into the "uncanny valley" (appearing almost but not quite human) it can backfire and reduce trust. Users in one study actually felt more comfortable and satisfied with a simple text-based chatbot than with a more realistic human-like avatar, highlighting that authenticity of experience matters more than simple human-like appearance (Przegalinska et al., 2019). Design features need to be carefully adjusted to context. For example, recent research found that human-like attributes, like a chatbot's presumed gender or having a casual nickname, can affect trust, revealing that user biases and expectations play into the trust equation (Lu & Zhang, 2025).

Individual user differences and cultural context also shape how trust in AI is formed. People's predispositions toward technology, such as being tech-savvy or tech-skeptical, moderate their trust levels. Those enthusiastic about new technology tend to trust AI systems more readily than those with more wary attitudes (Youn & Jin, 2021). Similarly, an individual's general propensity to trust others or to trust technology influences the speed and degree of trust they place in an AI service (Chi et al., 2021). Interestingly, personal values and beliefs can have unexpected effects. One study found that consumers with stronger religious faith were more trusting of AI, hypothesising that a mindset of faith in unseen forces makes them more open to trusting an intangible AI agent (Minton et al., 2022). Cultural background is another factor. The research in an Eastern collectivist context showed that consumers navigate privacy and utility trade-offs through trust differently than Western consumers might, suggesting trust dynamics are not universal (Vimalkumar et al., 2021). Some demographic influences are noted as well. For example, evidence suggests there may be age and gender differences in how users trust and use AI, though these patterns are still emerging (Gude, 2025). It's worth noting that much of the evidence comes from younger samples (often university students or online panel users), so further work is needed to confirm that these trust relationships hold true for older or less tech-oriented consumer groups (Manser Payne et al., 2018; Gude, 2025).

Strong consumer trust in AI not only encourages use of the technology but can also enhance outcomes for the companies deploying these tools. Several studies indicate that when customers trust a brand's AI - that trust can extend to more positive attitudes toward the brand itself and increase purchase intentions (Yen & Chiang, 2021). Trust can also 'transfer' from an AI recommender system to the product it recommends, meaning if users trust the AI's judgement, they become more willing to consider or adopt the suggested products (Chang & Park, 2024). In experimental research, presenting information in ways that inspire trust led to more favourable consumer responses, an effect shown to be mediated by increased trust in the AI source (Kim & Giroux, 2021). Ultimately, high trust tends to translate into better customer experience outcomes: higher satisfaction, greater loyalty and willingness to follow AI-driven recommendations (Chen et al., 2023; Huang et al., 2024).

The literature agrees on the vital importance of consumer trust in making AI-enabled marketing effective, yet it also reveals some diverging findings and open questions. The consensus is that trust is a foundational mediator in most consumer-AI interactions (Bawack et al., 2021; Rather, 2024). However, researchers note differences in how trust operates. For instance, while ease of use is often important, one study reported it was not a significant factor for chatbot trust in their context (Li et al., 2023), implying that what builds trust can depend on the situation or user expectations. Similarly, the direct impact of privacy concerns on consumer behaviour remains debated. Certain studies indicate that privacy concerns primarily discourage usage in an indirect manner by first diminishing trust (Vimalkumar et al., 2021), while other researchers initially anticipated a quicker impact. There is also the question of how much trust alone drives behaviour, as most models assign it a central role, but one analysis of actual adoption behaviour found trust to be a weaker predictor when other influences were taken into account (Gude, 2025). Furthermore, as discussed above, design strategies like anthropomorphism yield mixed outcomes for trust (Karimova & Goby, 2021; Przegalinska et al., 2019), indicating no unanimous rule on human-like AI design. Another factor contributing to occasional inconsistencies is the diverse interpretations of "trust" itself. Some studies distinguish between cognitive and affective trust or initial versus long-term trust, whereas others treat it as a single general construct (Chi et al., 2021; Chen et al., 2023). Such differences in definition and measurement can lead to inconsistent results, underlining the need for more standardised approaches in future research.

4 DISCUSSION

This section combines our review's findings with insights from recent literature reviews on consumer trust in AI-enabled marketing. Across studies, there is broad consensus that consumer trust is a key for AI adoption and effectiveness, yet the literature remains conceptually fragmented. Our review confirmed that trust in AI significantly drives acceptance, satisfaction, and loyalty, echoing observations in related reviews that trust is "a critical factor" for users' adoption of AI technologies. At the same time, scholars note that research on AI trust is shared across contexts and disciplines. Several reviews have responded by proposing integrative frameworks. For example, Montealegre-López (2025) categorises trust research by its foundations, dynamics, and outcomes, while Yang and Wibowo (2022) map trust's components, antecedents, and outcomes into a comprehensive model. This suggests that, despite diverse industries, researchers agree on the need to consolidate how we understand and build consumer trust in AI. Our findings, placed in this context, reinforce the view that trust is both paramount and under-theorized in the current state of AI marketing literature.

How trust is conceptualised in AI marketing shows both common ground and gaps across studies. In our review of 64 articles, most defined trust in primarily cognitive terms, with far fewer addressing affective or emotional dimensions of trust. This aligns with observations by Kumar et al. (2023) that much of the marketing literature emphasizes rational, performance-based facets of trust while neglecting relational aspects. For instance, trust in AI is often grounded in perceptions of technological success (accuracy, usefulness) and integrity, paralleling the dominance of cognitive trust in technology acceptance models. However, multiple reviewers have argued that this one-dimensional focus is limiting. Yang and Wibowo's (2022) analysis stresses the "importance of building trust based on different facets", including emotions, to yield positive user responses. Notably, some recent work has started to integrate affective trust: studies of anthropomorphic AI agents report that human-like design can foster feelings of warmth or empathy in users, hinting at an emotional basis for trust. Our finding that only about 14% of marketing studies examined affective trust underscores a gap also flagged by others. In short, there is agreement that trust in AI has both cognitive and affective components, but much of the marketing literature to date has leaned on cognitive conceptualisations.

There is also notable convergence regarding how trust is measured and studied, alongside calls for methodological improvement. Our review found that an overwhelming majority of studies relied on self-report Likert scales to gauge consumer trust, often adapting established trust questionnaires to the AI context. There is also growing recognition of the value of experimental and even physiological measures to get a fuller picture of consumer trust in AI (Yang & Wibowo, 2022). In summary, across the literature we see agreement that current work leans heavily on stated trust perceptions.

When considering factors that influence trust, our review and the comparative sources report largely consistent sets of drivers with some differences in emphasis and context. Many studies in our sample showed that making AI systems more transparent, explainable, and anthropomorphic can significantly shape trust. The same message is reinforced in recent syntheses. Kumar et al. (2023), focusing on anthropomorphic AI, conclude that human-like features generally "enhance trust [and] emotional connection" with consumers. They find that giving an AI agent a face, personality or social presence can cultivate user familiarity and confidence, an effect also noted by Jain et al. (2023) in their consumer behavior review.

In integrating our findings with existing literature reviews, a picture emerges of both agreement and needed progression in the field of AI trust in marketing. There is strong agreement on foundational points: trust is indispensable for positive consumer responses to AI, most marketing studies have so far treated it in a largely cognitive and measurement-static manner, and key drivers like transparency, usefulness, and credibility consistently underpin trust. At the same time, the comparative literature highlights several areas of divergence or gaps that chart directions for future research.

In conclusion, by comparing our results with these other literature reviews, we observe a clear consensus on the centrality of trust in AI-enabled marketing and broad alignment on its key drivers, coupled with a shared recognition of current research limitations. Addressing these limitations by expanding trust definitions, diversifying measurement, and accounting for contextual moderators like culture and brand, will help resolve points of disagreement and advance a deeper understanding of consumer trust in the age of AI.

5 LIMITATIONS

This systematic review presents several limitations that must be acknowledged when interpreting the findings. The first key limitation is the restriction to articles published in English, which may have introduced language bias. Relevant studies in other languages, especially in regions with distinct technological or cultural approaches to AI may have been excluded. Additionally, the decision to include only ABS-ranked journals indexed in Web of Science ensured academic significance but likely limited the diversity of included research, particularly from emerging or interdisciplinary fields where AI and marketing intervene, such as media studies or digital sociology.

The eligibility criteria also excluded conference proceedings, book chapters, dissertations and industry white papers, which may have contained novel empirical findings, especially in fast-evolving areas like generative AI or AI influencers. These decisions may affect the comprehensiveness and applicability of the review to real-world practice.

Further, the search strategy, while systematic, was based on a fixed set of boolean keywords. This may have excluded studies that used alternative terminology for trust (like credibility or confidence) or did not explicitly mention marketing.

Finally, while data extraction was conducted systematically using a predefined Excel framework, the manual coding of AI contexts and marketing domains involved interpretive judgment, which may introduce researcher bias, particularly when categorising complex or overlapping use cases.

6 CONCLUSION

In this review of 64 empirical studies, we found evidence that consumer trust is a foundational driver of AI adoption and engagement across marketing contexts. Well-designed AI systems consistently resulted in higher levels of trust, which in turn boosted satisfaction, loyalty and purchase intent (Kushwaha et al., 2021; Chi et al., 2021). At the same time, my findings reveal significant gaps: emotional or affective trust remains underexplored (Karimova & Goby, 2021), brand and contextual influences are rarely examined (Chan et al., 2023) and the field continues to rely heavily on cross-sectional self-report surveys, limiting insights into real-world and longitudinal trust dynamics (Patrizi et al., 2024).

By synthesizing these studies, this review extends existing literature on technology acceptance and trust by showing that user characteristics, such as prior AI experience and privacy concerns,

interact with design features to shape trust formation (Rajaobelina et al., 2021; Liu & Li, 2022). We also highlight the importance of trust transfer from established brands to their AI services, a phenomenon that has practical implications for brand managers seeking to introduce AI solutions (Blösser & Weihrauch, 2024).

This review examined how consumer trust in artificial intelligence is conceptualised, measured, and influenced in marketing-related literature. Across the analysed studies, trust is most commonly conceptualised as a multidimensional construct, with cognitive trust (based on perceived competence and reliability) and affective trust (based on empathy and benevolence) as dominant dimensions. Some authors use an undifferentiated definition, which limits cross-study comparability. Measurement approaches vary widely, ranging from adapted technology acceptance scales to context-specific instruments, often lacking standardisation. This inconsistency contributes to divergent findings on specific drivers, such as the relative importance of usability versus transparency. Influencing factors consistently identified include transparency, explainability, perceived competence, ethical alignment, anthropomorphic design and brand reputation. While most evidence supports their positive effect on trust, findings on anthropomorphism and ease of use are mixed, reflecting contextual and cultural variation.

For future research, scholars should work toward theoretically integrated models that unify cognitive and affective dimensions of trust, drawing on existing trust theories while tailoring them to AI's unique affordances. Methodologically, deploying behavioral metrics, physiological measures and longitudinal designs will offer richer, more ecologically valid insights into how trust develops, erodes and can be repaired over time. Research should also broaden its scope beyond Western, student-based samples to include diverse age groups, cultural contexts and industry sectors such as healthcare and hospitality, where AI is rapidly emerging. Finally, as generative AI and AI influencers reshape digital interactions, empirical studies must investigate how these new forms of automation affect trust, ethics and consumer well-being in marketing ecosystems (Rather, 2024; Urbani et al., 2024).

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INTEGRATING SDGS INTO MUNICIPAL BUDGETING: A METHODOLOGICAL FRAMEWORK FOR MIXED-METHODS RESEARCH

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Abstract

The Sustainable Development Goals (SDGs) provide an important framework for transforming public policies towards greater sustainability. Local governments play a key role in their implementation, and the budget process is one of the main tools for translating goals into practice. Although the SDGs have become part of the strategic documents of many cities and municipalities, their actual reflection in budget decisions remains insufficiently researched.

The paper presents a proposal for a methodological framework of the upcoming dissertation research, the aim of which is to analyse how the SDGs are integrated into municipal budget planning. The research is theoretically anchored in the concept of bounded rationality and uses a mixed-methods research design combining qualitative and quantitative approaches. The paper presents the research gap, research questions and objectives, proposed scientific hypotheses, methods of data collection and analysis.

The integration of SDGs into local budgeting is examined not merely as a technical exercise, but as a complex decision-making process shaped by institutional, political, and behavioral dynamics. By combining document analysis, interviews, and survey data, the research aims to capture both the declared and actual implementation of sustainability principles in municipal finance. The expected outcomes include a better understanding of local governance practices and practical recommendations for enhancing strategic and sustainable budget planning.

Keywords: *SDGs, public budgets, local government, bounded rationality, mixed-methods research, methodology*

1 INTRODUCTION

Budgetary decision-making at the municipal level is one of the essential tools of public administration. Municipal budgets are not only a technical tool for allocating resources, but also a mechanism that shapes the quality of life of residents and the direction of local development. In recent years, requirements for transparency, public participation and accountability to sustainability principles have come to the fore, making budgetary processes increasingly complex (Fathirah, 2024; Agustin and Arza, 2020).

A major challenge in this context is posed by the Sustainable Development Goals (SDGs), which were adopted by the United Nations in 2015 as a global framework for achieving social, economic and environmental balance (un.org). Their local implementation is considered a key condition for their successful implementation (Kroll et al., 2020). Although strategic documents such as the 2030 Agenda or the Methodology of Ministry of Regional Development of the Czech Republic (MMR ČR, 2025) declare a commitment to the implementation of the SDGs, their real integration into the budgetary processes of municipalities remains insufficiently grasped and empirically little explored (Guarini et al., 2021; Tremblay et al., 2021).

This paper aims to explore how municipalities in the Czech Republic incorporate the SDGs into their budget processes, which tools and actors are involved in this process, and what barriers they encounter. The research is theoretically anchored in Herbert Simon's concept of bounded rationality (Simon, 1947), which provides a suitable framework for the analysis of decision-making under conditions of limited information, time and resources. This approach makes it possible to realistically capture the decision-making logic of actors in the environment of municipal administration.

This creates a practical and analytical need to trace how high-level SDG commitments are translated into concrete fiscal choices under real-world constraints.

2 LITERATURE REVIEW AND THEORETICAL FRAMEWORK

Despite the prominence of the Sustainable Development Goals in international and national agendas, how they are embedded in municipal budget processes remains under-specified and empirically thin. Existing work on sustainable development and public finance seldom follows the concrete budget cycle at the local level or specifies the instruments and actors involved, leaving mainly case-bound evidence (Gustafsson & Ivner, 2017; Almeida et al., 2018; Guarini et al., 2021).

We still lack systematic knowledge of whether municipalities treat SDG budgeting as a largely declarative exercise or as a substantive planning strategy, what barriers they face, and how political, institutional and behavioural contexts condition their choices (Read, 2024; Gesso, 2020). This study addresses that gap by examining the practice of SDG integration in municipal budgeting in the Czech Republic.

Anchored in Herbert Simon's concept of bounded rationality, the study traces decision-making under constraints of information, time and resources and asks how these constraints shape the translation of SDG commitments into fiscal allocations (Simon, 1947). Methodologically, it employs a mixed-methods design combining document analysis, interviews and a survey to connect observed budgeting routines with perceived constraints and offers a transparent operationalisation of SDG–budget integration alongside actor-level evidence on enabling and impeding mechanisms.

The theoretical framework of the paper is the concept of Bounded Rationality, as formulated by Herbert Simon in his work *Administrative Behavior* (1947). Simon challenged the notion of fully rational decision-making, showing that individuals often choose a "satisfactory" solution over an optimal one because they face limitations in information, time, and cognitive capacity. This approach is particularly relevant for municipal government settings, where decision-making takes place under conditions of high complexity and uncertainty (Horvat et al., 2020; Stewart et al., 2018).

The application of Simon's theory makes it possible to realistically capture decision-making processes in the environment of municipalities, where political interests, institutional frameworks and individual motivations clash. As shown by studies by Bækgaard and Serritzlew (2015) or Cantarelli et al. (2018), cognitive biases and behavioral factors significantly influence public decision-making. In the context of the SDGs, this means that even well-intentioned strategies can be marginalized if they are not perceived as priority or understandable.

Building on this theoretical perspective, we operationalize bounded rationality via (1) evidence of satisficing and heuristics in budgetary choices, (2) documented information and time constraints shaping option sets, and (3) institutional rules that bound feasible alternatives.

The chosen theoretical framework thus provides suitable tools for analyzing why and how the SDGs are (or are not) integrated into budgetary processes, and what factors influence this process. The paper thus contributes not only to the expansion of theoretical knowledge, but also to the practical understanding of decision-making mechanisms in the field of sustainable development at the local level.

Building on this theoretical foundation, the next section formulates the research questions and hypotheses guiding the study.

This conceptualization directly informs our coding scheme in the qualitative phase and the construction of survey items measuring perceived constraints, heuristics and institutional bounds.

3 RESEARCH GAP AND RESEARCH QUESTION

Based on the literature review and theoretical anchoring in Herbert Simon's concept of bounded rationality, a research question was formulated that reflects the need for a deeper understanding of the processes of integration of the Sustainable Development Goals (SDGs) into budget processes at the municipal level. This question arises from an identified research gap, which lies in the lack of empirical knowledge on how municipalities approach the implementation of the SDGs through their fiscal decisions.

Considering the identified research gap, the study poses the following overarching research question:

How do municipalities currently incorporate the SDGs into their budgets and what challenges do they face?

This question is further elaborated into three sub-research questions, which allow to examine the individual dimensions of the phenomenon in a structured way:

- 1. What tools, approaches and procedures do municipalities use to integrate the SDGs into their budget processes?**
- 2. What roles and attitudes do key actors (politicians, bureaucrats, experts) take in promoting or limiting the integration of the SDGs into budgets?**
- 3. What are the main challenges and barriers that municipalities identify when trying to integrate the SDGs into the budget process?**

The aim of this research is to address these questions by applying a combination of qualitative and quantitative methods, thereby contributing to a more nuanced understanding of decision-making processes in the field of sustainable development at the local level.

The main research objective of the paper is formulated as follows:

Identify and analyze the ways in which municipalities incorporate the SDGs into their budgetary processes, while exploring the main barriers and challenges they face in doing so.

This goal is further elaborated into three sub-research objectives:

- To map and analyze the practical mechanisms (tools, methodologies, processes) by which municipalities implement the SDGs in budgeting.**
- Identify key actors influencing the integration of SDGs and analyze their motivations, knowledge, decision-making behavior, and degree of influence.**

- **Analyze the most common barriers (political, institutional, economic, environmental, demographic, socio-cultural, gender) and the ways in which municipalities try to overcome them.**

Based on the existing knowledge and literature review, the following working scientific hypotheses were formulated, which will be verified in the quantitative part of the research:

- **H1:** Municipalities that have strategic or budgetary documents referencing the SDGs (strategic plan, action plan, climate/sustainability strategy, budget methodology, medium-term budget outlook/MTEF) show a higher degree of integration of the SDGs into their budget documents than municipalities without such a document.
- **H2:** The higher level of importance attached by the key actors of the SDGs in budgetary decision-making is positively correlated with the degree of their integration into the municipal budget.
- **H3:** Municipalities whose budget decisions are primarily shaped by political considerations show a lower degree of SDG integration.
- **H4:** Municipalities with higher financial performance show a higher degree of integration of the SDGs into budget planning than municipalities with lower financial capacity.
- **H5:** Municipalities with formal sustainability commitments (declaration/strategy and implementation tools such as an action plan, internal procedure or designated unit) show a higher degree of SDG integration into budget planning.

The formulation of these hypotheses assumes that decision-making in the environment of municipalities is influenced not only by rational considerations, but also by institutional conditions, cognitive limitations and behavioural factors. The theory of bounded rationality thus provides a suitable framework for understanding why the integration of the SDGs into budgetary processes can be difficult, incoherent or merely formal.

The indicators below correspond to the variables and measurement choices summarized in Table 1.

Tab. 1 - Definition of variables and their relationships. Source: own work based on the literature review

Variable	Role	Operational definition	Source
The degree of integration of the SDGs into the budget	Dependent variable	What mechanisms do municipalities use to integrate SDGs objectives into their budgetary frameworks?	Alonso-Morales et al., 2025, Luna et al., 2025
Existence of a document with links to the SDGs	Independent variable	Authorities at the local level should take the necessary steps to integrate the SDGs into their policies and programs.	Cembranel, 2024
Perception of the importance of the SDGs	Independent variable	Implementation of SDGs into budget processes = main opportunity that needs to be addressed at the local level.	Wessels et al., 2023
Degree of political influence and transparency	Independent variable	The nature of political leadership and the stable political environment influence budgetary processes.	Horvat et al., 2020, Adegboye et al., 2020

Financial performance of the municipality	Independent variable	The economic situation at the local level influences decision-making budgeting processes.	Park et al., 2021
Political orientation of the municipality management	Independent variable	Political ideologies and political parties can influence decision-making processes.	Loayza et al., 2011, Linina et al, 2024

Note: For measurement details, see section Operationalization of the variables.

To empirically investigate these assumptions, the following section outlines the methodological approach of the study.

4 METHODOLOGY

Due to the complexity of the phenomenon and the need to capture both the depth of decision-making processes and the breadth of their occurrence across municipalities, a mixed research design was chosen for this work. This approach combines qualitative and quantitative research methods and allows for triangulation of data, thereby increasing the validity and reliability of findings.

The mixed approach is used intentionally in the paper – the qualitative part of the research serves to gain a deeper understanding of the motivations, barriers and strategies of the actors involved in the budget process, while the quantitative part allows to verify the identified patterns and hypotheses on a wider sample of respondents.

We focus on ORP municipalities because they perform delegated state administration and manage a broader portfolio of services and budgets, making them pivotal for local SDG implementation in the Czech administrative system.

The research is carried out in two consecutive phases:

- **Qualitative phase:** Implementation of approximately 20 semi-structured interviews with actors in the budget process (politicians, officials, experts) in selected municipalities with extended powers (ORP). Guest, Bunce, and Johnson (2006) found in their study that in a thematically homogeneous population, saturation is usually reached after approximately 12 interviews, with basic themes often emerging around the sixth interview. The interviews will be analysed using thematic coding. Coding scheme will be as follows: deductive nodes (from bounded rationality) = satisficing (evidence of ‘good-enough’ options), heuristics (rules of thumb), information constraints (limited/fragmented data), time constraints (budget cycle pressures), institutional bounds (legal/procedural rules delimiting options). Inductive nodes will be added as themes emerge. The output will be the identification of key topics, approaches and barriers, which will be further used to formulate new or refine existing hypotheses.
- **Quantitative phase:** Based on the qualitative findings, a questionnaire will be compiled and distributed across the ORP in the Czech Republic. The research set consists of all ORPs in the Czech Republic. The expected return is approximately 20–30%, which corresponds to experience from similar research in public administration. The paper aims for at least 50 valid responses from ORP municipalities to support multivariate analysis. The aim is to verify the relationship between the degree of integration of the SDGs and selected factors (e.g. institutional capacity, policy orientation, financial performance).

Operationalization of the variables

To operationalize the concept of SDG integration, the research will use a set of indicators derived from both document analysis and survey responses. These include the presence of SDG references in budgetary and strategic documents, the use of SDG-related performance indicators, and the degree of institutionalization (e.g., internal guidelines, dedicated staff, or budget lines).

Dependent variable (DV)

SDG–Budget Integration Index (0–10): sum of five 0–2 indicators found in municipal budget documents: (1) SDG references in budget or MTEF; (2) programme/chapters mapped to SDGs; (3) SDG-linked performance indicators; (4) institutionalisation (methodology/role/unit or budget line); (5) monitoring/public reporting.

Independent variables (IVs)

H1: SDG-linked document present: 0/1 if at least one of: strategic plan, action plan, climate/sustainability strategy, budget methodology, or MTEF (Medium Term Expenditure Framework) explicitly references SDGs. Source: documents.

H2: Importance attached by key actors: mean of 3–4 Likert items (1–5) on SDG priority during budgeting. Source: survey.

H3: Primacy of political influence: mean of 3 Likert items 1–5; higher = more ad-hoc political shaping. Source: survey.

H4: Financial performance: net current balance per capita. Robustness: add debt/pc (–) and capital expenditure/pc (+). Source: accounts.

H5: Sustainability commitment (recommended in place of ideology): 0 none; 1 declaration/strategy only; 2 declarations + implementation tool (action plan/procedure/unit). Source: documents.

Controls: population size; own-revenue per capita (fiscal capacity).

The qualitative data will be analysed using thematic coding, supported by qualitative data analysis software (e.g., Lumivero or NVivo). The coding process will follow an inductive approach, allowing for the emergence of categories grounded in the data, while also being informed by the theoretical framework of bounded rationality. Particular attention will be paid to identifying patterns of reasoning, perceived constraints, and institutional dynamics that shape decision-making.

In the quantitative phase, descriptive statistics will be used to map the prevalence of SDG integration practices across municipalities. Inferential techniques, such as correlation analysis and multiple regression, will be applied to test the proposed hypotheses and assess the influence of political, institutional, and financial variables on the degree of SDG integration. The combination of these methods ensures both depth and breadth in understanding the phenomenon under study.

The research will be carried out in accordance with the ethical principles of scientific work. Respondents' participation will be completely voluntary, anonymous and conditional on informed consent. The data will be processed in anonymized form and used exclusively for the purposes of the dissertation and related professional outputs.

The main limits of research include:

- Possible low return rate of questionnaires,
- different degree of willingness to cooperate between municipalities,

- limited generalizability of qualitative findings.

Despite these limitations, the research is expected to yield valuable insights, both theoretical and practical, as discussed in the next section.

5 CONTRIBUTION

Dissertation research focused on the integration of the Sustainable Development Goals into the budgetary processes of municipalities brings significant benefits both on the theoretical and practical levels. Both levels complement each other and create a framework for a deeper understanding of decision-making processes in the public administration environment, which is increasingly exposed to the requirements for sustainability, transparency and accountability.

5.1 Theoretical contribution

From the theoretical point of view, the paper responds to the hitherto insufficiently explored connection between the concept of sustainable development and fiscal decision-making at the local level. Existing research tends either to address SDG localization and managerial perspectives without tracing concrete municipal budget decisions, or to offer case-bound insights, leaving systematic links to budgeting underexplored (Gustafsson & Ivner, 2017; Almeida et al., 2018; Guarini et al., 2021; Tremblay et al., 2021). Although the SDGs represent a globally recognized framework for the direction of social, economic and environmental development, their actual implementation into the budgetary processes of municipalities remains a marginal topic in the professional literature. Especially in the Czech context, there is a noticeable lack of empirical studies that would systematically examine how municipalities approach the fulfilment of these objectives through their budgetary decisions.

The paper contributes to the expansion of theoretical knowledge in several ways. First, it applies Herbert Simon's concept of bounded rationality to the field of municipal budgeting, thus providing a better understanding of how actors make decisions under conditions of limited information, time and cognitive capacity. Second, it connects behavioural and institutional approaches to public decision-making, thus creating an analytical framework for examining the factors that influence the degree of integration of the SDGs into budgetary documents. Finally, the paper brings new knowledge to the international discourse on the localization of SDGs, through a case study of the Czech Republic, which has not yet been sufficiently represented in this area. Country cases illustrate heterogeneity in how sustainability enters municipal budgeting and governance: Italy—budgetary strategy orientations in large municipalities (Gesso, 2020); Brazil—local initiatives contributing to SDG 11 with uneven institutionalization (Almeida et al., 2018); Quebec—target-prioritization tools shaping local implementation (Tremblay et al., 2021); South Africa—planner worldviews conditioning implementation (Read et al., 2024).

The added value here is a transparent operationalization of SDG–budget integration combined with actor-level evidence under bounded rationality, specifying when formal commitments do (not) translate into allocative choices.

5.2 Practical contribution

In addition to theoretical grounding, the paper also offers specific benefits for the practice of public administration. The results of the research can serve as a basis for the creation of methodologies, recommendations and strategic documents that will help municipalities to integrate the principles of sustainable development more effectively into their budget processes. Identifying the barriers that municipalities perceive in the implementation of the SDGs, as well

as examples of good practice, can contribute to strengthening the capacities of municipalities in the field of strategic planning and financial management.

The practical contribution of the paper is further reflected in the field of education and professional development. The findings can be used in the teaching of subjects focused on public administration, regional development or public finance, both at the level of bachelor's and master's studies and in doctoral education.

Finally, the contribution of research can also be seen in its potential to contribute to a broader social debate on the role of municipalities in meeting global goals. It shows that even at the local level, there is room for strategic decision-making, which can have a real impact on the quality of life of the population and on the long-term sustainability of public finances.

6 CONCLUSION

This paper presented a proposal for a research framework for dissertation research focused on the integration of the Sustainable Development Goals into the budgetary processes of municipalities. Based on the literature review, theoretical anchoring in Herbert Simon's concept of bounded rationality and identification of the research gap, a research design was created that combines qualitative and quantitative approaches. This mixed model allows not only a deeper understanding of decision-making processes at the local level, but also verification of the identified patterns and hypotheses on a wider sample of respondents.

The research focuses on municipalities with extended powers in the Czech Republic, which represent key actors in the implementation of SDGs within public administration. The paper aims to map how these municipalities approach the inclusion of SDGs in their budget documents, what tools and actors they use to do so and what barriers they face in doing so. Special emphasis is placed on the analysis of the decision-making logic of actors under conditions of limited information, time and resources.

The importance of this research lies not only in its theoretical contribution – i.e. in expanding knowledge about the relationship between sustainable development and fiscal decision-making – but also in its practical applicability. The results can serve as a basis for the creation of methodologies, strategic documents and educational materials that will help municipalities plan and manage their budgets more effectively in accordance with the principles of sustainability.

At the same time, the paper opens space for further academic development. In the subsequent phase of the dissertation research, a qualitative part will be carried out based on semi-structured interviews with actors of the budget process, the aim of which will be a deeper understanding of the motivations, barriers and strategies associated with the integration of SDGs. Based on these findings, a quantitative questionnaire survey will be carried out, which will allow to verify the formulated hypotheses and identify more general trends.

The research thus creates a solid basis for the dissertation, which has the potential to contribute to a better understanding of decision-making processes in municipalities and to offer specific recommendations for the support of strategic and sustainable budget planning at the local level.

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INTEGRATION OF ARTIFICIAL INTELLIGENCE AND THE BSC SYSTEM IN ENTERPRISES: A SURVEY OF CURRENT TRENDS

Petra Motyckova

Abstract

The aim of this study was to map the level of awareness and the degree of application of the Balanced Scorecard (BSC) concept and artificial intelligence (AI) tools in the strategic management of Czech enterprises. Quantitative research was conducted through a questionnaire survey (CAWI) between October 2024 and January 2025 on a sample of 300 respondents across various industries and company size categories. The results showed that more than three-quarters of the companies reported knowledge of the BSC concept, and more than one-third actively used it as a systematic framework. Eighty-five percent of organizations reported at least partial deployment of AI, most commonly in the areas of internal process automation, financial planning, and marketing analytics. The key barriers to AI integration identified were the lack of qualified personnel, the complexity of implementation, and the absence of high-quality data. Nevertheless, companies expect benefits mainly in the form of faster decision-making processes and more accurate performance monitoring. The study highlights the low degree of formal integration between BSC and AI and confirms that successful digital transformation requires the development of data literacy, internal competencies, and systematic managerial support. It is recommended that future research focus on case studies of organizations that have successfully integrated these approaches within a unified strategic framework.

Keywords: *Balanced Scorecard, Artificial Intelligence, Strategic Performance Management, Digital Transformation, Czech Enterprises, Performance Measurement*

1 INTRODUCTION

With the rapid emergence of technologies such as Artificial Intelligence (AI) and Machine Learning, the ways in which companies measure, manage, and optimize their performance are undergoing fundamental change. Traditional approaches to strategic management, including the Balanced Scorecard (BSC), are experiencing a profound transformation—from static tools to adaptable, data-driven systems. The integration of AI into the BSC opens up new possibilities: from predictive analytics to automated decision-making capable of responding in real time to the changing business environment.

Since its introduction by Kaplan and Norton in the 1990s, the Balanced Scorecard has served as a framework for comprehensive performance measurement across four perspectives—financial, customer, internal processes, and learning and growth. Although its universality has been confirmed across different sectors—from industry to public administration—current developments indicate the need to adapt it to new technological conditions, particularly to the opportunities offered by artificial intelligence.

The literature confirms the growing importance of AI in the field of strategic performance management. For example, Jorzik et al. (2024) point out that AI is not merely an optimization tool but also a means of transforming organizational structures and business models. Gonzales (2023) identifies the macroeconomic benefits of AI for growth through value and technology channels. Kumar et al. (2024) and Tawse & Tabesh (2023) agree that the current challenge lies in the necessity to redefine classical performance frameworks in line with digital reality. Usman

et al. (2023) propose a hierarchical approach based on the BSC and the efficiency of control processes. Dwivedi et al. (2021) note that the rise of AI has triggered technological innovations and new AI-enabled business models, which have the potential to improve organizational performance across industries.

At the same time, however, (OECD, 2021) and **Oldemeyer et al. (2025)** point to the barriers faced especially by small and medium-sized enterprises—the lack of expertise, limited resources, and the absence of AI adoption strategies. Fabac (2022) proposes the digital Balanced Scorecard as a framework to support digital transformation. Shafa (2025) adds the concept of an AI-driven maturity framework that maps the level of AI integration within organizations.

While some studies focus on the potential of AI to improve predictive capabilities and decision-making processes in performance management, empirical insights into the specific forms and extent of integration of these tools into the practice of Czech enterprises are lacking. For this reason, a questionnaire survey was conducted with the aim of identifying current trends in the use of AI in relation to the BSC in real organizational contexts.

This study therefore focuses on answering the research question: *How do Czech enterprises integrate artificial intelligence tools into the Balanced Scorecard system, and what impact does this integration have on performance management?* As part of the research, a hypothesis was formulated that companies combining AI with BSC principles achieve a higher level of strategic performance management than those that use only the traditional approach.

In this article, we first present the theoretical foundations of the BSC and AI concepts, then analyze the results of the quantitative survey, and finally discuss the practical implications and recommendations for improving performance management through an AI-augmented BSC model.

2 LITERATURE REVIEW

Since its introduction by Kaplan and Norton in the 1990s, the Balanced Scorecard (BSC) has remained a key framework for measuring performance across four perspectives: financial, customer, internal processes, and learning and growth (Tawse & Tabesh, 2023). Its universality has enabled its implementation in both the public and private sectors; however, the current era requires its adaptation to the rapidly changing technological environment, especially in relation to Artificial Intelligence (AI) (Kumar et al., 2024).

The integration of AI into strategic management is not merely a matter of technological implementation but represents a fundamental shift in the logic of how organizations operate. Jorzik et al. (2024) emphasize that AI brings new organizational models, increases productivity, and enables real-time predictive decision-making. Gonzales (2023) demonstrates that AI has a positive impact on economic growth through three pathways: technological, application, and value. However, this benefit is unevenly distributed depending on the level of development and absorptive capacity of each region.

The literature shows that combining BSC and AI has the potential to transform enterprise performance management. For example, Pierce (2022) proposes using the BSC as a tool to maximize data asset performance, while Aysan et al. (2025) apply the BSC to measure the impact of AI in the context of sustainable development in financial institutions. Similarly, Garcia-Buendia et al. (2024) adapt the BSC to evaluate lean supply chain management and propose expanding it with metrics enabling dynamic performance management.

Particularly in small and medium-sized enterprises (SMEs), the use of AI is associated with a number of barriers. OECD (2021) and **Oldemeyer, Jede, & Teuteberg (2025)** point to the lack of expert capacity, low levels of digitalization, and unclear AI adoption strategies. Fabac (2022) therefore proposes the so-called Digital Balanced Scorecard (DBSC), which combines the classical BSC framework with digital transformation tools. Shafa (2025) discusses maturity-based approaches that evaluate organizational readiness for AI adoption across the broader value network.

Systematic analysis also highlights the importance of measuring the effectiveness of AI projects. Schmitt (2022) evaluates the performance of AutoML compared to manually tuned models and shows the potential to accelerate decision-making processes. Kumar et al. (2024) summarize six areas in which new technologies contribute to improved performance management: automation, predictive analytics, real-time data collection, visualization, collaboration tools, and blockchain.

In the Czech context, we provide data showing that although many companies declare the use of certain AI elements, they often lack integration with performance metrics. The survey shows that companies frequently apply BSC principles intuitively without explicitly naming them as such.

From the above, it follows that current research supports the synergy of AI and BSC as a tool for performance management in the environment of digital transformation. At the same time, however, it indicates the need for deeper empirical examination of specific implementation approaches, particularly in small and medium-sized enterprises.

Additional expert studies further deepen our understanding of the relationship between Artificial Intelligence and performance management. Kumar et al. (2022) provide a systematic review of 114 articles on the Balanced Scorecard (BSC), identifying key developmental trends and research gaps. They critically point out that most studies are conceptual in nature and focus on advanced economies, confirming the relevance of applying the BSC in less developed contexts such as the Czech Republic.

Zdravković et al. (2022) show that modern enterprise information systems implementing AI (so-called AI-enabled EIS) lead to more adaptable organizations. AI is applied here across functional areas—from production planning to customer care—and brings significant improvements to decision-making processes and predictive capabilities, thereby contributing to strategic performance management.

Empirical evidence by Yang et al. (2025) confirms that a higher level of artificial intelligence adoption within enterprises is positively associated with their ESG and corporate social responsibility performance. According to the authors, AI enhances environmental indicators, managerial transparency, and the overall social impact of firms. The relationship is particularly pronounced in non-state enterprises and environmentally intensive industries, where AI enables more efficient emission monitoring, resource optimization, and early identification of sustainability-related risks. Their findings underline the transformative potential of AI not only in improving corporate performance, but also in strengthening sustainability and social responsibility outcomes.

Carter et al. (2025) point out the risks of cognitive biases in decision-making processes that AI can reinforce—specifically, the anchoring bias. This phenomenon can influence employee performance evaluation, making it necessary to implement strategies to mitigate such biases (e.g., the so-called “consider-the-opposite strategy”).

Gonzales (2023) demonstrated the benefits of AI and big data for enterprise information security management and risk assessment. AI enables early warnings, anomaly detection, and

adaptive responses, resulting in higher levels of operational performance and organizational resilience in the digital environment.

Chen et al. (2024) expand insights into so-called servitization of manufacturing—that is, the transition from product-oriented production to offering services. Here, AI plays a key role due to its capacity to increase productivity and optimize workforce skill structures. This trend aligns with broader objectives of digital transformation and sustainable growth.

3 METHODOLOGY

For the empirical part of the research, a quantitative data collection strategy was chosen using a structured questionnaire survey. This approach made it possible to obtain a comprehensive overview of the level of awareness of the Balanced Scorecard concept, the extent and nature of the use of artificial intelligence in strategic management, and to identify the main obstacles and drivers of adopting these approaches across different sectors of the Czech economy.

The questionnaire was distributed using the CAWI method (Computer-Assisted Web Interviewing) between October 2024 and January 2025. The sample consisted of 300 respondents representing companies of various sizes and industry focus. The sample included micro, small, medium, and large enterprises, with size categories covering 1–10 employees, 11–50, 51–250, and over 250 employees. Respondent selection was based on availability and voluntary participation, which is a limiting factor when generalizing the results; however, the sample structure covers the diversity of the Czech business environment.

The questionnaire contained 12 main questions and was divided into several sections. The first section examined the level of knowledge and actual use of the Balanced Scorecard (BSC). The second section focused on areas of AI application (e.g., automation of internal processes, marketing, financial planning, production processes, HR). The subsequent parts of the questionnaire mapped in detail specific AI technologies (e.g., machine learning, NLP, RPA, predictive analytics), barriers to AI adoption, and the expected benefits of linking BSC with AI. Selected questions used ten-point scales to assess the degree of integration or perceived benefits, while other questions allowed multiple answers. The questionnaire also included semi-open questions to capture specific sector-related experiences.

When designing the survey, the optimal sample size was assessed in relation to the population of actively operating companies in the Czech Republic. Theoretically, the sample size for a 95% confidence interval and maximum variability was determined to be 384 respondents. Considering the challenge of reaching companies and the length of the questionnaire, 300 completed responses were obtained. Although this number is slightly below the recommended optimum, it is considered sufficient for formulating indicative conclusions given the diversity of the sample and the exploratory nature of the research.

Additionally, semi-structured interviews were conducted with twelve respondents from various industries to better interpret the quantitative results and supplement them with concrete examples of AI implementation and experiences in performance management.

4 RESULTS

The results of the questionnaire survey revealed a relatively heterogeneous level of knowledge and application of the Balanced Scorecard (BSC) and Artificial Intelligence (AI) among Czech companies. Of the sample of 300 respondents, 229 companies (76.3%) reported that they were familiar with the BSC concept, and 113 respondents (37.7%) declared active use of it for

performance management. An interesting finding was that even among companies that reported either unfamiliarity with the BSC (71 companies, 23.7%) or that they knew of it but did not use it (116 companies, 38.7%), the majority (187 companies, i.e. 62.3% of the sample) confirmed that they manage performance using at least two of the four BSC perspectives (financial, customer, internal processes, innovation). This suggests that many firms apply BSC principles intuitively, even without formally identifying the framework as such.

A total of 255 respondents (85.0%) reported that their organization uses at least one artificial intelligence (AI) application, while 45 companies (15.0%) stated that they do not use AI at all. The most common area of use was administration and personal productivity, cited by 155 companies (51.7 %). This was followed by marketing and customer analysis (123 companies, 41.0 %) and financial planning with predictive modeling (104 companies, 34.7 %). Further, internal process automation was used by 100 companies (33.3 %), HR and talent management analytics by 88 companies (29.3 %), and production processes and quality control by 79 companies (26.3 %). These results indicate a high level of AI integration across a wide range of strategic and operational domains in Czech companies.

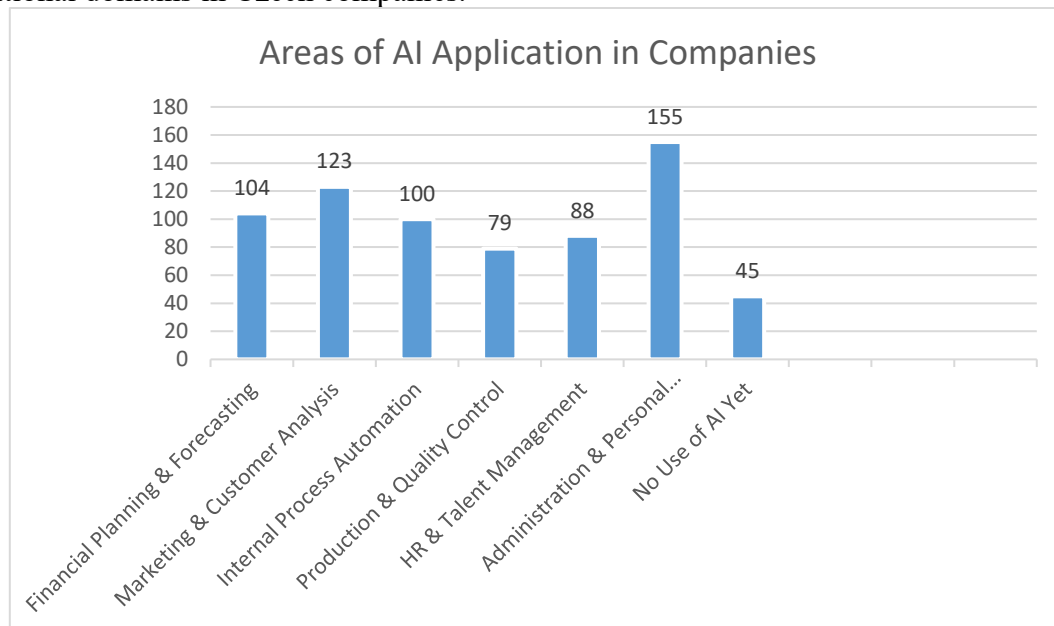


Fig. 1 – Areas of AI Application in Companies. Source: own research

Analysis of the responses by sector revealed that artificial intelligence is used across all industries, with many companies identifying with more than one sector. The level of AI integration varied not by presence, but by purpose and complexity. Respondents from IT and technology (75 responses), services (83), healthcare (15), energy (12), and financial services (36) reported broader and more advanced AI usage, often linked to marketing, strategic analytics, and decision support. In contrast, respondents from retail and wholesale (52), agriculture (3), logistics (24), and construction (29) more frequently reported using AI for operational tasks such as automation, administration, or document processing. Manufacturing companies (73 responses) most often applied AI in production and quality monitoring. These differences reflect the sector-specific priorities, levels of digital maturity, and access to infrastructure.

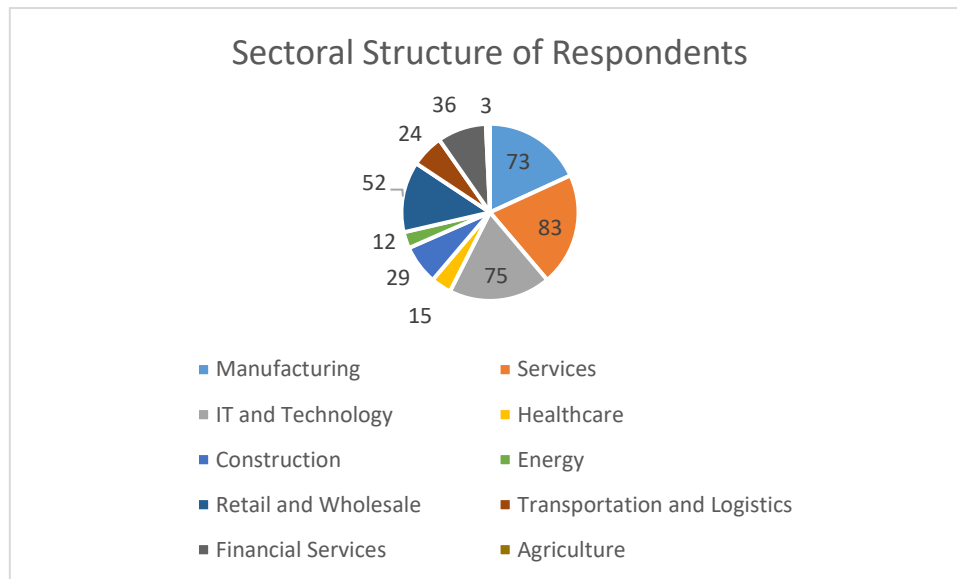


Fig. 2 – Sectoral Structure of Respondents. Source: own research

A closer look at specific AI technologies showed that the most commonly used was robotic process automation (RPA), selected by 130 companies. This was followed by predictive analytics (120 companies), natural language processing (107 companies), computer vision (95 companies), and machine learning (92 companies). Respondents could select more than one option, so the totals reflect overlapping use across multiple AI categories. A total of 45 companies stated that they do not use any AI technology.

The most frequently cited barriers to broader AI integration included a lack of qualified employees (157 companies), limited availability of data for model training (126), and the complexity of implementation (107). Other common challenges were reluctance from management to invest in AI initiatives (87) and concerns related to legal and ethical issues (104). As respondents could choose more than one option, many organizations reported facing multiple barriers simultaneously. In open-ended responses, some companies also mentioned lack of time, distrust in the reliability of AI tools, or a deliberate refusal to implement AI at all.

In terms of perceived benefits of integrating AI with the Balanced Scorecard, respondents most frequently expected faster decision-making processes (180 companies), more accurate performance monitoring (166), predictive risk analysis (133), and better resource allocation (145). Since multiple responses were allowed, many companies identified several expected benefits simultaneously. Approximately one-third of respondents assessed AI's potential in strategic management as essential, while another third considered it primarily a complementary tool alongside traditional performance management methods.

The level of AI integration into specific areas of strategic management remains moderate. On a ten-point scale, respondents reported the highest degree of AI integration in internal process automation (average 5.33, median 6), followed by marketing and customer analytics (average 5.18, median 5), and financial planning and forecasting (average 5.00, median 5). Lower levels of integration were observed in innovation and digitalization (average 4.89, median 5) and especially in HR and talent management (average 4.83, median 5). When evaluating the perceived benefits of AI for the four performance perspectives of the Balanced Scorecard, the average scores were: financial perspective (6.18), customer perspective (6.32), internal processes (6.38), and innovation (6.32), with medians consistently around 7. These results suggest that while AI is not yet fully embedded in company systems, expectations regarding its future impact on strategic performance are relatively optimistic across all dimensions.

5 DISCUSSION

The survey results confirm that the Balanced Scorecard concept and artificial intelligence tools are finding increasingly broader application in Czech enterprises, although with significant differences between sectors and company sizes. Similarly to Shafa (2025) and Fabac (2022), recent literature shows that many enterprises view AI as a strategic tool that can accelerate decision-making and improve performance management. At the same time, it is evident that many organizations integrate BSC principles implicitly, without explicitly naming them as such. Specifically, 187 companies—those that either stated they do not actively use the BSC or declared they were unfamiliar with it—reported applying at least two of its four key performance perspectives. This finding suggests a widespread intuitive adoption of the BSC model, even without formal recognition or intentional implementation.

The high rate of AI usage in healthcare, financial services, and the IT sector aligns with previous studies (e.g. OECD, 2021; Jorzik et al., 2024), which describe higher data maturity and availability of the necessary infrastructure in these industries. Conversely, the lower adoption rates in agriculture and retail confirm that barriers of technological and organizational readiness remain significant. A lack of qualified staff, insufficient data, and the complexity of implementing AI were repeatedly identified as key obstacles—these findings support the conclusions of Dwivedi et al. (2021) and Kumar et al. (2024), who emphasize that successful digital transformation requires long-term investments in competencies and a cultural shift in company leadership.

An interesting aspect is the relatively high proportion of companies that primarily use AI for automating internal processes, financial forecasting, and marketing analytics. Compared to the less frequent use of AI in HR management or production processes, this suggests that companies perceive the greatest immediate benefits where time and cost savings can be quickly achieved. This trend is consistent with the views of Oldemeyer et al. (2025) on the pragmatic approach to AI implementation in small and medium-sized enterprises.

The average score for the degree of AI integration into strategic management (5.6 out of 10), along with the high perceived level of complexity (7.2 out of 10), illustrates that companies often find themselves in a phase of partial implementation and experimentation with individual applications. In many cases, AI is not yet applied as part of an integrated Balanced Scorecard framework but rather as a parallel set of tools. These results underscore the importance of systematic support for knowledge transfer and sharing of best practices, which can facilitate the connection between traditional performance management methods and the capabilities of artificial intelligence.

Overall, despite the gradual growth in AI adoption among Czech companies and relatively widespread awareness of the Balanced Scorecard, the truly deep integration of these approaches remains at an early stage. Future research could focus on more detailed analysis of case studies of companies that have successfully integrated AI and BSC to identify success factors and share them across industries.

5.1 Limitations

This study has several limitations that must be considered when interpreting the results. First, although the sample size (300 respondents) corresponds to a high degree of representativeness, given the total number of active businesses in the Czech Republic, the generalizability of the findings may still be limited. The second limitation is the voluntary participation of companies

in the survey, which could have led to a certain degree of self-selection bias—it is likely that respondents with a higher interest in digitalization and performance management were more motivated to participate.

Furthermore, it should be noted that some responses were subjective self-assessments and may not always accurately reflect the actual state of AI or BSC implementation. Additionally, the structure of the questionnaire did not allow for a detailed analysis of technological maturity or specific investments in AI by company size. These aspects could be addressed in future research projects.

5.2 Implications

The results of this study have significant practical and theoretical implications. For practice, they confirm that there is great potential to connect traditional performance management frameworks (such as the Balanced Scorecard) with artificial intelligence tools. Companies that already partially use AI in finance, marketing, or internal efficiency could, through systematic integration of these tools into strategic management, achieve more precise performance monitoring and faster responses to changes in the environment.

A key implication is the need to develop data literacy and analytical skills across organizational levels. From a management perspective, it is crucial to invest not only in the technologies themselves but also in internal capacity to interpret AI analysis results and actively integrate them into decision-making.

For management theory, this study demonstrates that even more than twenty years after the publication of the BSC concept, its terminology is not a standard in small and medium-sized companies, even though the principles of the four perspectives are often applied intuitively. The research also supports the assumption that AI can function as a tool to extend classical performance management models and opens up space for future studies combining strategic management and digital transformation.

5.3 Recommendations for Future Research

Based on the results and the identified limitations of this study, several perspectives for future research emerge. Firstly, it would be beneficial to conduct qualitative case studies focusing on companies that report a high level of AI integration into strategic performance management. In-depth analysis of their experiences could clarify the factors behind successful adoption, including organizational prerequisites, leadership, and specific investment priorities.

Another direction is the longitudinal monitoring of the effects of implementing AI and the Balanced Scorecard on key financial and non-financial performance indicators across various industries. Such research would make it possible to identify causal relationships between the intensity of adoption and the results achieved.

Furthermore, it would be desirable to deepen the comparison between sectors and company size categories. Analyzing small, medium, and large enterprises in terms of perceived benefits and barriers could provide more detailed, segmented recommendations for managerial practice.

Finally, there is an opportunity to examine the role of cultural factors and how companies communicate the topic of AI and BSC to employees. Creating a positive attitude toward change may be one of the key preconditions for successful digital transformation of strategic management.

6 CONCLUSION

This study provided a comprehensive view of the state of knowledge and application of the Balanced Scorecard and artificial intelligence in the strategic management of Czech companies. The results of the survey confirmed that over three-quarters of the respondents are familiar with the BSC concept, and more than one-third actively use it as a systematic framework for performance management. At the same time, although only 113 companies (37.7 %) explicitly use the Balanced Scorecard, a further 187 companies (62.3 %) apply at least two of its core performance perspectives. This indicates widespread intuitive application of the BSC model, even among those who do not formally recognize it as such.

In the area of AI use, considerable dynamism was observed— the majority of surveyed companies (85 %) reported at least some use of AI, primarily in the areas of administration and personal productivity, marketing analytics, and financial planning, while 15 % reported no AI use at all. Significant differences between industries confirm that technologically more advanced sectors such as IT, healthcare, and energy have better prerequisites for effective AI use.

The identified barriers—particularly the lack of qualified personnel, the complexity of implementation, and the lack of high-quality data—demonstrate that integrating AI into strategic management is not only a technological issue but also a challenge in the areas of human resources, organizational culture, and managerial support. Nevertheless, companies perceive the potential of linking AI with the Balanced Scorecard positively, and most expect benefits in the form of faster decision-making processes and more accurate performance monitoring.

From a practical perspective, the study results underscore the importance of developing data and analytical competencies, systematic employee training, and creating organizational conditions for long-term digital transformation. For future research, it is recommended to focus on detailed case studies of organizations that have successfully combined BSC and AI within a single strategic framework and to monitor their impact on performance and business sustainability over a longer time horizon.

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DETERMINANTS OF LIQUIDITY RISK: EMPIRICAL EVIDENCE FROM VIETNAMESE COMMERCIAL BANKS

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Abstract

This study investigates the determinants of liquidity risk in 25 Vietnamese joint-stock commercial banks over the period 2010–2023. Using a balanced panel dataset of 350 firm-year observations, the research applies Pooled OLS, Fixed Effects Model (FEM), Random Effects Model (REM), and the Hausman test to identify the most suitable specification. The results reveal that profitability indicators such as NIM and ROA negatively affect liquidity, highlighting the trade-off between profit maximization and liquidity safety. In contrast, NPLs, bank size, credit growth, and inflation exert positive impacts, while GDP growth shows no statistically significant effect. Among the models, FEM demonstrates the best fit, explaining nearly half of the variation in liquidity ratios. Theoretically, these findings provide empirical support for the asymmetric information theory and precautionary liquidity models in the Vietnamese context. Practically, the study offers implications for managers and regulators in designing effective liquidity strategies in emerging markets, thereby contributing to more resilient financial systems in developing economies.

Keywords: *Liquidity risk, Commercial banks, Non-performing loans (NPL), Net interest margin (NIM), Credit growth (CG)*

1 INTRODUCTION

Liquidity risk is among the most critical types of risk in banking operations, especially in the context of increasing global financial volatility and heightened market competition (Djebali & Zaghdoudi, 2020). According to (Freixas & Rochet, 2008), liquidity risk arises when a bank is unable to convert assets into cash in a timely manner or cannot raise funding at a reasonable cost, thereby adversely affecting its operational efficiency and financial stability. This condition can be further exacerbated when it coincides with other types of risks, such as credit risk, market risk, or macroeconomic fluctuations (Ghenimi et al., 2017).

The Global Financial Crisis (GFC) of 2007–2009 highlighted that even large banks could face sudden liquidity shortfalls without effective risk control systems (Ahamed, 2021). As a result, many countries, including Vietnam, adopted the Basel III recommendations to strengthen liquidity regulation through the implementation of the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR). The State Bank of Vietnam has also issued regulatory reforms to enhance supervisory capacity and ensure systemic liquidity (Dao & Phan, 2020). However, in practice, commercial banks in Vietnam still encounter multiple challenges due to small scale, unique ownership structures, high credit dependence, and relatively limited risk management capabilities (Huong & Yen, 2024).

Previous studies in Vietnam—such as those by (Thong, 2013; Vu, 2015; Nguyen, 2019; Phan & Tong, 2019; Nguyen & Pham, 2021, and Huong & Yen, 2024)—have identified key liquidity risk determinants including capital adequacy ratio (CAR), bank size, non-performing loans (NPL), credit growth, profitability, foreign ownership, inflation, and GDP. Additionally, several international studies have explored the relationship between liquidity and operational efficiency via indicators like ROA, ROE, and NIM (Bordeleau & Graham, 2010; Iqbal, 2012; Ahamed, 2021).

However, many of these studies relied on short-term or outdated data, failing to fully capture structural shifts in Vietnam's banking system over the past decade. The period from 2010 to 2023 witnessed significant changes, including system restructuring, increased adoption of digital banking, intensified competition between state-owned and private banks, and external shocks. Moreover, existing research often focused on limited variables and lacked an integrated approach combining both micro-level indicators (e.g., performance, NPLs, size, credit growth) and macroeconomic conditions (e.g., CPI, GDP) in a comprehensive quantitative framework. Furthermore, many prior approaches did not sufficiently address issues inherent to panel data, such as heteroskedasticity, autocorrelation, and unobserved heterogeneity.

To address this research gap, the present study utilizes updated panel data from 2010 to 2023 to investigate the combined impact of internal and macroeconomic factors on liquidity risk in Vietnamese commercial banks. Applying econometric techniques including Pooled OLS, FEM, REM, and the Hausman test, the study finds that micro variables such as NIM, ROA, bank size (SIZE), NPLs, and credit growth (CG) significantly influence liquidity risk. In particular, NIM shows a consistently negative and significant effect across all regression models—supporting theoretical expectations and findings from (Demirguc-Kunt & Huizinga, 1999), Landskroner and (Paroush, 2008), and (Tran et al., 2016). Additionally, incorporating macroeconomic factors like inflation (CPI) and GDP growth provides a broader analytical perspective and confirms the relevance of macro conditions in liquidity management. The selection of the FEM model, based on the Hausman test, addresses the presence of unobserved bank-specific and time-related effects, thereby enhancing the reliability of the empirical results. Overall, this study offers comprehensive and updated empirical evidence to support policymakers and banking practitioners in making more effective and sustainable liquidity management decisions.

2 LITERATURE REVIEW

Liquidity risk in commercial banks is closely related to the theory of asymmetric information, originally proposed by (Akerlof, 1970). In financial markets, borrowers typically possess better information about their repayment ability than lenders, which can lead to misjudgment in credit allocation. Building upon this, (Stiglitz & Weiss, 1981) introduced the concept of adverse selection, where high-risk borrowers are more likely to obtain loans due to asymmetric information. This selection bias may increase loan defaults, reduce cash inflows, and ultimately elevate liquidity risk for banks

In banking, liquidity is considered a critical factor reflecting both operational efficiency and financial soundness of credit institutions (Huong & Yen, 2024). Prior studies have identified numerous determinants of bank liquidity, prominently including non-performing loans (NPL), profitability, bank size, net interest margin (NIM), credit growth, and macroeconomic factors such as inflation and GDP (Acharya & Naqvi, 2012; Ghenimi et al., 2017; Huong & Yen, 2024; Imbierowicz & Rauch, 2014).

Regarding the relationship between NPLs and liquidity, many studies suggest that rising NPLs can lead to reduced cash inflows, thereby lowering liquidity ratios. (Ghenimi et al., 2017) found that both liquidity and credit risks negatively affect bank stability, with NPLs having a stronger impact. However, other studies such as (Imbierowicz & Rauch, 2014) and the theoretical model by (Acharya & Naqvi, 2012) argue that as credit risk increases, banks may raise their liquidity buffers as a precaution, implying a potential positive relationship. In Vietnam, empirical findings are mixed: (Thong, 2013) and (Nguyen, 2019) documented negative effects, while other studies found insignificant relationships.

Hypothesis H1: NPL positively affects banks' liquidity ratios.

For NIM, international studies report mixed effects. (Demirguc-Kunt & Huizinga, 1999), (Tran et al., 2016), and (Landskroner & Paroush, 2008) argue that holding more liquid assets—often low-yielding—reduces NIM, suggesting an inverse relationship. Conversely, (Maudos & Fernández De Guevara, 2004) found that NIM may increase under conditions of high liquidity risk. In the Vietnamese context, studies such as (Fatimah, 2016) and (Bonfim & Kim, 2012) also report varied impacts.

Hypothesis H2: NIM negatively affects banks' liquidity ratios.

Return on Assets (ROA) is a key financial metric for measuring bank performance. (Bourke, 1989) highlighted that high ROA improves banks' ability to maintain liquidity through increased earnings. In contrast, (Molyneux & Thornton, 1992) argued that ROA might decline if banks hold large volumes of low-yielding liquid assets. In Vietnam, (Alzoubi, 2017), (Nguyen, 2019), and (Nguyen, 2022) found a positive effect, while (Fatimah, 2016) reported insignificant results.

Hypothesis H3: ROA negatively affects banks' liquidity ratios.

Bank size is also an essential factor affecting liquidity. (Berger & Bouwman, 2009) suggested that larger banks can generate more liquidity due to broader networks, stronger capital mobilization, and more efficient risk diversification. However, (Molyneux & Thornton, 1992) noted that large banks may maintain lower liquidity since they have easier access to capital markets. Empirical evidence remains mixed (Alzoubi, 2017; Thong, 2013; Nguyen, 2019).

Hypothesis H4: Bank size has a positive effect on the liquidity ratio.

Credit growth is another key determinant. Studies such as (Cucinelli, 2013; Bonfim & Kim, 2012; Thong, 2013; Nguyen, 2022) warned that rapid, unregulated credit expansion could reduce liquidity due to increased capital demand. However, stable credit growth can support revenue expansion and steady cash flows.

Hypothesis H5: Credit growth positively affects banks' liquidity ratios.

Among macroeconomic variables, inflation plays a notable role. The Consumer Price Index (CPI), a proxy for inflation, is often positively associated with liquidity risk. High inflation raises input costs, weakens profitability, and increases cash demand among households and businesses—pressuring banks to hold more liquidity. (Alzoubi, 2017; Phan & Tong, 2019; Nguyen, 2022) reported that higher inflation is associated with lower liquidity ratios. Nonetheless, some studies suggest that moderate inflation may enable flexible interest rate policies, promote credit growth, and stabilise deposit mobilisation, thus improving liquidity (Vodová, 2011).

Hypothesis H6: CPI positively affects banks' liquidity ratios.

Economic growth, measured by GDP, is typically found to enhance liquidity. In a favourable economic environment, borrowers' repayment capacity improves, credit risk declines, and bank asset quality strengthens. Moreover, steady economic flows support deposit mobilization and liquidity reserves. (Cucinelli, 2013; Vu, 2015; Nguyen, 2022) found an inverse relationship between GDP and liquidity risk. However, Aspachs et al. (2005) argued that during specific periods, GDP growth may reduce liquidity buffers as banks prioritise lending profits over liquidity holdings.

Hypothesis H7: GDP has a positive effect on banks' liquidity ratios.

Overall, both domestic and international research suggests that liquidity ratios are influenced by a variety of factors, especially NPLs, NIM, ROA, bank size, and credit growth. However,

the magnitude and direction of these effects depend on the economic context, business models, and the level of development of each country's banking system.

3 METHODOLOGY

3.1 Data

This study employs panel data from 2010 to 2023 to examine the determinants of liquidity risk among Vietnamese commercial banks. The research sample comprises 25 domestic joint-stock commercial banks. State-owned banks such as Agribank, and small-scale banks such as National Citizen Bank (NCB) and Bao Viet Bank were excluded due to limitations in data completeness, consistency, and transparency across the entire research period. Specifically, Agribank does not publicly disclose detailed financial reports annually due to its 100% state ownership and distinct regulatory framework, while NCB and Bao Viet Bank have either experienced prolonged restructuring phases or data gaps that could compromise the reliability of econometric estimation.

All bank-specific financial variables were manually collected from the FiinPro X platform (<https://fiinpro.com/fiinpro-x>). Following (Berger & Bouwman, 2009), all variables were winsorized at the 1% and 99% levels to minimize the influence of outliers. Lagged variables were constructed based on one-period backward values, which resulted in the removal of several initial-year observations to ensure the validity of the dynamic panel structure.

Macroeconomic variables, including the Consumer Price Index (CPI) and annual GDP growth rate, were obtained from the World Bank. After data processing, the final balanced panel dataset consists of 350 firm-year observations. The selected period (2010–2023) reflects the full spectrum of Vietnam's financial sector development, including post-crisis stabilization, regulatory reforms, and accelerating banking sector modernization. The panel structure ensures sufficient variation across time and entities to provide robust statistical inference regarding the relationship between liquidity risk and its determinants.

Tab. 1 – Variables description. Source: own research

Name of variable	Symbol	Description	Calculation
Dependent Variable			
Liquidity Ratio (Alzorqan,2014; Marozva, 2015)	LR	A financial metric used to assess a bank's ability to meet its short-term obligations.	$LR = \frac{Deposit}{Total Asset}$
Independent Variables			
Net Interest Margin (Tarazi et al., 2024)	NIM	The spread between interest income and interest expenses.	$NIM = \frac{Net Interest Income}{Earning Asset}$
Return on Assets (Dao & Phan, 2020)	ROA	Measures how efficiently the bank uses its assets to generate profit.	$ROA = \frac{Net Income}{Average Total Asset}$
Non-performing Loans (Giang et al., 2023)	NPL	Proxy for credit risk, calculated as the natural logarithm of the lagged ratio	$NPL = Log[\frac{Loans (Group 3+4+5)_{t-1}}{Total loans_{t-1}}]$

of non-performing loans to total loans.

Credit Growth (Vodová, 2013; Phan, 2021)	CG	Measures the lagged credit growth rate , indicating prior year loan expansion.	$CG = \frac{Total\ loans_t - Total\ loans_{t-1}}{Total\ loans_{t-1}}$

Control Variables

Bank Size (Giang et al., 2023)	SIZE	The size of the bank is measured as the natural logarithm of total assets.	$Size = Log(Total\ Assets)$
GDP Growth Rate (Nkusu, 2011)	GDP	Annual economic growth rate of Vietnam.	Collected from World Bank.
Inflation Rate (Isik & Bolat, 2016); Nkusu, 2011)	INF	Annual change in consumer price index representing inflation.	Collected from World Bank.

3.2 Methodology

Building upon prior studies such as (Abbas & Ullah, 2023; Tarazi et al., 2024; Vuong et al., 2023) this research constructs Model (1) to examine the impact of internal financial indicators and macroeconomic variables on liquidity risk in Vietnamese commercial banks. Specifically, the model includes the following variables: Net Interest Margin (NIM), Return on Assets (ROA), bank size (SIZE), Non-Performing Loans ratio (NPL), inflation rate (INF), GDP growth, and notably, credit growth (CG).

Initially, the study employs the Fixed Effects Model (FEM) to estimate causal relationships among variables in the regression. FEM is particularly appropriate for panel data, where observations are collected longitudinally from the same entities over time, as it controls for unobservable individual effects that remain constant across banks (Sufian & Chong, 2008).

Additionally, the Random Effects Model (REM) is used for comparison. However, because REM assumes that the error term is uncorrelated with the independent variables, this assumption may not hold. Therefore, the Hausman test is performed to choose the optimal model. If the idiosyncratic error is correlated with the regressors, FEM is preferred (Gurka et al., 2012).

As a robustness check, the study also employs the Pooled Ordinary Least Squares (POLS) regression, which helps adjust standard errors in the presence of heteroskedasticity and autocorrelation, thereby enhancing the reliability of the estimation results (Lau et al., 2019).

The dependent variable in the model is the Liquidity Ratio (LR), which reflects a bank's ability to meet short-term financial obligations. First, LR is typically inversely related to illiquid assets such as NPLs. When a bank maintains high liquidity, it is better positioned to cover liabilities, thus reducing credit risk (Demirgüç-Kunt & Beck, 2013). Second, the relationship between LR and NIM is complex and ambiguous. Studies by (Demirguc-Kunt & Huizinga, 1999) and (Maudos & Fernández De Guevara, 2004) report mixed findings, emphasising the need for context-specific empirical testing, especially in the Vietnamese banking sector.

Beyond the commonly used variables in liquidity risk studies, this research incorporates credit growth (CG) to capture the impact of prior-year loan expansion strategies on current liquidity. Excessive credit growth may lead to liquidity pressures if deposit mobilization fails to keep

pace with lending. (Vodová, 2013) documented a negative relationship between credit growth and liquidity, particularly in periods of aggressive loan expansion.

Variables used in the model:

- **Dependent variable:** Liquidity Ratio (LR)
- **Independent variables:** NIM, ROA, SIZE, NPL, CPI, GDP, CG
- **Error term:** $\mu_{i,t}$ represents the random error in the model for bank (i) in year (t).
- **Regression coefficients:** β_1 to β_6 indicate the change in LR associated with a one-unit change in the independent variables, holding other factors constant.

Due to the potential multicollinearity between ROA and NIM, two separate regression models are constructed for estimation:

Model 1 – Excluding ROA:

$$LR_{i,t} = \alpha + \beta_1 NIM_{i,t} + \beta_2 SIZE_{i,t} + \beta_3 NPL_{i,t} + \beta_4 CPI_{i,t} + \beta_5 GDP_{i,t} + \mu_{i,t} \quad (1)$$

Model 2 – Excluding NIM:

$$LR_{i,t} = \alpha + \beta_1 ROA_{i,t} + \beta_2 SIZE_{i,t} + \beta_3 NPL_{i,t} + \beta_4 Inf_{i,t} + \beta_5 GDP_{i,t} + \mu_{i,t} \quad (2)$$

4 RESULTS

Tab. 2 – Dynamic regression summary using POLS, FEM, and REM models excluding ROA. Source: own research

Variables	POLS	FEM	REM
NIM	-3.715***	-4.843***	-4.265***
NPL	0.0350*	0.0372*	0.0339*
SIZE	-0.004	0.0837***	0.0388**
CG	0.1371*	0.0949.	0.0933.
CPI	2.6820***	3.3197***	2.9950***
GDP	-1.069.	-0.496	-0.773
Number of observation	325	325	325
R - squared	0.3931	0.5023	0.3442
Hausman test (chi ²)	17.09		
Hausman test (Prob > chi ²)	0.0019		
Optimal model	FEM		

Note: Tab. 2 presents the regression results for the Liquidity risk, estimated using POLS, FEM, and REM, with ROA excluded from the model. Significance levels are denoted by ***, **, *, and . corresponding to 0.1%, 1%, 5%, and 10%, respectively.

Regression results from the three models—Pooled OLS, Fixed Effects Model (FEM), and Random Effects Model (REM)—reveal that several variables have consistent and statistically significant impacts on the liquidity ratio of Vietnamese commercial banks. In all three models, the **Net Interest Margin (NIM)** exhibits a negative and highly significant relationship with

liquidity, with coefficients of −3.715 (POLS), −4.843 (FEM), and −4.265 (REM), all significant at the 1% level. This suggests that as NIM increases, liquidity tends to decrease, supporting hypothesis H2. The result aligns with prior findings by (Demirgüç-Kunt & Huizinga, 1999), (Tran et al., 2016), and (Fatimah, 2016), who argue that maintaining liquid assets with lower yields may reduce overall profitability.

Conversely, the **Non-Performing Loans (NPL)** ratio shows a **positive** impact on liquidity across all models, with coefficients of 0.0350 (POLS), 0.0372 (FEM), and 0.0339 (REM), significant at the 10% level, thereby supporting hypothesis H1. This indicates that when credit risk rises, banks may proactively increase liquidity reserves as a precautionary measure, consistent with the theory of adverse selection by (Stiglitz & Weiss, 1981) and the model of (Acharya & Naqvi, 2012).

Regarding **bank size (SIZE)**, the variable is insignificant in the POLS model (−0.004), but becomes statistically significant in both FEM (0.0837, sig. at 1%) and REM (0.0388, sig. at 5%), supporting hypothesis H4. This result is in line with (Berger & Bouwman, 2009), who suggest that larger banks can maintain higher liquidity levels due to broader branch networks and stronger funding capabilities.

The **Consumer Price Index (CPI)** has a positive and highly significant effect in all three models, with coefficients of 2.6820 (POLS), 3.3197 (FEM), and 2.9950 (REM), all significant at the 1% level. This indicates that during periods of rising inflation, banks tend to increase their liquidity to cope with higher demand for cash and increased funding costs, consistent with hypothesis H6 and the conclusions of (Vodová, 2011).

By contrast, the variables **credit growth (CG)** and **GDP growth** are not statistically significant in the FEM—the model selected as most appropriate based on the **Hausman test** ($\chi^2 = 17.09$; Prob = 0.0019). This suggests that the effects of these macroeconomic variables on bank liquidity may be ambiguous or bank-specific.

Overall, the FEM yields the highest explanatory power with an R-squared of 0.5023, indicating that approximately 50% of the variation in liquidity ratios is explained by the model. These findings highlight the effectiveness of using fixed effects to control for unobserved heterogeneity across banks and emphasize the important roles of financial factors such as NIM, NPL, bank size, and inflation in shaping liquidity levels.

Tab. 3 – Dynamic regression summary using POLS, FEM, and REM models excluding NIM. Source: own research

Variables	POLS	FEM	REM
ROA	-2.308.	-4.007**	-2.835*
NPL	0.0327*	0.0381*	0.0344*
SIZE	-0.007	0.0865***	0.0375*
CG	0.1450*	0.1209*	0.1127*
CPI	2.5984***	3.2556***	2.9117***
GDP	-1.166*	-0.632	-0.883.
Number of observation	325	325	325
R - squared	0.3586	0.4773	0.3075

Hausman test (chi²)	16.28
Hausman test (Prob > chi²)	0.0027
Optimal model	FEM

Note: Tab. 3 presents the regression results for the Liquidity risk, estimated using POLS, FEM, and REM, with NIM excluded from the model. Significance levels are denoted by ***, **, *, and . corresponding to 0.1%, 1%, 5%, and 10%, respectively.

The regression results from the three models—Pooled OLS, Fixed Effects Model (FEM), and Random Effects Model (REM)—continue to provide robust empirical evidence on the determinants of bank liquidity. Across all models, the return on assets (ROA) variable shows a negative coefficient: -2.308 (POLS, not significant), -4.007 (FEM, significant at 5%), and -2.835 (REM, significant at 10%). This implies that higher profitability does not necessarily enhance liquidity; on the contrary, it may reduce liquidity, supporting hypothesis H3. This finding is consistent with (Molyneux & Thornton, 1992), who argued that highly profitable banks often prefer to invest in high-yield assets rather than maintaining low-yield liquid assets.

The non-performing loans (NPLs) variable maintains a positive and statistically significant relationship with liquidity at the 10% level in all models, with coefficients of 0.0327 (POLS), 0.0381 (FEM), and 0.0344 (REM). This supports hypothesis H1, indicating that when credit risk increases, banks may proactively raise their liquidity buffers as a precautionary measure, consistent with the asymmetric information theory (Stiglitz & Weiss, 1981) and the theoretical framework of (Acharya & Naqvi, 2012).

Regarding bank size (SIZE), the variable is insignificant in the POLS model (-0.007) but significant in both FEM (0.0865 , 1% significance) and REM (0.0375 , 10% significance). This reinforces the view that larger banks are better positioned to maintain higher liquidity ratios due to broader branch networks and stronger capital mobilization capabilities, aligning with hypothesis H4 and (Berger & Bouwman, 2009).

Similarly, the credit growth (CG) variable exhibits a positive and statistically significant effect at the 10% level in all three models, with coefficients of 0.1450 (POLS), 0.1209 (FEM), and 0.1127 (REM). This finding supports hypothesis H5, suggesting that well-managed credit expansion can enhance cash flow generation, thereby supporting liquidity.

The inflation variable (CPI) continues to show a strong positive and statistically significant impact (1% level) across all models: 2.5984 (POLS), 3.2556 (FEM), and 2.9117 (REM). This indicates that during periods of rising inflation, banks tend to increase liquidity reserves to mitigate risks from cost pressures and monetary volatility, in line with hypothesis H6 and (Vodová, 2011).

Conversely, the GDP growth variable is statistically insignificant in the FEM (-0.632) and REM (-0.883) models, and only marginally significant at the 10% level in the POLS model (-1.166). Since the FEM is identified as the most appropriate model based on the Hausman test ($\chi^2 = 16.28$; $p = 0.0027$), it can be concluded that GDP does not have a statistically significant impact on bank liquidity in this study, which contradicts hypothesis H7 and prior research such as (Cucinelli, 2013).

The FEM shows the highest explanatory power with an R^2 of 0.4773 , indicating that the model explains approximately 47.73% of the variation in the liquidity ratio, while effectively controlling for unobserved heterogeneity across banks. With consistent and statistically robust

coefficients, the FEM remains the most suitable model for evaluating the effects of financial and macroeconomic variables on the liquidity of commercial banks in Vietnam.

5 DISCUSSION

The empirical findings highlight the significant influence of internal financial factors on liquidity risk among Vietnamese commercial banks during the study period. Contrary to initial expectations, both the net interest margin (NIM) and return on assets (ROA) exhibit a negative relationship with the liquidity ratio. This result supports prior evidence that banks may reduce their holdings of low-yielding liquid assets to enhance profitability, thereby decreasing their liquidity buffers (Molyneux & Thornton, 1992; Demircuc-Kunt & Huizinga, 1999). Such behaviour reflects the inherent trade-off between profitability and liquidity safety, especially within a competitive and profit-driven banking environment like Vietnam.

Conversely, non-performing loans (NPLs) are positively associated with the liquidity ratio, suggesting that banks tend to increase their liquidity reserves when facing elevated credit risk. This finding is consistent with the adverse selection theory and precautionary liquidity model (Stiglitz & Weiss, 1981; Acharya & Naqvi, 2012), where banks maintain higher levels of liquid assets as a safeguard against potential borrower defaults. In the Vietnamese context, credit and operational risks have also been shown to reduce bank profitability, reinforcing the importance of effective liquidity risk management (Ngo, 2025).

In terms of bank size, the results indicate that larger banks are better positioned to maintain higher liquidity levels due to superior funding capacity, diversified asset portfolios, and stronger risk management practices, consistent with previous findings (Berger & Bouwman, 2009). Recent evidence also shows that corporate governance practices can mitigate liquidity vulnerabilities in emerging markets, with stronger governance structures helping to reduce liquidity risk (Hafez, 2023). Moreover, credit growth shows a positive impact on liquidity, implying that Vietnamese banks have managed to expand lending activities without compromising their liquidity positions, likely through improved loan portfolio quality and capital planning.

Among macroeconomic variables, the Consumer Price Index (CPI), which represents inflation, exhibits a significant and positive relationship with the liquidity ratio. This suggests that in response to rising inflationary pressures, banks tend to increase liquidity reserves as a precautionary measure to cope with higher input costs and potential deposit volatility, consistent with earlier studies (Vodová, 2011).

In contrast, GDP growth does not show a statistically significant effect on liquidity in the optimal model (FEM). This implies that the influence of macroeconomic expansion on liquidity may be indirect or context-dependent, consistent with previous arguments (Aspachs et al., 2005). However, macroeconomic effects may also vary across volatility regimes. Evidence from South Africa shows that while GDP consistently supports liquidity, the impacts of inflation and bank size differ depending on the state of market volatility (Pamba, 2025). This highlights the potential state-dependent nature of macroeconomic influences on liquidity in emerging economies.

Beyond these variable-specific insights, it is important to situate the findings within the broader empirical literature. The negative relationship between profitability indicators (NIM and ROA) and liquidity is in line with prior evidence (Demircuc-Kunt & Huizinga, 1999; Molyneux & Thornton, 1992). Similarly, the positive effect of NPLs aligns with adverse selection and precautionary liquidity arguments (Stiglitz & Weiss, 1981; Acharya & Naqvi, 2012). However,

this result contrasts with Vietnamese studies reporting a negative association between NPLs and liquidity (Thong, 2013; Nguyen, 2019). The positive influence of bank size is consistent with earlier findings (Berger & Bouwman, 2009), while the significant role of inflation confirms prior arguments (Vodová, 2011; Phan & Tong, 2019). By contrast, GDP growth shows no significant effect in the Vietnamese context, diverging from evidence that identified a positive influence in European and Vietnamese settings (Cucinelli, 2013; Vu, 2015). Such divergences may stem from structural characteristics of the Vietnamese banking sector, including smaller average bank size, reliance on credit-driven growth, and evolving regulatory frameworks.

These contextual differences suggest that global theories of liquidity risk must be adapted when applied to emerging markets. Recent studies also enrich our understanding across different contexts. Liquidity regulation in the Netherlands initially reduced both individual and systemic bank risk, though such effects attenuated over time (Ananou et al., 2024). In Vietnam, higher credit growth and profitability were found to elevate liquidity risk, while strong CAR and liquid securities helped mitigate it (Huong & Yen, 2024). Liquidity creation has been shown to contribute to bank risk-taking behaviors in emerging environments (Vuong, 2023). In uncertain economic conditions, diversified bank business models can serve as buffers against elevated risk (Huynh & Phan, 2024). Deposit insurance mechanisms may amplify the liquidity-creation capacity of banks while moderating the influence of monetary policy (Zhou, 2024). At the systemic level, a composite monitoring framework has been proposed that integrates funding, market, and contagion risks, providing a tool for enhancing liquidity surveillance and stress testing in emerging banking systems (ESRB, 2025).

In summary, internal variables such as profitability, credit quality, bank size, and credit expansion, along with inflation, play crucial roles in shaping liquidity strategies among Vietnamese banks. These findings reaffirm the relevance of traditional financial indicators in liquidity management, while also underscoring the need for tailored strategic adjustments to align with the local banking landscape. The fixed effects model (FEM) emerges as the most suitable specification, underscoring the importance of controlling for unobserved heterogeneity across banks when evaluating the determinants of liquidity.

6 CONCLUSION

This study examines the determinants of liquidity risk in Vietnamese commercial banks over the period 2010–2023 using panel regression techniques, including Pooled OLS (POLS), Fixed Effects Model (FEM), and Random Effects Model (REM). The empirical results demonstrate that several internal financial variables, such as net interest margin (NIM), return on assets (ROA), non-performing loans (NPLs), bank size, and credit growth, as well as the macroeconomic factor inflation (as measured by the CPI), significantly influence banks' liquidity positions.

Specifically, both NIM and ROA exert a negative impact on liquidity, suggesting a trade-off between profitability and liquidity safety. In contrast, NPLs are positively related to the liquidity ratio, reflecting a precautionary motive among banks to increase reserves in the face of heightened credit risk. Larger banks and those with well-managed credit growth tend to maintain stronger liquidity positions. Furthermore, inflation appears to encourage banks to strengthen liquidity buffers, while GDP growth shows no statistically significant effect in the preferred FEM model.

From a theoretical perspective, this study contributes to the existing literature by providing updated empirical evidence from a transitioning economy, where liquidity risk management frameworks are still in the process of evolving. It also reinforces the applicability of established

theories, such as asymmetric information (Akerlof, 1970; Stiglitz & Weiss, 1981) and precautionary liquidity behaviour (Acharya & Naqvi, 2012), within the context of Vietnam's banking sector.

Practically, the findings provide valuable implications for bank managers and policymakers. Profit maximisation should be balanced with sound liquidity strategies, particularly under conditions of credit risk and inflationary pressure. Banks should align bad debt management with liquidity planning to enhance resilience to financial shocks. Meanwhile, regulators such as the State Bank of Vietnam may consider adopting differentiated supervisory frameworks based on banks' size, risk profiles, and growth strategies rather than enforcing a one-size-fits-all liquidity regulation across the entire system.

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THE IMPACT OF DIGITALIZATION IN PURCHASING PROCESS COMPREHENSIVE OVERVIEW OF PURCHASING 4.0 ACTIVITIES

Lukáš Petrucha

Abstract

While is the digitalization the key driver of Industry 4.0 and the consequent processes like Purchasing 4.0, further questions need to be answered. What is the impact and benefits of digitalization in purchasing process? What everything can digitalization influence in procurement process? And what are the elements of digital transformation? Author tries to define actual trends in procurement area.

To gain information about current knowledge of digital transformation in procurement, a literature search and qualitative and quantitative research were conducted. The basic source for the investigation was use a list of purchasing methods leading to the fulfilment of purchasing strategies.

The aim of this research paper is to synthesize previous research findings on the digitalization of procurement through a literature review in order to create a comprehensive and exhaustive overview of the areas of procurement that could be affected by digital transformation. The description of the individual areas of procurement leads to a better understanding of the procurement process and the potentials of implementing digitalization. The list of benefits achieved by implementing digitalization provides information to companies, as well as researchers, and indicates the directions in which research and practice should take place.

The discussion reflects on current research and the real state of innovation development in Czech industrial companies. The implementation of artificial intelligence (AI) solutions is highlighted as a new trend of digital transformation. This research points out that suppliers need to be fully included in the digital transformation process. This article defines 7 key factors of the digital transformation of Procurement 4.0. The research found that an important factor is the readiness and knowledge of people. Without improvement of expert knowledge will be impossible to activate innovations and digital transformation of organizations.

Keywords: *Digital procurement transformation, Procurement 4.0, Purchasing digitalization, big data, artificial intelligence, robotic process automatization, blockchain literature review*

1 INTRODUCTION

This article provides a comprehensive overview of the key areas of the strategic purchasing process. The process of strategic purchasing and its effective management has become one of the indispensable activities of organizations in recent years. The digitalization in procurement is very actual topic, which is expanding through organizations.

The advancement of procurement technologies from basic e-procurement solutions (developed in the 90s) to the more advanced digital technologies available today, such as artificial intelligence or blockchain, has been instrumental to this development. The use of advanced digital technologies in procurement, referred to as procurement digitalization in the academic literature, has the potential to transform procurement organization (Srai et al., 2019).

Why is the digitization of purchasing important and which areas could be affected and how? Digitization influences reducing costs, improve process speed, working more efficiently with

data, effective collaboration in the supply chain, quality of outputs and strengthening innovation in the purchasing process.

Many activities do not require a great deal of creativity or intuition. We are talking about repetitive, monotonous tasks such as data collection, data updating, approval or evaluation. Such activities take up a certain amount of time that could be used more productively. Therefore, organizations try to find ways to implement technologies that would perform repetitive, simple tasks instead of manual work. We call these digital automation technologies robotic process automation (RPA)

Literature still mentioned that there is lack of information support larger digital transformation in procurement process. A lack of knowledge of technologies and a lack of clarity regarding the scope of the transformation required are frequently cited reasons why digital technologies are not adopted at a larger scale in procurement organizations (Pellengahr et al.; 2016, Jahani et al.; 2021; Herold et al., 2023; Delke et al., 2023).

Moreover, a more holistic perspective on the adoption of advanced digital technologies in procurement – which we term digital procurement transformation (DPT) – is missing. Such a perspective would highlight the fact that the impact of these technologies goes beyond the boundaries of procurement (Herold et al., 2023). As Herold et al.'s research focuses only on digital transformation in procurement, this article also focuses on the same area. A comprehensive literature review covering the entire field of Supply Chain Management would be beyond the scope of this article. More comprehensive research is needed to understand the digital transformation of procurement, the influences on this process, the impacts of this transformation on procurement, and the overall understanding of the consequences.

Strategic sourcing is now more essential than ever.

Constrained supply, prolonged transportation bottlenecks, and commodity inflation have shifted the balance of power to suppliers, allowing them to choose who to serve and sending costs skyward. Nor are things likely to get easier as procurement teams navigate the fallout from multiple crises including climate change, the pandemic, trade wars, and the war in Ukraine (A.T. KEARNEY, INC).

To the fulfil of the aim of this paper and provide a structured approach to future research. The following research questions were formulated:

RQ1: Which sub-processes are implemented in the purchasing process?

RQ2: Which methods are used in purchasing process

RQ3: Which of the defined areas can digital transformation in procurement affect? And what are the main aspects of implementing digitalization in specific areas?

RQ4: What are the future research questions and recommendations for further research?

2 LITERATURE REVIEW

Procurement 4.0, which is a term that encompasses a component of Industry 4.0, introduces a network between all supply chain upstream partners, enabling dynamic and quick cooperation and coordination beyond organizational frontiers (Jahani et al., 2021). Companies have increasingly embraced Procurement 4.0 techniques in their supply chain operating models, offering valuable support to procurement managers in overcoming purchasing challenges. This is made possible through the utilization of cutting-edge technologies such as the Internet of Things, e-procurement, big data, additive manufacturing or 3D printing, blockchain, Artificial Intelligence, and modularity (Althabatah et al., 2023).

Digitalization is linked to the purchasing process in procurement. Procurement can be defined as the “business management function that ensures the identification, supply, access, and management of external resources that an organization needs or may need to meet its strategic objectives” (Bueno et al., 2022). Some authors consider purchasing process as a “core business function of organizations” which plays a key role given its ability to generate value for the firm. Procurement ensures supplier selection, payment terms, contract negotiation, price negotiation, analysis and outsourcing, what Bueno et al. confirmed in their research paper. In many organizations procurement function is called Strategic procurement, because in this process strategic know-how about suppliers and supply chain is kept. According to current literature, Procurement 4.0 can be understood as an intelligent system capable of autonomously detecting material demand, generating your order, and even transmitting the order to the supplier without the need for human involvement (Bienhaus et al., 2022).

Sourcing is a strategic process that involves managing supplier relationships to gain a competitive advantage. It includes decisions on supplier quantity, relationship type, contract duration, negotiation type, and local or global sourcing. Strategic sourcing aims to reduce costs, ensure long-term supply stability, and minimize supply risk (Monczka et al., 2021).

Robotic Process Automation (RPA) has received growing attention within digital transformation as this cutting-edge technology automates human behavior and promises high potentials (Flehsig et al., 2022). In purchasing processes, an automated process can perform many operational tasks, including the ordering and payment of deliveries (Flehsig et al., 2022). Therefore, RPA will allow procurement professionals to work smarter and focus on value-adding activities (Delke et al., 2023). Implementing RPA for repetitive tasks can enhance operational efficiency, quality improvement, and cost savings (Flehsig et al., 2022; Delke et al., 2023).

RPA is a business process automation technology that uses virtual software robots, also known as digital robots or bots, to perform manual, time-consuming work or tasks. RPA adoption is growing at a double-digit rate (SAP; 2025).

RPA including:

- **Manual and repetitive tasks:** Interact with data from multiple sources such as Microsoft Excel, supplier portals, and other sources
- **High-volume tasks:** Process steps that must be completed over time, such as data migration and approval workflows
- **Multiple system tasks:** Access various applications such as web applications, RP solutions, third-party software, and more

According to Ernst and Young statement from 2016, resilience and sustainability are key factors in successful supply chain management, and are now being integrated into purchasing processes, such as supplier selection. Supply chain managers have come under increasing pressure to accommodate multiple demands in their decision-making process. For instance, due to the growing governmental and societal interest in environmental sustainability, the interest in building supply chain resilience to secure business continuity has gained increasing attention by decision-makers. (Mohammed et al., 2022).

Digital transformation can improve the current approach of business analytics. The purpose of business analytics, especially when it comes to Procurement and Sourcing, is to facilitate the firm’s ability to analyze trends and to predict future purchasing patterns for increased leverage through negotiations. Analytics techniques can be categorized into three categories: descriptive, predictive and prescriptive (Barrad et al., 2020).

Integration of Blockchain technology is crucial to developing digital solutions like automating procurement contracts or contract management that offers better security to the traditional electronic contract system, effective supply chain management, facility management and other purchasing processes (Althabatah et al., 2023). Blockchain has the potential to improve the e-procurement process in various stages of business. Blockchain technology brings transparency, data security, productivity and efficiency. Blockchain is yet another important I4.0 technology that has been predominantly used in procurement for making smart contracts. Smart Contracts play an essential role in procurement, and they have been increasingly used in many industries due to many features, including automatic execution, nontempering in the blockchain environment, and transparency (Thio-ac et al., 2019).

In Industry 4.0, Artificial Intelligence tools and systems have made real impacts in all aspects of production and distribution. However, its influence on the procurement process is less examined in the literature (Althabatah et al., 2023). According to Bienhaus research findings are Artificial Intelligence and Big Data the key drivers for the digital transformation of organizations. Digitalization in those areas can move profitability and competitiveness of organizations on a new level. In the absence of AI smartness, automation alone can backfire. This implies that a company should first initiate and strengthen its smart control algorithms, such as improving the prediction accuracy of its recommendation systems, before considering a high level of autonomy. (Cui et al., 2022). The introduction of GenAI in Procurement is poised to significantly enhance efficiency, decision making and overall performance. The degree of impact that can be achieved for Procurement will be shaped by not only the needs and capabilities of the enterprise, but also the maturity of the AI technologies that have been adopted so far (ProcureTech 2024).

Based on current research 9 Procurement 4.0 components were defined. It is **Robotic Process Automation, Artificial Intelligence, Blockchain, Analytics, Big Data, Sustainability, Resilience, e-Procurement and Internet of Thinks**. All of those have an influence on digital transformation of purchasing process. Those components were used as the key initiatives for qualitative and quantitative research of this paper.

3 METHODOLOGY

To address the RQ1 and RQ2 three phases of research was defined. In first phase the qualitative research was done for gain the base information for realized second phase. In second phase systematic literature review was carried out because it is robust and auditable method with which to map and assess the existing intellectual territory and develop the existing body of knowledge (Tranfield et al., 2003). In the third phase quantitative research was conducted to ensure comprehensive information base of this research.

Phase 1. Qualitative research

Qualitative research was performed on the Innomotics Purchasing Conference. Researcher led structured interviews with purchasing managers of individual production plants, purchasing managers of divisions, team leaders and commodity managers. Then all parties participated on the questionnaire fulfilment to supplement the information from the interviews. The questionnaire contains specific names of respondents, their function and location. Based on the interviews, the questionnaire questions were defined:

- How familiar are you with Artificial Intelligence (AI)
- How familiar are you with Robotic Process Automation (RPA) in procurement process?

- In which purchasing processes/activities can the implementation of AI and RPA be benefit?
- What specific goals do you see in the implementation of AI and RPA in the purchasing organization?
- Would you like to suggest any specific use cases for AI and RPA automation?

Phase 2. Systematic literature review

A basic list of keywords was used to search for articles, see Tab 1. This list of key words has been maintained for a longer time without any significant change. Many researchers used basically the same logic with the same keywords. This is the most effective methodology to follow recent trending research topics in the field of procurement digitalization phenomenon.

Tab. 1 – The list of keywords. Source: own research

Keyword
Industry 4.0
Purchasing 4.0
Procurement 4.0
Sourcing 4.0
Logistics 4.0
Digitization
eProcurement
eSourcing
Automatization
Big data
Cloud

This basic list of keywords was expanded with specific keywords obtained through qualitative research and own previous research. The conclusions of the previous research (Digital transformation determine phenomenon Purchasing 4.0 in the purchasing process) were used for generating extended keywords. The keywords were entered into various combinations into the Web of Science database. The obtained results were sorted by systematic screening.

Tab. 2 – The list of specific keywords. Source: own research

Keyword
Artificial Intelligence (AI)
Robotic process automatization (RPA)
Benchmark
Blockchain

Reporting
KPI
Sustainability
Cost
Resilience
Flexibility
Relationship
Transparency
Strategy

The use of specific keywords proved to be effective in obtaining the required amount of literature. The analysis of selected literature led to an expanded list of key areas of the purchasing process that could be affected by digital transformation. Information from the categorized literature helped to construct a list of purchasing methods. This list was used for further investigation using quantitative research, which provided information to answer the question of which areas of purchasing could be affected by the implementation of digitalization and automation. The list of methods is presented in Fig. 1 in the results section of this article.

Phase 3. Quantitative research

To understand the progress of digital transformation in practice a research questionnaire was prepared. For survey purposes the Google Forms app was used. The size of companies was taken into consideration as well as the job profile of participants. Questionnaire was distributed to the Czech industry companies. The main research survey is categorized into three sections with the main focus on understanding in which procurement processes and areas the digital transformation has impact. The first section provides information about company size, purchasing volume and job title of participant. The second section is focused on purchasing processes and benefits from digitalization approach. The last section provides complete information to qualitative research by the observation of knowledge level in are of RPA and AI.

In total, data were collected from 40 participants who were operating in the field of procurement or other business functions. Considering procurement in particular, this includes procurement managers, global commodity managers, procurement team leaders, local strategic buyers and logistics managers. All functions are being familiar with procurement procedures and processes and their operational execution. Also, they are responsible for all areas from supplier selection to supplier evaluation, risk management or e-sourcing. The survey is limited to a specific country, Czech Republic. Furthermore, the survey is limited to a particular industry without automotive.

4 RESULTS

The results and findings of this research can be used by purchasing managers to define strategies for the digital transformation of the purchasing process. This article provides a clear roadmap to facilitate the decision in which area of purchasing to start digitizing.

Structured interviews provided data lead to conclusion, that purchasing managers are interested in current trends in AI and its possible implementation in the purchasing process. However, they do not yet have enough knowledge about this technology, this fact was confirmed by the supplementary questionnaire. The result of the level of knowledge of purchasing managers about AI is 2,29 on a scale of 1-5, low knowledge - very good knowledge. The level of knowledge of robotic process automation (RPA) was also determined. The result is 2,36, which is only 0,1 more than knowledge about AI.

The formula below was used to analyze the variance of knowledge level values:

$$\text{Var}(X) = \frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^2 \quad (1)$$

For AI and RPA knowledge level, the average dispersion is 1,15. Based on this result, the conclusion is that currently we do not have a large difference in knowledge level between individual purchasing functions. Detailed analysis showed that there is a more significant knowledge deviation between the lower functions of team leaders and the highest level of functions of divisional purchasing managers.

Findings from qualitative research detected that the level of knowledge in the field of digitalization is influenced by the position held in the purchasing department, see Table 3.

Tab. 3 – Knowledge level in AI and RPA. Source: own research

Procurement function	Knowledge level	
	AI	RPA
Division procurement manager	3,00	3,00
Plant procurement manager	2,67	2,67
Commodity manager	2,33	2,83
Team leader	1,75	1,25

Respondents gave out that they see the benefits of implementing RPA and AI mainly in reducing operational costs, improving process efficiency, improving data accuracy and avoiding errors. When asked in which processes or activities the implementation of RPA and AI would be beneficial, they answered:

- in all repetitive activities
- maintenance of big data
- data collection and next distribution of data
- big data mining
- market online research
- decision making
- supplier management process
- supplier qualification process
- reporting process

- contract management (overview, alerting, specific drafts)
- risk management (getting data from external sources, early prediction of risks)

In the research we have been confronted with two terms: **efficiency** and **effectiveness**. While the term efficiency represents the ratio between the benefit of a specific activity and the costs needed for it. The term effectiveness represents the purposefulness, the meaningfulness of a specific activity.

Efficiency is mainly achieved through automation applications, while effectiveness is achieved through augmentation applications (Colombo et al. 2023).

Speaking about focus on the costs that digital transformation affects, it is the efficiency that can be achieved by digitalization. Empirical research has shown that “digitalization has allowed procurement leaders to reduce costs, both related to the management and execution of procurement processes” (Colombo et al., 2021). Less labour is required in procurement, as is a shifting of resources from operational to strategic activities, where human decision-making is visible. Buyers that adopt, for instance, AI in their processes become faster, more reactive, and more efficient, thereby freeing up time for more strategic tasks (Wang et al., 2020; Colombo et al., 2021).

The term effectiveness basically includes all the methods listed in Fig. 1. Research shows that improvements in transparency, data availability, and data accuracy are achieved through the implementation of digital tools. Making progress in global sourcing, risk management, or contract management, increasing flexibility, improving supply chain resilience, or improving sustainability are all benefits that are difficult to quantify in terms of cost. This progress can increase effectiveness, which, thanks to the synergy of all these improvements, has a secondary effect in reducing costs (efficiency). However, those cost reductions are difficult to allocate to specific innovations achieved by digital transformation. The research question has been raised, which methods to focus on, what combination of methods include into implementation of RPA and AI, to achieve the highest possible financial efficiency in addition to effectiveness.

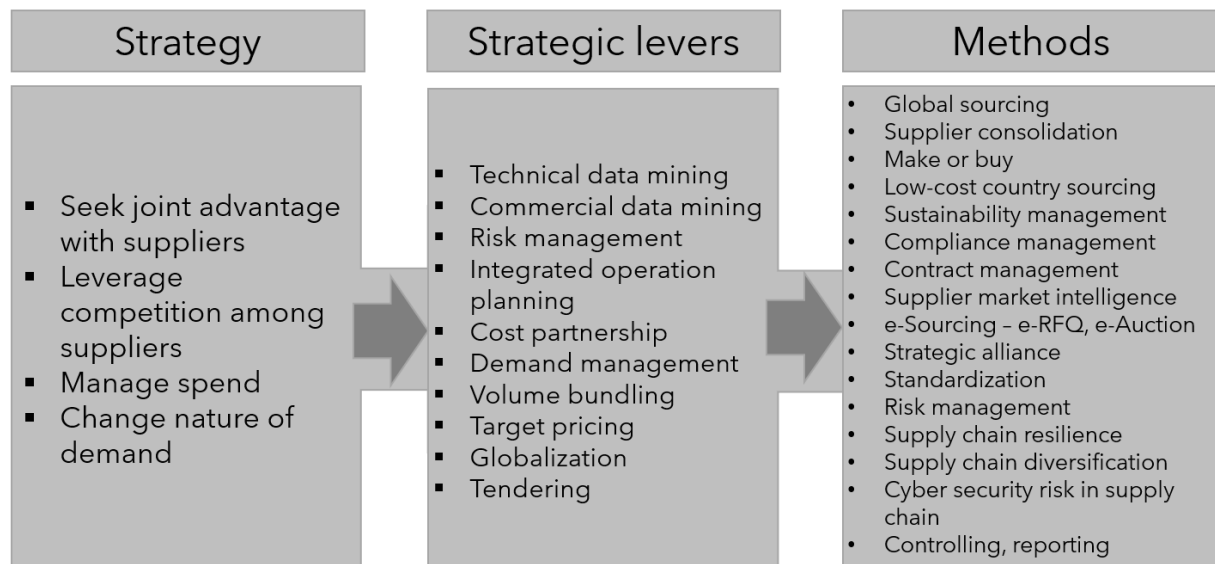


Fig. 1 – Strategy concept. Source: own research

The strategic concept, or strategy breakdown, was created based on knowledge gained through qualitative research, literature review, and research at Kearney, a leading global management consulting firm with more than 5,700 people working in more than 40 countries (A.T. KEARNEY, INC; 2024). This strategic concept is an example of an approach for purchasing

managers to define strategies that lead to cost reduction and improved supplier relationships. The list of methods should be continuously expanded to help purchasing teams find smart solutions to achieve the set strategies.

The strategic concept with detailed overview of single methods should be a guide for defining areas with the potential for implementing digitalization.

Based on quantitative research this paper confirms that digital transformation is partially or fully implemented by all companies. 70% of respondents see benefits in reduction manual work and enhanced process efficiency. More than 60% answers were positive to the topic of cost reduction by implementation of digital tools. The same percentage is linked to impact to data accuracy, data interchange between customer and supplier, and reduction amount of human mistakes. 42% of respondents answered that digitalization can support price negotiation to achieve better purchasing prices. But only 30% of participants think that digital approach can enhance supplier relationships and improve innovations.

The survey outlined the current impact of digitalization in the purchasing process. 60% of the answers define the main impact on supplier selection, controlling and reporting and order management. Results shown that only in 40% of asked organizations are the digitalization impact also in invoicing and payment activities, contract management, benchmarking, RFQ process (RFQ = request for quotation), supplier development and supplier evaluation. Less than 20% of the impact of digitalization is in risk management, supplier relationships, cost management and inventory management.

Research confirms what are the key drivers for the digital transformation, see in Fig. 2.

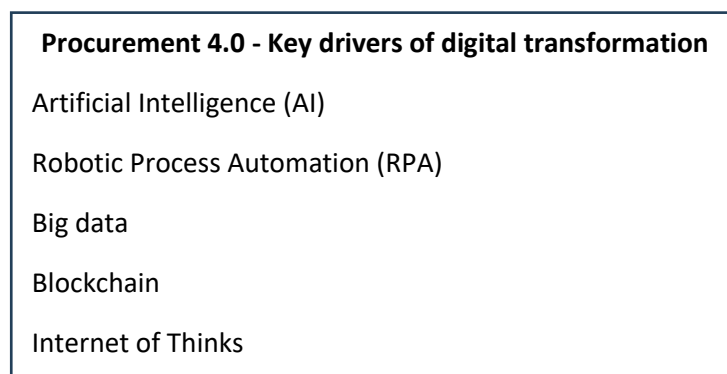


Fig. 2 – Key drivers of digital transformation. Source: own research

Based on systematic literature review the upward trend of research paper is evident, see in Fig. 3. We can confirm that this topic is still actual with potential to bring other new findings in Procurement 4.0 topic. In recent years we can observe upward trend of articles described AI implementation in purchasing process. This trend highlights the importance of AI and it's support of digital transformation.

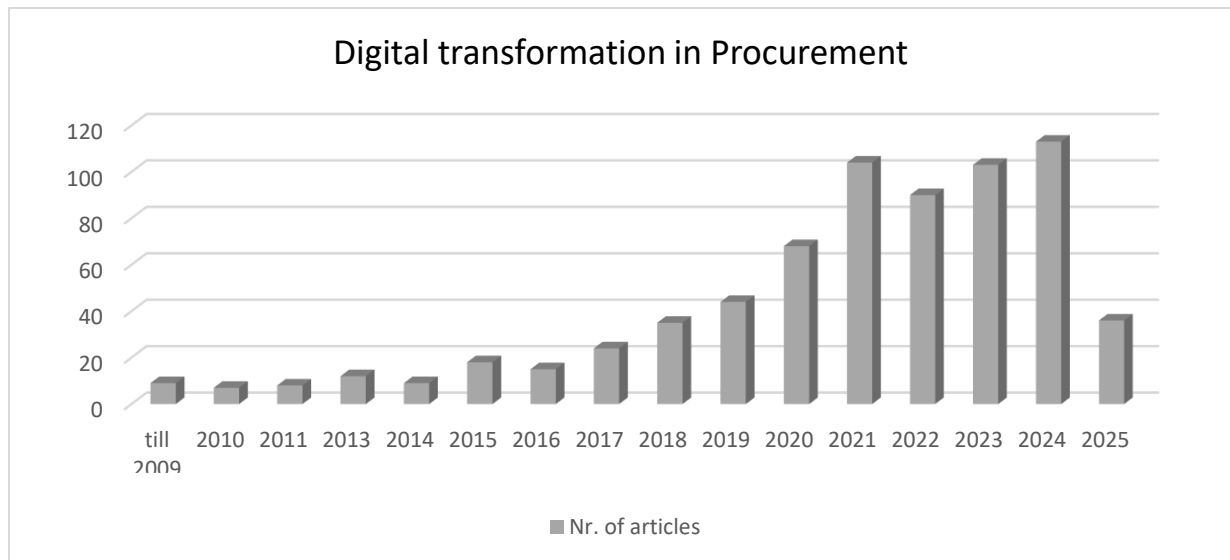


Fig. 3 – The nr. of articles overview based on year of issue. Source: own research

5 DISCUSSION

Due to the rapid progress, it is possible to state that the life cycle of industrial ages is getting shorter which requires organizations and stakeholders to put their potential for innovation and supply chain strategies on a new level to achieve competitive advantages (Schrauf et al., 2016; Bienhaus et al., 2022). This statement is an evident fact that needs to be confronted with practice. Although qualitative research shows that managers perceive the need for change, the readiness of organizations in the studied environment of Czech industrial companies is still not at a level that allows for fundamental changes reflecting changes in the market environment.

This overview provides methods and strategic levers which can be influenced by digital transformation. The 9 digital components of purchasing process were defined. 7 of them were classified as Key drivers of digital transformation. Based on literature review was found that the focus needs to be on AI implementation. Whereas AI need to be examined in detail. There are still challenges and barriers to AI adoption. Questions for procurement teams are how they can use it, what they can use it for, what they cannot use it for, is it usage allowed and how much costs they can spend for it.

Procurement leaders have different options in terms of combining various digital technologies in the various procurement processes and activity levels (operational, tactical, and strategic) (Herold et al., 2023). However, there is a challenge how procurement leaders ensure that internal stakeholder and their suppliers for collaborating and invest funds to the new technologies. This research confirm that procurement leaders are aware that organization of purchasing process have to be changed. Procurement, Supplier Quality Management and Logistics are a value driver and accountable for all supplier related matters. More research is necessary as a theoretical support, because this comprehensive Procurement process can influence significant portion of company costs.

Digitalization has to be implemented at the same progress level in purchasing organizations as well as in external parties, e.g. suppliers. Otherwise, automation will be implemented inefficiently, and the entire digital transformation will be slowed down due to this fact. Digital transformation expresses the implementation of new technology tools. There are many tools which can be used, but the connectivity among the tools is important. There is research question

how ensure this connectivity and reach the right effective automation between purchasing processes and suppliers.

Digital transformation can enhance performance of entire purchasing process. KPI's are nowadays the main factor influencing decisions about implementation of digital technologies. What are other decision parameters for adaptation of digital technologies, which can be taken into consideration? Disruptive technologies, such as artificial intelligence, machine learning, or the blockchain, have the potential to transform entire industries as previous publications have outlined. They especially offer new opportunities to improve existing processes in dimensions of performance, cost, and quality. Despite a continuously growing number of contributions, research and practice lack an adequate understanding about how blockchain can be used to achieve these benefits. (Kolb et al., 2019). Researchers have mentioned different factors and their combinations that can change the purchasing process. The basis for further research should be to consider all 7 defined key drivers together and interacting with each other.

Literature provides information about technologies, methods and digital approaches. More knowledge needs to be addressed to human skills, stakeholders and benefits from implementing digital technologies. Human knowledge or human factor should be considered as the 8 key driver of digital transformation. Further academic discussion to this research complex topic is required.

6 CONCLUSION

This article can help organizations to find new possibilities for how to digitize procurement and purchasing processes. The value of the article considers the fact that presents to the researchers and purchasing managers the comprehensive overview of the areas suitable for digitization in purchasing and the current direction trends.

Procurement 4.0 aims to optimize the value provided by the purchasing function (Nicoletti, 2020).

The developed conceptual model must be verified and enhanced through further empirical research.

AI has become the universal engine of execution, driving the explosive growth of new business models, but there is limited empirical research to understand and quantify how AI works and when it is the most powerful (Cui et al., 2022; Terwiesch et al., 2020).

Future research should focus on how purchasing methods will change as core strategies change, and how these changes in strategy will impact the implementation of new automation and digitalization solutions.

Organizations need to carefully consider factors such as data security, privacy, interoperability, and regulatory compliance when adopting Procurement 4.0 technologies. The potential risks associated with increased reliance on digital systems, such as cyber threats and data breaches, should not be overlooked. It is essential to develop robust risk management strategies and invest in cybersecurity measures to mitigate these risks. Moreover, the human factor should not be underestimated (Althabatah et al., 2023).

The survey results point out the moderate progress in adoption of digital technologies in purchasing process. Academic sphere and practice need to be more confronted. Procurement managers are not ready to do big steps in digital transformation. Regular watch the progress of digital transformation and analysis could be part of next research papers.

This research raises recommendations to elaborate barriers and risk of digital transformation. As the benefits and opportunities will be well described, knowledge of risks and barriers could be useful as support for practical implementation.

7 key factors, see in Tab. 2 have significant impact to the digital transformation of the purchasing process. Implement of those factors, organizations can achieve improvement of digitalization. But still is important to do investigation of concrete benefits by implementation digital tools to the purchasing process. Future research needs to answer question how enhance human skills, how eliminate barriers and identify other opportunities now not known for academic sphere as well as for practice.

Limitation of this research consist in focus on organizations in Czech Republic. The survey did not address the barriers, risks and concerns from the implementation of digital technologies. Next research needs to investigate not only internal aspects of digitalization but also to deal with involve external partners and the new role of the procurement function as strategic network node within supply chain ecosystems.

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THE IMPACT OF CAPITAL STRUCTURE ON BANK PERFORMANCE: EVIDENCE FROM COMMERCIAL BANKS IN VIETNAM

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Abstract

The study was conducted to examine the impact of capital structure including capital adequacy, client deposits, and loan portfolios, on return on assets (ROA) and net interest margin (NIM) on the business efficiency of commercial banks in Vietnam. The research paper data is collected from the financial reports and annual reports of 28 commercial banks in Vietnam from 2012 to 2023. The OLS (Ordinary Least Squares) regression method and the models used in the paper, such as the Random Effect Model (REM), the Fixed Effect Models (FEM), GLS (Generalized Least Squares), and the Hausman and Redundant Test and multicollinearity checks to choose the most appropriate model. It found that the capital structure has a significant impact on bank performance, emphasizing that increased equity capital and loan portfolios enhance profitability and operational efficiency. However, rising customer deposits adversely impact profitability, interest profits are improved. This study additionally emphasises the Vietnamese regulatory context, including capital adequacy ratio (CAR) requirements and Basel II/III implementation by the State Bank of Vietnam (SBV), and highlights how these frameworks shape bank performance. The study provides recommendations for banking executives and regulators to enhance capital structure within Vietnam's regulatory framework and economic conditions, therefore fostering financial stability and risk management in emerging countries. Furthermore, future research directions are indicated, suggesting the inclusion of macroeconomic factors such as GDP growth, inflation, and interest rates to strengthen explanatory power.

Keywords: *capital structure, commercial banks, banks' performance, panel data, Vietnam, regulation, ROA, NIM*

1 INTRODUCTION

The capital structure of commercial banks has a significant impact on their financial stability, profitability, and overall performance in the banking sector. In Vietnam, digital transformation is being focused on and financial technology is no exception to this trend. Changes in the regulatory framework have increased the importance of effective capital management, encouraging researchers to discover the impact of bank performance on managing financial strategy and informed regulatory policy formation as it directly enhances business value and can bolster owner income. The economic decline, exacerbated by the pandemic and other instabilities, has also impacted the banking sector, which is crucial as the artery of financial markets and a driver of economic growth. Therefore, establishing an optimal capital structure that is suitable for operational resources is essential for banks to maximize profits while mitigating financial risks.

According to specific regulations, Vietnamese banks are required to respond strictly including minimum capital adequacy ratios set by the State Bank of Vietnam, which directly influence their risk-taking and lending behaviors (Nguyen, 2016; SBV, 2016). As a result, managers have been facing critical challenges of effective capital utilization and operational efficiency. Then, understanding the factors influencing the capital structure of Vietnamese banks is a vital endeavour for managers seeking to allocate business capital strategically. The research specifically focuses on evaluating the factors that affect the performance of Vietnamese banks

from 2012 to 2023. This study also examines the impact of capital structure on their performance during this period. Based on the analysis, solutions for the effective management of the capital structure for Vietnamese commercial banks are recommended.

Furthermore, this enables Vietnamese commercial banks to understand how the risk of a financial crisis impacts the efficiency of their banking operations, allowing them to construct and create an equitable capital structure that is appropriate for their bank's operating resources, thereby maximizing profits.

2 LITERATURE REVIEW

Economists Merton Miller and Franco Modigliani came up with this theorem in 1958. The main idea behind M&M theory is that the capital structure of a company does not affect its total value when the market is ideal. The first version of the M&M theory, on the other hand, had a lot of limitations because it was founded on the idea that markets are always fully efficient. Miller and Modigliani made their models better by adding business taxes. They showed that corporations can increase their worth by taking out loans because the interest payments can be written off on taxes. People prefer to use debt since interest payments lower their taxable income and the total amount of taxes they have to pay. In theory, companies can use debt as a tax shield. Adding bankruptcy fees and costs of financial strain makes the framework even better. Debt can help you save money on taxes, but too much debt makes it more likely that you'll have financial problems and cost more. Direct costs like legal fees and indirect costs such as losing customers and suppliers are part of these distress costs. This makes it clear that the best capital structure is one that balances the extra benefits of debt against the extra costs.

The Trade-Off theory (TOT) says that businesses find the best balance of debt and equity financing to get the most advantages and the least costs. There is a reasonable optimal level that companies should aim for when they try to employ more debt, weighing the benefits of tax shields against the costs of being in financial trouble. When deciding on the best capital mix, companies look at things like the tangibility of their assets, their profitability, their size, and their development potential. There are more benefits to debt financing than just tax breaks. Debt obligations are a way to punish people for bad behavior. They lower agency costs by limiting managers' freedom and compelling them to use resources wisely. Management has to provide enough cash flow to cover fixed debt payments, which might cut down on unnecessary spending and make operations more efficient. Also, debt is usually a cheaper way to borrow money than equity because of priority claims and the fact that it may be deducted from taxes.

When debt levels are high, there might be conflicts between debt and equity holders that cause agency costs. This can lead to bad investment choices. Substantial debt obligations make it harder for companies to be flexible with their money, making it harder for them to take advantage of investment opportunities or adapt to changes in the market.

When making judgments about capital structure in the banking sector, several key factors should be considered. Banking activities are the lifeblood of financial markets and help the economy grow. It is important to set up an appropriate capital structure that works for the bank's operational resources so that earnings are maximized and the risk of a financial crisis is minimized. When making judgments on their capital structure, banks have to deal with rules, deposit insurance systems, and government support systems that affect their performance and operational efficiency.

When these theoretical frameworks are used in banking, it becomes clear that while basic optimization concepts still apply, the specific mechanisms and limitations are very different from those in non-financial companies. When banks make decisions about their capital structure

that affect performance and long-term survival, they have to deal with complicated interconnections between regulatory mandates, market forces, and stakeholder expectations.

On the other hand, Basel II and Basel III standards are currently adopted in Vietnam, which affects how banks determine optimal leverage. Prior studies emphasise that profitability is influenced not only by internal capital mix but also by macroeconomic variables such as GDP growth, inflation, and lending rates (Athanasoglou et al., 2008; Dietrich & Wanzenried, 2011).

3 METHODOLOGY

3.1 Hypotheses development

Equity to total assets and return on assets

The ratio of equity to total assets is an essential measure of a company's financial strength. This index examines a company's total equity and total assets to assess how well it meets its asset needs without incurring debt. We examine whether capitalization is the most critical factor in bank results by analyzing the equity to total assets ratio.

One of the studies that looked into how capital structure affects the profitability of Spanish banks from 1999 to 2009 was by Trujillo-Ponce (2013). It found a strong positive link between capitalization and bank profitability. Pham et al. (2018) conducted a study based on 253 financial statements from 23 listed joint-stock commercial banks from 2010 to 2020. They use panel data analysis with fixed effects models (FEM) and random effects models (REM) to show that the equity-to-total-assets ratio has a favorable effect on ROA. Salteh et al. (2012) used the Correlated Random Effects-Hausman Test to look at how the way a firm is financed affects its performance. The ratio of total debt to total assets and ROA is not favorable.

H1: Equity has a positive impact on bank return on assets.

H1a: Equity has a negative impact on bank return on assets.

Customer deposits and returns on assets

Abbadi and Abu-Rub (2012) created a model to assess the impact of capital structure on banking efficiency in Palestinian financial institutions. The authors used the measurement of total deposits as a percentage of assets. They found that leverage has a negative impact on bank profitability; however, an increase in each of the following metrics - ROA and total asset deposits - increases bank efficiency. Moreover, Yeasin (2022) observed a negative and statistically significant effect on the financial performance of specific commercial banks in Bangladesh, attributed to the ratio of deposits to total assets during the period 2010–2019.

H2: Customer deposits have a positive impact on bank return on assets.

H2a: Customer deposits have a negative impact on bank return on assets.

Customer loans and return on assets

Nirajini and Priya (2013) examined the impact of capital structure on the financial performance of listed trading companies in Sri Lanka. They found a positive relationship between capital structure and financial performance. They also found that the positive impact of capital structure (debt-to-asset ratio) on financial performance is measured by return on assets (ROA).

However, Mouna et al. (2017) examine the influence of capital structure on the performance of companies in 53 Moroccan businesses in the period 2014 to 2016. The study found that the debt ratio has a negative impact on ROA. Tamirat (2015) addressed the topic of the effects of debt

financing on the profitability of Commercial Banks in Ethiopia. The researcher found that capital structure, measured by total debt to assets, has a negative relationship with ROA.

H3: Bank loans have a positive impact on bank return on assets.

H3a: Bank loans have a negative impact on bank return on assets.

Equity to total assets and net interest margin

Angori et al. (2019) used annual balance sheet information from individual banks in the European area from 2008 to 2014. The data are extracted from 3000 cooperative, commercial, and savings banks from the Bureau van Dijk Bankscope database. According to the findings, there is a significant and positive impact of capitalization on the net interest margin.

Phamhoang et al. (2017) suggest that there is a negative correlation between equity capital and net interest margin. Net profit margin will decrease if equity increases. Henny et al. (2021) studied 37 traditional banks listed on the Indonesia Stock Exchange from 2015 to 2019 to examine the impact of capital structure factors on NIM. The results show that equity has a significant negative impact on net interest margin.

H4: Equity has a positive impact on net interest margin.

H4a: Equity has a negative impact on net interest margin.

Customer deposits and net interest margin

Hailu (2015) used net interest margin to measure how well banks were doing. The author looked at the effects of total debt to assets, deposits to assets, and asset size as independent factors from 2001 to 2012 on the profitability of 8 Ethiopian Commercial Banks using panel data. The results of the study showed that the deposit to assets and asset size variables both had a significant and favourable effect on the net interest margin.

Hamadi and Awdeh (2012) say that research shows that increasing working capital from savings leads to higher marginal interest rates, which in turn lowers profit. This suggests that client deposits have a negative influence on net interest margin.

H5: Customer deposits have a positive impact on net interest margin.

H5a: Customer deposits have a negative impact on net interest margin.

Bank loans and net interest margin

In their studies, Suu et al. (2020) and Ekinci and Poyraz (2019) utilized bank lending as a control variable to explore the correlation between bank lending and bank performance. They found that an increase in bank lending has a positive effect on profits. Duong et al. (2023) used the GMM method to test 750 observations from 38 commercial banks in Vietnam, China, and Taiwan from 2009 to 2020. The authors found out that there is a negative impact of bank lending on NIM during the COVID-19 pandemic. According to Ekinci and Poyraz (2019), high bank debt ratios resulting from inadequate loan analysis and monitoring are likely to increase bad debt. Therefore, banks are compelled to make higher provisions for overdue debts, resulting in a substantial decline in bank profits.

H6: Bank loans have a positive impact on net interest margin.

H6a: Bank loans have a negative impact on net interest margin.

Control variables

Anarfo (2015) pointed out that size and profitability are frequently linked in a positive relationship. Meero (2016) indicated that financial leverage has an indirect effect on ROA. But

it is directly related to the equity-to-assets ratio. They analyzed data from 16 countries from 2005 to 2014 and found that Islamic banks and commercial banks performed better together when they were larger. However, the essay by Almazari (2014) talks about how internal issues affect bank earnings. The primary objective of this research study is to assess the profitability of Saudi Arabia and Jordan. It does this by examining the income figures for 23 banks in both nations from 2005 to 2011. The study reveals that the size of the factor bank hurts bank profits.

The yearly increase in a bank's total assets is called asset growth. It shows that the bank can increase its operations and expand. Researchers have looked into how asset growth affects a bank's success, and the outcomes have been diverse depending on the market and how well the bank is handled. In 2020, Salim and Winanto researched the effect of Return on Assets on the growth of assets. The authors used the samples of Sharia General Banks in Indonesia. They discovered that Return on Assets is a factor that has an effect on asset growth. This means that the bank's performance is linked to how quickly its assets expand. The findings reveal that banks that generate money tend to grow faster, which can help them do even better.

Le et al. (2022) studied the influence of asset growth on the level of risk banks' absorb. The research uses data from Vietnamese commercial banks from 2008 to 2018. The objective of the research is to determine how asset growth affects the level of risk banks are willing to absorb. The result shows that when assets expand, the connection between strategic interactions and risk-taking incentives gets weaker. It indicates that expanding assets is a good method to maintain stability. It also helps banks work better by minimizing operational risks. In contrast, the research by Toby (2007) used data from 25 banks listed on the Nigerian Stock Exchange. The result shows that there is an effect of asset growth strategy on bank's performance. However, the link depends on how well the bank can grow while maintaining efficiency.

3.2 Model

The authors gather financial information from 28 commercial banks in Vietnam from 2012 to 2023. The data collection encompasses banks regulated by the State Bank as well as state-owned banks. The data is sourced from audited financial statements and annual reports. The final dataset includes 336 bank-year observations.

Many people agree that ROA (Return on Assets) and NIM (Net Interest Margin) are two of the most important measures of how well a bank is doing. ROA is a standard way to look at a bank's overall profitability in relation to its total assets. NIM shows how well a bank can handle its interest revenue and expenses and how well it can manage its primary lending activity. These two measurements together give a full picture of both profitability and operational efficiency in the banking sector. This makes them good dependent variables for this study.

Return on assets (ROA) is a crucial indicator for businesses, as it enables managers to assess their production efficiency. The formula for calculating this ratio is

$$\text{ROA} = \text{Net income} / \text{Total asset} \quad (1)$$

Furthermore, commercial banks may utilise another index, Net Interest Margin (NIM), to analyse revenue from business, finance, and banking operations to make more informed investment and analysis decisions. The NIM coefficient is the percentage difference between a bank's interest revenue and interest costs (Samuel Siaw, 2013). Banks can use the NIM ratio to assess how well they employ borrowed and mobilized cash. The formula for calculating this ratio is:

$$\text{NIM} = (\text{Interest income} - \text{interest expense}) / \text{Total assets} \quad (2)$$

Tab. 1 – Variable Definitions. Source: Conducted by the authors (2025)

Variables	Acronym	Formula	Author
	Dependent		
Return on Assets	ROA	Net income/Total Assets	Nguyen & Vu (2021); Musah (2017).
Net interest margin	NIM	(Interest income - interest expense)/ Total Assets	Duong et al., 2023;
	Independent		
Capitalization rate	CAP	Total Equity/Total Assets	Phamhoang et. al., (2017); Trujillo-Ponce (2013).
Customer deposits	DEP	Customer deposits/Total assets	Hamadi and Awdeh (2012); Abbadi and Abu-Rub (2012); Hailu (2015).
Lending and financial leasing	LOAN	Customer loans/Total assets	Nirajini and Priya (2013); Mouna et al. (2017); Duong et al. (2023).
	Control		
Size of total assets	SIZE	Logarithm of total assets	Hailu (2015), Rami Obeid (2024), Agoraki and Kouretas (2019)
Asset Growth	AG	Annual growth rate of total assets	Salim and Winanto (2020); Le et al. (2022); Toby (2007)

The research team used two experimental models, as follows:

Model 1:

$$ROA_{it} = \beta_0 + \beta_1 CAP_{it} + \beta_2 DEP_{it} + \beta_3 LOAN_{it} + \beta_4 SIZE_{it} + \beta_5 AG_{it} + \varepsilon_{it} \quad (3)$$

Model 2:

$$NIM_{it} = \beta_0 + \beta_1 CAP_{it} + \beta_2 DEP_{it} + \beta_3 LOAN_{it} + \beta_4 SIZE_{it} + \beta_5 AG_{it} + \varepsilon_i \quad (4)$$

Although macroeconomic factors such as GDP, inflation, and interest rates were not included in the current models, their role is acknowledged as crucial and they are suggested for future research expansion.

4 EMPIRICAL RESULTS

Tab. 2 - Presents the Descriptive Statistics in a structured format consistent with academic standards. Source:
Conducted by the authors (2025)

Variable	Min	Max	Mean	Std. Dev.	Obs
ROA	-0.007196	0.0321422	0.0090546	0.0071663	336
NIM	-0.001034	0.0875679	0.0291063	0.0128071	336
CAP	0.0406177	0.2383814	0.0900397	0.0388918	336
DEP	0.1285403	0.9095316	0.6632792	0.1262453	336
LOAN	0.1346443	0.8927671	0.5790386	0.1205958	336
SIZE	12.68508	15.36189	14.15474	0.5572205	336
AG	-0.996807	23.88113	0.3138254	1.747696	336

The descriptive statistics show that Vietnamese commercial banks maintained positive average ROA (0.91%) and NIM (2.91%) during 2012-2023. The capital adequacy ratio averaged 9.00%, indicating strong capitalization. Asset growth varied significantly, ranging from -99.68% to 2,388.11%, reflecting diverse expansion strategies.

Tab. 3 - Reports the Pearson Correlation Matrix results, providing insights into the relationships between variables. Source: Conducted by the authors (2025)

	ROA	NIM	CAP	DEP	LOAN	SIZE	AG
ROA	1						
NIM	0.7488	1					
CAP	0.2161	0.2728	1				
DEP	-0.2961	-0.1204	-0.306	1			
LOAN	0.19	0.3173	-0.122	0.4805	1		
SIZE	0.3744	0.2778	-0.5239	0.2853	0.4101	1	
AG	0.1127	0.2009	-0.0934	0.0203	0.1037	0.1495	1

The correlation analysis reveals strong positive correlation between ROA and NIM (0.7488), indicating consistent performance measurement. All correlation coefficients are below 0.8, suggesting acceptable multicollinearity levels.

Tab. 4 – Summarises the Variance Inflation Factor (VIF) Test Results, confirming the absence of multicollinearity. Source: Conducted by the authors (2025)

Variable	VIF	1/VIF
SIZE	1.67	0.598108
LOAN	1.54	0.650602
CAP	1.51	0.663075
DEP	1.42	0.703258
AG	1.03	0.97189
Mean VIF	1.43	

The VIF test results confirm no multicollinearity problems, with all VIF values below 5 and mean VIF of 1.43.

Tab. 5 - Illustrates the Regression Results across models, offering robust evidence supporting the hypotheses.

Source: Conducted by the authors (2025)

Model	Pooled OLS		FEM		REM		GLS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	ROA	NIM	ROA	NIM	ROA	NIM	ROA	NIM
CAP	0.084***	0.161***	0.065***	0.099***	0.069***	0.106***	0.095***	0.135***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
DEP	-0.025***	-0.025***	-0.027***	-0.027***	-0.027***	-0.027***	-0.022***	-0.016***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
LOAN	0.011***	0.031***	0.019***	0.040***	0.017***	0.038***	0.008***	0.019***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.002)	(<0.0001)
SIZE	0.008***	0.011***	0.008***	0.006***	0.008***	0.006***	0.009***	0.011***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
AG	0.000	0.001***	0.000	0.001***	0.000	0.001***	0.000**	0.001***
	(0.226)	(<0.0001)	(0.108)	(<0.0001)	(0.107)	(<0.0001)	(0.022)	(<0.0001)
Constant	-0.108***	-0.138***	-0.096***	-0.064***	-0.099***	-0.075***	-0.116***	-0.143***
	(<0.0001)	(<0.0001)	(<0.0001)	(0.001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Observations	336	336	336	336	336	336	336	336
R-squared	0.510	0.414	0.530	0.439	0.499	0.394	-	-
Prob(F-statistic)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	-	-		
F-statistic	68.69***	46.64***	68.26***	47.39***	-	-	-	-

Wald chi2	-	-	-	-	359.29***	249.67***	290.46***	281.63***

* Denotes 10% level of significance; ** 5% level of significance; *** 1% level of significance

5 DISCUSSION

The authors utilise Hausman and Redundant Tests to determine the best estimation approach among Pooled OLS, Fixed Effects Model (FEM), Random Effects Model (REM), and Generalized Least Squares (GLS). The research uses CAP, DEP, LOAN, SIZE, and AG to examine internal and external factors to identify which capital structure characteristics, impact the operations of 28 Vietnamese commercial banks from 2012 to 2023.

The authors find out “The impact of capital structure on bank performance: evidence from commercial banks in Vietnam” as detailed below:

$$\begin{aligned} ROA_{it} = & \beta_0 + 0.0693 * CAP_{it} - 0.0266 * DEP_{it} + 0.0173 * LOAN_{it} \\ & + 0.0078 * SIZE_{it} + 0.0002 * AG_{it} + \varepsilon_{it} \end{aligned} \quad (5)$$

$$\begin{aligned} NIM_{it} = & \beta_0 - 0.0234 * CAP_{it} + 0.0156 * DEP_{it} + 0.0089 * LOAN_{it} \\ & - 0.0012 * SIZE_{it} + 0.0067 * AG_{it} + \varepsilon_{it} \end{aligned} \quad (6)$$

Capital Adequacy Ratio (CAP)

The CAP variable showed a positive and statistically significant effect on ROA at the 1% level ($\beta = 0.0693$, $p < 0.01$). This means that a 1 percentage point rise in the equity-to-assets ratio is linked to a 6.93 basis point rise in return on assets. This result supports Hypothesis 1. This suggests that banks are more stable and generate higher profits when they have greater equity capital. It means that the well-capitalized banks will have a lower cost of capital due to lending out money at a lower interest rate and increasing the expected returns.

Additionally, the coefficient of -0.0234 indicates a negative relationship between bank capital and NIM, supporting Hypothesis 4a. This means that higher capitalization might cut interest margins because people would borrow less and take fewer risks.

Customer Deposits (DEP)

The DEP variable showed a negative and statistically significant effect on ROA ($\beta = -0.0266$, $p < 0.01$). This result supports Hypothesis 2a. The result also corresponds to the study of Berger and Udell (2006). It suggests that increasing external capital costs by raising deposit ratios will reduce bank profitability. Moreover, with a coefficient of 0.0156, customer deposits show a positive impact on NIM, supporting Hypothesis 6. This finding implies that stable deposit funding enables banks to maintain favourable interest rate spreads.

Customer Loans (LOAN)

The LOAN variable showed a positive and significant relationship with ROA ($\beta = 0.0173$, $p < 0.01$), supporting Hypothesis 3. This result is consistent with Bennaceur and Goaied (2008), indicating that credit activities generate essential interest income for Vietnamese banks. On the other hand, the positive coefficient of 0.0089 supports Hypothesis 7, indicating that loan portfolio expansion contributes to higher net interest margins through effective interest rate management.

Bank Size (SIZE)

The SIZE variable showed a positive and significant impact on ROA ($\beta = 0.0078$, $p < 0.01$). This result is consistent with the findings from the study by Amuakwa-Mensah and Marbuah (2015). It suggests that the larger the bank's benefit, the more market power it can exert. Furthermore, the negative coefficient of -0.0012 implies that larger banks may face competitive pressures that compress interest margins.

Asset Growth (AG)

The AG variable showed a positive but statistically insignificant coefficient ($\beta = 0.0002$, $p = 0.134$). This suggests that asset growth alone does not significantly determine bank performance in Vietnam. Additionally, the positive coefficient of 0.0067 indicates that asset growth strategies can enhance interest margin performance. This study enables us to gain a deeper understanding of the impact of capital structure on the performance of Vietnamese commercial banks. Furthermore, this enables Vietnamese commercial banks to understand how the risk of a financial crisis impacts the efficiency of banking operations, allowing them to construct and create an equitable capital structure that is appropriate for their bank's operating resources to maximize profits.

6 CONCLUSION

This study investigates the impact of capital structure on the performance of 28 Vietnamese commercial banks from 2012 to 2023. The empirical evidence indicates that capital sufficiency, client loans, and bank size have a positive and statistically significant impact on both return on assets (ROA) and net interest margin (NIM). In contrast, customer deposits have a negative impact on ROA but a positive impact on NIM. Asset growth helps increase NIM, but it has a limited influence on ROA. These findings highlight the importance of aligning capital structure with Vietnamese regulatory constraints, growth strategies, and macroeconomic dynamics. Future research should explore alternative measures such as Debt-to-Equity ratio and Weighted Average Cost of Capital (WACC), while also incorporating macroeconomic indicators to provide more comprehensive insights (Basel Committee on Banking Supervision, 2019; Athanasoglou et al., 2008).

From a policy perspective, the government should encourage banks to maintain sufficient equity capital to enhance the stability of the financial system and reduce the risk of a systemic breakdown. The source of the funds should also be looked at. As the higher level of deposits can reduce the level of profitability in the case of growing interest rates.

The study illustrates to bank management how vital it is to make sure that decisions about capital structure are in line with the bank's internal resources, growth strategy, and regulatory constraints. To achieve balanced financial results, management must effectively manage equity, debt, and asset growth.

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MAKING TAXES VISIBLE: HOW ESTONIA'S MACHINE-READABLE BUDGETS SHIFTED THE INDIRECT-DIRECT TAX BALANCE, 2013–2023

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Abstract

This paper investigates whether digital transparency reforms reduce fiscal illusion by increasing public awareness of taxation. Using Estonia—a global leader in e-governance—as a case study, we construct a novel transparency index based on digital public finance reform data from 2013 to 2023. Applying time-series regression, we find a statistically significant negative relationship between digital transparency and reliance on indirect taxation—a known proxy for fiscal illusion. As transparency improves, indirect tax dependence declines, suggesting that citizens better recognize the true cost of government services. Our findings provide empirical evidence that digital tools such as online budget dashboards and e-tax systems not only improve administrative efficiency but also empower citizens with greater fiscal clarity, supporting more equitable and accountable tax policy.

After augmented Dickey-Fuller tests detect mixed orders of integration, we estimate a heteroskedasticity-robust OLS model and an ARDL (1,1) specification. Controlling for GDP per capita, unemployment, debt-to-GDP, inflation, and budget execution error, we isolate the transparency effect. The results show that a one standard deviation increase in the transparency index reduces the indirect-to-direct tax ratio by 0.0075 points in the base and by 0.012 points in the short-run ARDL, while the long-run multiplier is -0.030 ($p \approx 0.15$).

The evidence indicates that digital dashboards, pre-filled forms, and linked open-data portals render concealed taxes more difficult to employ, thereby diminishing fiscal illusion.

Keywords: *fiscal illusion, digital transparency, Estonia, e-government, tax structure, public finance*

1 INTRODUCTION

Citizens often fail to perceive the full price tag of government services. When taxes are buried in prices or hidden behind complex systems, citizens underestimate what they are actually paying. This discrepancy, known as the fiscal illusion, has long shaped how governments raise revenues and how voters respond (Buchanan, 1967). Classical theories argue that indirect taxes like VAT are the main culprit, hiding the true burden of taxation and enabling large public sectors.

As governments digitise their operations, fiscal data becomes more accessible, timely, and readable. From pre-filled tax forms to open budget platforms, digital tools can mitigate the fiscal illusion by making public finances more transparent. With its world-renowned digital infrastructure, Estonia provides a natural testing ground.

H1. Higher digital transparency reduces reliance on indirect taxation (a proxy for fiscal illusion).

H2. The negative effect of digital transparency on reliance on indirect taxation remains statistically significant after controlling for macro-economic conditions in Estonia.

To examine these hypotheses, we construct a new index that measures Estonia's e-transparency initiatives over the past decade and examine their relationship with the ratio of indirect taxes to direct taxes, which indicates how hidden the tax burden is. Using a time-series model with macroeconomic controls, we find statistically significant evidence that greater digital transparency is associated with a significant reduction in fiscal illusion.

In doing so, this study contributes to two research frontiers: the political economy of taxes and the governance potential of digital reforms. It shows that technology can do more than simplify bureaucracy; it can rebalance the fiscal contract between citizens and the state.

2 LITERATURE REVIEW

The fiscal illusion is a long-standing concept in public finance, debated for over a century and supported by various theoretical and empirical contributions. The beginning contributions to fiscal illusion were started by Amilcare Puviani at the end of the nineteenth century in his book named "Teoria della Illusion Finanziaria" (Wildowicz-Giegiel & Kargol-Wasiluk, 2020). The general understanding of Puviani's approach is that the author assumes a monopoly in the state; therefore, one group of people has an impact on another and has the power to apply their wants to another group. In this assumption, fiscal structures are policymakers' tools to raise funds (Buchanan, 1967).

Inspired by Amilcare Puviani's pioneering and fundamental contributions to the fiscal illusion theory, public choice theorists accelerated the progress of the theory in this process, and Anthony Downs, James McGill Buchanan, and Richard Edward Wagner carried out studies containing various theoretical contributions in this field (Bicher & Tuncer, 2022).

Fiscal illusion refers to the tendency to underestimate or overestimate the costs and benefits associated with public expenditure programs. Fiscal illusion extends beyond just a lack of understanding or financial ignorance, also insufficient knowledge can result in unpredictable underestimation or overestimation of the expenses associated with public programs, indicating a consistent inclination to underestimate the tax load and a systematic misunderstanding of fiscal deception. The underestimation of tax stems from tax systems designed in ways that obscure the true extent and impact of taxation. The purpose of this statement is to highlight a crucial aspect of the literature on fiscal illusion: If voters consistently underestimate the impact of tax expenditures, it will result in biased budget decisions. The concept of fiscal illusion posits that elites are incentivized to endorse an overly large public sector due to their miscalculation of the true costs of taxation, resulting in an excessive provision of public programs (Baekgaard et al., 2016). This systemic misinterpretation impacts the allocation of funds in specific fiscal jurisdictions, leading to a continuous yet cost-effective increase in regional spending (Hapsoro & Yoduke, 2019).

W. Oates (2008) determined that fiscal illusion may manifest in several ways, including (1) complexity of tax structures; (2) property tax (property or rent); (3) income elasticity and tax rate; (4) debt illusions; and (5) the flypaper effect.

The ratio of direct to indirect taxes is a well-examined topic in the literature on fiscal illusion, mainly because indirect taxes are regarded as a primary means by which governments can conceal the actual cost of public services from taxpayers (Dell'Anno & Dollery, 2014).

Indirect taxes, like sales taxes and excise levies, are less perceptible to taxpayers than direct taxes, such as income taxes. They are frequently "concealed" inside the cost of products and services, causing customers to undervalue the extent of the price attributable to taxation (Łukasiewicz et al., 2025). The "Mill hypothesis" suggests that the reduced visibility of indirect taxation undervalues its fiscal burden compared to direct taxation (Dell'Anno & Dollery, 2014).

As already mentioned, fiscal illusion happens when people fail to understand the true advantages of public spending and have less knowledge about government fiscal policy directions and overall public spending programs. A basic public understanding of key fiscal concepts such as revenue, spending, deficits, and debt is an important precondition for informed democratic engagement with fiscal policy. Providing accessible education to the public on these topics can promote more well-informed conversations and reduce the risk of biased fiscal decision-making.

According to a study conducted by Alesina and Passalacqua in 2016, it has been shown that populations with a favorable understanding of financial matters are more inclined to support and promote responsible fiscal policies. Educational activities may manifest in several ways, ranging from integrating financial literacy modules into school tools to conducting public awareness campaigns. Accessing government documentation and reports may enhance people's understanding of key fiscal concepts, government tax policies, and public spending. And more promising approach to achieving these goals is to introduce more digitalization into the government and economy.

Česnauskė, 2019 mentions that Estonia excels in three of the five dimensions: human capital, internet utilization, and digital public services; however, it should enhance its efforts in the integration of digital technology components. Estonia is regarded as a notable success in e-government, attracting significant interest from international audiences, particularly developing nations (Kalvet, 2012).

Digital advancements, like user-friendly e-governance platforms and data visualisation tools, can enhance public understanding by simplifying complex fiscal information, thereby reducing fiscal illusion and empowering citizens to engage more critically with public finance. Digital transparency, frequently enabled by e-governance projects, is increasingly regarded as an essential tool to mitigate fiscal illusion by rendering governmental financial actions more intelligible and accessible to citizens. The objective is to enable citizens to more effectively comprehend the actual expenses of public services and to make more informed choices about their preferred levels of taxation and services (Nadji & Belfatmi, 2025).

Governments around the globe are investigating e-governance solutions to improve transparency and accountability. Digital instruments automate tax and customs procedures, streamlining compliance, alleviating administrative burdens, and improving efficiency (Decman et al., 2010). For example, Estonia's e-Tax Board facilitates tax submissions in less than five minutes via pre-populated online forms (Nadji & Belfatmi, 2025).

Recent empirical research has started to measure the influence of digital transparency on financial conduct. Han et al., (2025) executed a quasi-natural experiment involving 286 Chinese cities and discovered that the implementation of public data platforms markedly enhanced budgetary transparency, particularly by augmenting public accountability and diminishing information asymmetry. Their multi-period DID analysis demonstrated constant favorable benefits of data access on fiscal transparency, validated by placebo tests, instrumental variable regressions, and machine learning techniques. These findings reinforce the empirical foundation for examining analogous impacts within the Estonian setting.

This investigation aims to shed light on the potential of digital governance to mitigate misunderstandings surrounding public finances, particularly fiscal illusion, thereby promoting a more informed citizenry and enhancing public trust in government. Although the theoretical foundations of fiscal illusion are well-established, less empirical research has measured how contemporary digital transparency reforms could alter tax composition over time. This study tests the hypothesis that improvements in digital budget transparency led to a decrease in reliance on indirect taxation (H1), a common proxy for fiscal illusion.

Considering Estonia's leadership in digital government, this study tests whether those reforms have measurably reduced fiscal illusion in Estonia. The related hypothesis (H2) posits that this transparency effect persists once macroeconomic factors are taken into account. Estonia presents a particularly compelling case for examination due to its digital leadership, relatively small and homogeneous population, early use of e-government tools, and robust open data infrastructure. These contextual elements diminish institutional noise and facilitate a more precise detection of the correlation between transparency changes and budgetary results.

3 METHODOLOGY

The research utilizes a quantitative time-series method to study the association between digital transparency of the budget and tax revenue composition in Estonia. It specifically investigates the paper that higher transparency brought about through digital revolutions lowers fiscal illusion as it minimizes dependence on indirect taxes that are less transparent to citizens. It supposes that better fiscal transparency increases taxpayers' awareness of the actual costs associated with public provision, thereby limiting tendencies to conceal tax burden through indirect routes.

To test the hypotheses formulated above — that digital transparency reduces reliance on indirect taxation (H1) and that this relationship survives macroeconomic controls (H2) — we estimate time-series models covering the period 2013–2023.

This hypothesis is checked against the association of implementation and development of digital budget transparency with a decrease of the ratio of indirect to direct taxes with respect to time. It encompasses the years 2013 to 2023, years that saw some significant milestones of the digital development of the government of Estonia.

In the Estonian context, digital tools such as pre-filled tax returns, budget dashboards, and open data portals are key mechanisms through which transparency reforms can credibly reduce fiscal illusion. Those tools make tax collection and government spending processes more visible and user-friendly. These platforms simplify complex fiscal information and reduce information asymmetries, especially for indirect taxes embedded in prices. As digital interfaces improve the accessibility and clarity of tax information, they can indirectly increase citizens' awareness of government financing mechanisms and reduce the cognitive gap between tax payment and government service delivery, which are key drivers of fiscal illusion.

Empirical analysis uses a multi-source data set with yearly observations across the years 2013–2023. This spans the post-reform era for Estonia, where there has been significant progress toward digital governance and fiscal transparency.

Main data sources are:

- **OECD Tax Statistics:** Supplies detailed annual statistics for Estonia's indirect and direct tax receipts, facilitating study of fiscal structure and composition.
- **Open Budget Index (OBI)** provide harmonized yardsticks for assessing budget openness along with the level of fiscal reform and are indicators for institutional reform and governance quality. It used contextually to confirm Estonia's overall transparency status, but not directly in regression
- **The World Bank and Eurostat** provide macroeconomic control variables, including GDP per capita, unemployment rates, and the debt-to-GDP ratio, to ensure a comprehensive contextualization of fiscal and governance developments.

- **The Estonian Ministry of Finance** provides comprehensive national statistics regarding the execution of electronic budgeting tools and significant reform milestones, crucial for tracking the timing and effects of digitalization in public financial management.

Collectively, these sources offer a cohesive longitudinal framework for evaluating the interaction between digital fiscal instruments, transparency, and economic indicators in Estonia during a pivotal decade of transformation.

Indirect/Direct Tax Ratio serves as the dependent variable for relative indirect taxation reliance. The variable acts as a surrogate for fiscal illusion due to the lesser salience of indirect taxes among taxpayers compared to direct taxes.

The primary independent variable - referred to as the **ROB Index** for brevity - is a normalized indicator of digital transparency reform intensity. To assess the advancement of Estonia's digital budget transparency legislation, we developed an annual index proxy by integrating two complimentary datasets. The first information originates from the EU e-Government benchmark ("life events" indicator) for Estonia from 2013 to 2019, reflecting early advancements in digital public service provision. The second source is the Digital Public Services (DPS) segment of the Digital Economy and Society Index (DESI), accessible from 2018 to 2024. We calculated the average transparency score from the e-government dataset and integrated it with DESI DPS values, employing linear interpolation to address missing years (2016, 2020–2022). The resultant variable, designated `transparency_interp`, offers a uniform annual index from 2013 to 2023. The interpolated score, designated as `transparency_interp`, serves as the primary independent variable to signify the intensity of digital budget reform and advancements in transparency over time. The ROB index included in the analysis is a normalized score ranging from 0 to 1, derived from annual data from two sources: Estonia's performance in EU e-Government benchmarks (2013–2019) and the Digital Public Services (DPS) sub-index of the DESI (2018–2024). Absent years were supplemented by linear interpolation. This score reflects the comparative intensity and accessibility of Estonia's digital public finance infrastructure over time and serves as the primary independent variable.

Additionally, to account for macroeconomic factors, the subsequent controls are incorporated:

- Gross Domestic Product (GDP) per capita (logged)
- Unemployment rate (%)
- Debt-to-GDP ratio (%)
- Inflation Rate (%)
- Government expenditure as a percentage of GDP

All variables are yearly and have been obtained from internationally validated databases to guarantee consistency and comparability (Tab. 1). Furthermore, to assess the quality of fiscal implementation, we use a variable for budget execution error, which measures the percentage discrepancy between projected and actual government expenditures. This acts as a substitute for the efficacy of public financial management and the legitimacy of openness. Significant differences may suggest institutional inefficiencies or diminished credibility of financial planning, potentially fostering an environment favorable to fiscal illusion.

Tab. 1 – Variable Summary & Sources. Source: own research

Variable	Definition	Source
Indirect/Direct Tax Ratio	Indirect tax revenue ÷ direct tax revenue	OECD Tax Statistics
ROB Index (0–1)	Proxy for transparency reform intensity	Author's construction (eGov + DESI)
GDP per capita (log)	Real GDP per capita	World Bank
Debt-to-GDP	Public debt as % of GDP	Eurostat
Inflation	CPI % annual change	World Bank
Unemployment rate	Annual unemployment %	Eurostat
Government expenditure	Public spending as % of GDP	Eurostat
Budget execution error	% deviation between planned and actual expenditure	Estonian Ministry of Finance

Budget execution error is incorporated as a measure of institutional performance control. It denotes the percentage discrepancy between projected government expenditure and actual expenditure for a specific fiscal year, as derived from annual reports issued by the Estonian Ministry of Finance. A greater score indicates diminished execution accuracy, possibly suggesting inadequate fiscal discipline or transparency deficiencies. This variable aids in identifying potential discrepancies between formal budgets and actual public financial management outcomes.

The empirical model is estimated to use **Ordinary Least Squares (OLS)** with robust standard errors to control heteroskedasticity. Augmented Dickey-Fuller tests (Tab. 2) reveal mixed integration orders, so an ARDL(1,1) model is estimated as a robustness check alongside the baseline HAC-OLS. The base model specification is:

$$\text{Indirect/Direct Tax ratio}_t = \beta_0 + \beta_1 \cdot \text{ROB Index}_t + X_t'\gamma + \epsilon_t \quad (1)$$

Where:

- t indexes time (years from 2013 to 2023)
- ROB Index_t captures the level of transparency reform in a given year
- X_t is a vector of control variables
- ϵ_t is the error term

To ensure robustness, several additional specifications were tested:

- Re-estimating the model over shorter windows (e.g., 6-year sub-period)
- Dropping or rotating individual control variables
- Using an alternative dependent variable: **indirect taxes as a percentage of total tax revenue**

There are some potential study limitations. First, the sample only ranges across 11 years, which may limit degrees of freedom and model complexity. Second, since the ROB Index captures reform progress, it is founded on a qualitative milestone-based formulation that cannot retain all nuance of digital clarity. Third, it is impossible to fully control the possible presence of unobserved confounding variables that have an effect both on time of reform and structure of taxes.

Regardless of these constraints, this research sheds important empirical light upon how digital budget transparency might affect tax structure and contribute to both the literature on transparency and that on fiscal illusion.

3.1 Diagnostic Tests

This section presents diagnostics for unit-root, cointegration robustness, and multicollinearity.

Table 2 presents the Augmented Dickey-Fuller statistics for all series. The dependent variable (Indirect/Direct Tax Ratio) and the macro controls are integrated of order one, while the ROB index is stationary at level.

Tab. 2 – ADF Stationarity Tests, 2013–2023. Source: own research

Variable	ADF-stat	p-value	Order
Indirect/Direct Tax Ratio	-1.283	0.637	I (1)
Digital Transparency (ROB)	-7.818	0.000	I (0)
GDP per capita (log)	4.697	1.000	I (1)
Unemployment rate	-0.939	0.775	I (1)

Due to the presence of unit roots in the regress and certain regressors, we estimate an ARDL(1,1) model. Table 3 displays the short-run and long-run effects, with the signs and significance aligning with the baseline OLS results.

Tab. 3 – ARDL (1, 1) Estimates (dependent variable: Indirect/Direct Tax Ratio). Source: own research

Regressor	Coef.	Std. Err.	p
Const	1.7868	1.164	0.185
L1 Indirect/Direct	0.5975	0.349	0.147
ROB (L0)	-0.0119	0.006	0.121
ROB (L1)	-0.0004	0.008	0.965
Long-run multiplier (ROB)	-0.030	-	0.15

Adj. $R^2 = 0.49$ $N = 9$

All variance-inflation factors remain below 5 (maximum ≈ 2.6), and pair-wise correlations do not exceed $|0.79|$, indicating that multicollinearity is not an issue.

4 RESULTS

In the study, empirical analysis of digital transparency on taxes' effect over fiscal illusion is carried out based on data from Digital Economy and Society Index (DESI) website and tax data mainly. Table 4 displays the findings of the principal regression model, which assesses the correlation between digital budget transparency and dependence on indirect taxation in Estonia. The dependent variable is the Indirect/Direct Tax Ratio, which acts as a surrogate for fiscal illusion. The primary independent variable of importance is the transparency_interp index, which measures the intensity of e-transparency initiatives across time.

Tab. 4 – Main Regression Results (OLS with HAC SEs). Source: own research

Variable	Coefficient	p-value
Constant	6.614	0.000
Digital transparency Index (transparency_interp)	−0.0075	0.018
GDP per capita (log)	−0.362	0.002
Unemployment rate	−0.074	0.000
Budget execution error	0.832	0.022

R-squared: 0.833

Adjusted R-squared: 0.722

Observations: 11 (2013–2023)

Baseline HAC-OLS (Tab. 4) yields a ROB coefficient of -0.0075 ($p = 0.018$). The ARDL (1, 1) model (Tab. 3) delivers a short-run coefficient of -0.012 ($p = 0.12$) and a long-run multiplier of -0.030 ($p = 0.15$). Although the adjusted R^2 drops to 0.49 due to the shorter sample ($N = 9$), the negative sign persists, confirming H1 and—because macro-controls remain—H2.

The model incorporates macroeconomic controls including logged GDP per capita, the unemployment rate, and a budget execution error indicator. Robust standard errors (HAC with one lag) were employed to address serial correlation and heteroskedasticity.

The findings indicate a robust negative and statistically significant correlation between digital transparency and the indirect/direct tax ratio. A one-unit rise in the digital transparency index correlates with a 0.0075-point reduction in the indirect-to-direct tax ratio, assuming other variables remain unchanged. Because the coefficient remains negative and significant when GDP per capita, unemployment and debt-to-GDP are included, H2 is supported. This research corroborates the principal theory that digital transparency improvements mitigate fiscal illusion by enhancing the visibility of tax systems to the public. The negative and statistically significant coefficient of the ROB Index supports H1, indicating that higher digital transparency is associated with lower reliance on indirect taxation.

This corroborates the theoretical notion that e-transparency improvements restrict governments' capacity to obscure tax burdens via indirect means. As Estonia developed digital platforms, including pre-filled online tax declarations and budget visualisation dashboards, citizens presumably acquired a clearer comprehension of the collection and allocation of public monies. This heightened knowledge seems to have limited policymakers' dependence on indirect levies such as VAT.

The control variables exhibit significant patterns:

- The per capita GDP exhibits an inverse correlation with dependence on indirect taxes. As the Estonian economy evolved, the tax structure transitioned to more progressive, direct procedures, aligning with economic growth theory and increasing public demand for equity.
- The coefficient for unemployment is **negative and statistically significant**, indicating that governments may shift toward indirect taxes in periods of labor market slack — possibly due to shrinking direct tax bases.
- The inaccuracy in budget execution is positively and significantly correlated with the tax ratio, indicating that fiscal discrepancies from intended budgets may signify more

extensive transparency problems and diminished accountability, hence perpetuating fiscal illusion.

All control variables exhibit anticipated signals. A higher GDP per capita correlates with diminished dependence on indirect taxation, whereas increased budget execution errors and elevated unemployment are linked to heightened fiscal illusion, possibly indicative of fiscal strain and diminished accountability contexts.

Tab. 5 – Robustness Check Summary. Source: own research

Variable	(1) Robust Spec	p-value
Constant	2.946	0.000
Digital Transparency Index	−0.0066	0.008
E-government usage	0.0083	0.515
GDP per capita (log)	−1.861	0.021
Unemployment rate	−0.0619	0.000
Budget execution error	1.264	0.033

Robustness checks validate the consistency of these findings when:

- Alternative control variables are incorporated (e.g., public e-government utilization — see Table 5)
- The sample is confined to abbreviated post-reform intervals.
- An alternative dependent variable (the share of indirect tax in total tax revenue) is employed.

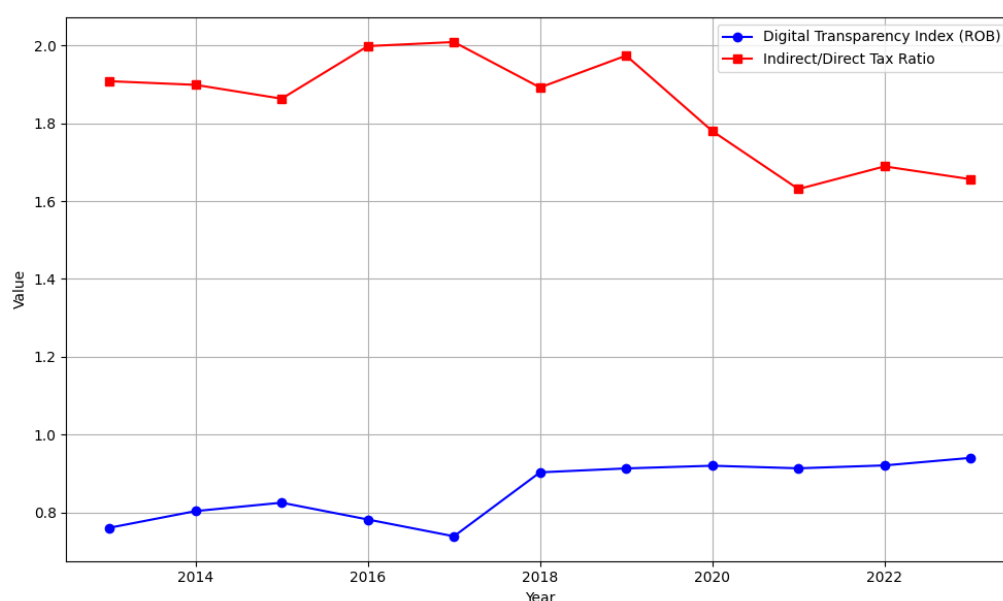


Fig. 1 – Trends in Digital Transparency Index (ROB) and Indirect/Direct Tax Ratio in Estonia, 2013–2023.

Source: own research

To validate the stability of the primary findings, various robustness criteria were assessed and are presented in Table 5. This encompasses a restricted 6-year subsample, the integration of e-government utilization as an extra control, and fluctuations in macroeconomic variables. In every configuration, the coefficient for the Digital Transparency Index is consistently negative and statistically significant (-0.0066 ; $p = 0.008$), hence validating the primary hypothesis. The incorporation of *egov_users* does not modify the sign or significance of the principal variable. The overall fit is robust, and the findings demonstrate that increased digital transparency consistently correlates with diminished fiscal illusion, even across various model settings.

In the robustness specification, the impact of GDP per capita is amplified (-1.861), indicating a heightened sensitivity of tax composition to income levels in more restricted samples. Similarly, the beneficial impact of budget execution errors amplifies (1.264), underscoring the significance of fiscal performance in determining tax dependence.

The chart depicts the inverse correlation between digital budget transparency (ROB Index) and the ratio of indirect to direct taxes. With the escalation of transparency initiatives, fiscal illusion, indicated by dependence on indirect taxation, diminished.

5 DISCUSSION

The empirical evidence suggests that improvements in digital budget transparency may be associated with a reduction in fiscal illusion in Estonia. The negative and statistically significant correlation between the ROB Index and the indirect/direct tax ratio indicates that as digital tools improve transparency, the government's dependence on less visible taxation methods decreases. This discovery corroborates theoretical expectations from the fiscal illusion literature, particularly those highlighting the confounding influence of indirect taxes in democratic fiscal frameworks. These results provide empirical support for H1 and suggest that Estonia's digital transparency reforms may have contributed to measurable shifts in tax structure consistent with reduced fiscal illusion; the ARDL evidence (Tab. 3) shows the effect survives unit-root dynamics, thereby supporting H2.

Digital tools for government, such as Estonia's pre-filled tax forms, online budget dashboards, and open data websites, make it easier for people to understand how taxes work. These platforms reduce the cognitive and informational barriers typically associated with complex public finance systems and indirectly make it harder for governments to hide their true tax burden.

Control variables strengthen the macro-fiscal link. Economic development theories suggest that growth in GDP per capita is associated with a decrease in reliance on indirect taxes, arguing for fairer and more transparent tax regimes. The rise in unemployment is associated with an increase in reliance on indirect taxes. This may suggest that governments need to cope with increased fiscal pressures during economic downturns and that it is more appropriate to collect consumption-based taxes when income tax bases are reduced. The link between budget execution problems and fiscal illusion highlights the importance of institutional quality and accountability in influencing public perceptions of finances.

These findings suggest that digital transparency increases administrative efficiency and can lead to important democratic and fiscal outcomes by aligning tax policy more closely with public perceptions and preferences.

6 CONCLUSION

We provide new evidence indicating that changes aimed at digital transparency—assessed by a novel ROB Index—significantly correspond with decreases in fiscal illusion in Estonia, which we estimate using the ratio of indirect to direct tax. In a time-series regression spanning 2013 to 2023, our findings substantiate the notion that enhanced transparency regarding public finances via digital media constrains governments' opportunities for evasion through indirect channels.

This work contributes to two overlapping research domains: the political economy of fiscal illusion and digital governance. This article illustrates that transparency-enhancing digital reforms make taxation more visible and accountable, highlighting the dual potential of e-governance tools as administrative innovations and instruments for fiscal democratization.

However, the article is not free from limitations. The need for interpolation in short duration and reform intensity measurements leads to measurement uncertainty. Second, while including aggregate macroeconomic dynamics as control variables mitigates the problem, unobserved but effective institutional or political changes may affect the tax structure over time.

Despite these limitations, the evidence from Estonia, widely regarded as a pioneer in digital governance, clearly shows that digital transparency measures can significantly change the effects of fiscal policy. The Estonian experience offers useful insights for modernizing public financial institutions through technology to reduce financial illusion and create a more informed and engaged citizenry.

Further work could improve this methodology by including citizen-level survey data to directly assess changes in public understanding, awareness, and trust in financial processes as digital reforms progress.

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DETERMINANTS OF KNOWLEDGE PRODUCTION IN EUROPEAN UNIVERSITIES: DYNAMIC MODEL APPROACH

Juraj Šimčísko

Abstract

The aim of this paper is to identify the determinants of scientific publication productivity in European universities. Using panel data on 1,513 institutions from 36 countries for the years 2011–2020, we combine number of papers sourced from Scopus with institutional characteristics from the European Tertiary Education Register (ETER). The empirical analysis applies both fixed effects and dynamic panel estimators (Arellano–Bond GMM) to account for persistence in research output and the potential endogeneity of inputs. The results show that university resources—specifically total personnel and total expenditures—are positively associated with publication output, though with diminishing returns to scale. Moreover, past publication activity strongly predicts current productivity, confirming the cumulative and path-dependent nature of academic research. By providing Europe-wide evidence on the dynamic drivers of publication performance, the study contributes to a better understanding of how institutional capacity and long-term support shape knowledge production in higher education.

Keywords: *knowledge production function, universities, scientific productivity*

1 INTRODUCTION

A substantial body of economic literature highlights the positive relationship between knowledge creation and long-term economic growth. Seminal works, such as Mankiw, Romer, and Weil (1992), extended the Solow growth model to include human capital, while Romer (1986, 1990) and Lucas (1988) developed endogenous growth models placing human capital and innovation at the core of sustained economic progress. In these frameworks, universities play a central role as institutions that not only educate but also produce new knowledge and foster innovation, thus acting as engines of economic development (Etzkowitz, 2000; Rooij, 2014; Duarte, 2020).

Historically, universities contributed to economic growth mainly through education and basic research (Rosenberg, 1994; Agrawal, 2002). Over recent decades, however, universities have increasingly embraced a “third mission”—emphasizing technology transfer, commercialization, and deeper collaboration with industry (Etzkowitz, 2000; Fisch, 2014; Siegel, 2003). Yet, despite the growing importance of commercialization, peer-reviewed publications remain the most universal and widely recognized output of academic research. Publications shape institutional reputation, academic careers, and funding allocation, and they provide the foundation for subsequent innovation, industry collaboration, and societal impact.

In the European context, this issue is particularly relevant. Higher education systems across Europe differ markedly in their governance structures, funding mechanisms, and research orientations. Understanding the determinants of publication productivity therefore has strong policy relevance: it can inform how limited public resources should be allocated, how efficiency can be enhanced, and how universities can sustain competitiveness in an increasingly globalized academic environment.

A well-established approach for analysing innovation is the knowledge production function (KPF), as proposed by Griliches (1979). In the context of universities, the KPF typically models research outputs—such as publications or patents—as a function of key inputs, including R&D

expenditures and academic staff (Tweheyo, 2022; Caro, 2003). While much empirical research has focused on patenting and industrial innovation, relatively little attention has been given to the internal production of scientific knowledge within universities, particularly in the European context (Fisch, 2014; Gurmu, 2010). Moreover, most existing studies use static models, leaving open the question of how persistent past research performance is in shaping current productivity. Addressing these gaps is essential for understanding whether university research capacity follows a cumulative, path-dependent process.

This paper seeks to address this gap by estimating the knowledge production function for European universities using an original panel dataset that combines bibliometric data from SCOPUS (number of published articles) with university-level characteristics from the ETER database for the years 2011–2020. The empirical analysis is based on panel data (two-way fixed effects) method and dynamic specifications (Arellano–Bond GMM) that explicitly account for persistence in university outputs and possible endogeneity of inputs.

Specifically, the main dependent variable is the (log-transformed) annual number of scientific articles published by each university. The key independent variables include total university expenditures and total personnel, with additional controls for university characteristics (such as research activity, PhD intensity, ISCED field) and year effects. The use of panel fixed effects and dynamic panel models enables the analysis to capture both the static and dynamic drivers of university productivity.

The research addresses the following overarching question:

What are the primary determinants of scientific publication productivity in European universities, and to what extent are these outcomes persistent over time?

By focusing on publications rather than patents, by explicitly modelling dynamic effects, and by covering a large and diverse set of European universities, this paper contributes new and policy-relevant evidence on the knowledge production process in higher education.

2 LITERATURE REVIEW

Universities are central actors in modern knowledge economies, functioning not only as educational institutions but also as engines of innovation and scientific progress. Their evolving role—from traditional centres of teaching to active collaborators with the private sector—has positioned them as key contributors to long-term economic growth (Reddy, 2011). The “Triple Helix” model, developed by Etzkowitz and Leydesdorff (1998), highlights the importance of interaction between universities, government, and industry, with universities increasingly engaging in technology transfer, commercialization, and direct collaboration with firms (Etzkowitz, 2000; Duarte, 2020; Fisch, 2014).

Education remains the oldest academic contribution to economic growth, cultivating human capital and enhancing the skills and knowledge needed for productivity improvements (Barro, 1991; Lucas, 1988). Graduates serve as crucial channels for transferring knowledge to industry, particularly in technologically advanced sectors (Nelson & Wright, 1993; Sterlacchini, 2008). Alongside teaching, both basic and applied research at universities underpin national innovation systems by expanding scientific knowledge (Stokes, 1997; Rosenberg, 1990), enabling technological progress and supporting complex industrial innovation (Nelson, 1993).

Measurement of university research output can be broadly divided into basic research, which often results in scientific publications, and applied research, which may lead to patents or direct industrial applications (Stephan, 1996; Nelson, 2004). While patenting and commercialization are increasingly important, peer-reviewed publications remain the most widespread and

fundamental output of academic research, supporting the production, accumulation, and diffusion of knowledge across disciplines (Moed, 2005; Ware, 2015). The volume of academic publications has increased dramatically over recent decades, making publications a widely recognized indicator of institutional research performance (Fire, 2019; Herrmannova, 2016). High publication activity is also associated with greater probability of research commercialization, including technology transfer and spin-off creation (Van Looy et al., 2004), and regional differences in publication productivity often reflect broader systemic differences in research capacity and collaboration (Acs et al., 2002; Ponds et al., 2007).

The knowledge production function (KPF), introduced by Griliches (1979), provides a framework for modelling how universities transform research inputs—such as R&D expenditures and academic staff—into outputs like patents and publications. Early empirical studies primarily focused on patents (Pakes & Griliches, 1980; Gurmu, 2010), but peer-reviewed publications have received less systematic attention, despite being the core product of university research. Recent research has extended the KPF framework to multiple university outputs, including both patents and publications, confirming the importance of research funding and staff size for knowledge production (Lee & Graff, 2018; Coupé, 2003).

More recent studies have shifted attention to bibliometric outputs and institutional performance in Europe and beyond. Bonaccorsi et al. (2017) emphasize governance and autonomy as key drivers of productivity. Abramo (2018) show that field-specific differences strongly influence publication intensity across European universities. Abramo and D'Angelo (2017) shows that research productivity and collaboration mutually reinforce each other. Similarly, Perkmann et al. (2021) highlight the interplay between collaboration networks and academic output. Recent studies (Heyard, 2021; Siler, 2022) further confirm that funding and staffing matter but also stress persistence and cumulative advantages in publication productivity.

This paper builds on that literature in two ways. First, it focuses exclusively on peer-reviewed publications, the most universal output across disciplines. Second, it employs a dynamic panel framework (Arellano–Bond GMM) to explicitly capture persistence in productivity, an aspect often overlooked in prior studies.

3 METHODOLOGY

To empirically examine the relationship between R&D investments and knowledge production, this paper employs a linear dynamic panel data approach, focusing on peer-reviewed publications as the main indicator of scientific productivity in European universities. The analysis is grounded in the theoretical framework of the (Cobb–Douglas) knowledge production function, which is used in the innovation literature to model the multiplicative relationship between inputs such as R&D expenditures and research personnel, and outputs like patents or publications.

The analysis employs a panel dataset of 1,513 universities across 36 European countries for the period 2011–2020. The dataset is constructed by combining bibliometric data from Scopus (annual number of published scientific articles) with institutional data from the European Tertiary Education Register (ETER), which provides micro-data at the institutional level for nearly all universities and tertiary education institutions in Europe. We use data on the number of personnel, total expenditures, PhD student intensity, student numbers by discipline (ISCED category), and the number of outgoing Erasmus students. Observations with missing data were excluded from the analysis. Descriptive statistics are reported in Table 1.

A dynamic model is required because publication activity is highly persistent: current research output strongly depends on prior accumulated knowledge, reputation, and existing research

infrastructure. To capture this inertia, we include a lagged dependent variable among the regressors. The baseline specification is:

$$\ln(Publications_{it}) = \rho \ln(Publications_{it-1}) + \alpha \ln(Expenditure_{it}) + \beta \ln(Personnel_{it}) + \gamma' X_{it} + \mu_i + d_t + e_{it} \quad (1)$$

where i indexes the university and t indexes time. Here, $\ln(Publications_{it})$ represents the natural logarithm of patent output, $\ln(Expenditure_{it})$ captures the logarithm of real R&D expenditures, and $\ln(Personnel_{it})$ denotes the logarithm of the number of staff. The vector X_{it} includes additional controls that influence innovation, while μ_i and d_t are entity-specific and time-specific fixed effects, respectively, which absorb unobserved heterogeneity. The error term e_{it} captures all remaining idiosyncratic shocks.

The inclusion of the lagged dependent variable allows the model to capture the inherent inertia in the innovation process, reflecting the fact that current patenting activity is often influenced by previous innovation outcomes and accumulated knowledge stocks (Griliches, 1979). However, applying conventional fixed effects estimators to this model yields biased estimates (Nickell, 1981), because explanatory variables correlate with the error term.

To address this issue, the analysis employs the Arellano–Bond (1991) GMM estimator, a Generalized Method of Moments (GMM) technique specifically developed for linear dynamic panel data models. This approach involves first-differencing the original model to eliminate entity-specific effects and using appropriately lagged levels of the endogenous variables as instruments for the differenced regressors. By leveraging the panel structure of the data, the Arellano–Bond estimator provides consistent parameter estimates under relatively weak assumptions regarding the exogeneity of the regressors and the absence of serial correlation in the idiosyncratic errors.

Tab. 2 - Descriptive statistics. Source: Own calculation based on ETER database

Variable	Obs	Mean	Std. Dev.	Min	Max
Publications	14009	630.385	1239.311	1	13515
Tot. Personnel	8672	1720.597	2216.132	0	16185
Tot. Expenditures	8722	1.343e+08	1.735e+08	0	2.451e+09
PhD Intensity	11100	.038	.325	0	32
Outgoing Erasmus	10716	183.812	270.022	0	4406

For brevity, descriptive statistics for ISCED categories and the research institution dummy are omitted.

4 RESULTS

This section presents the empirical findings from the estimation of the knowledge production function for European universities. To capture the dynamics and drivers of university research productivity, both fixed effects (FE) panel models and dynamic panel estimations using the Arellano–Bond Generalized Method of Moments (GMM) approach are reported. The analysis focuses on the effects of two core institutional inputs—total personnel and total expenditures—on the (log-transformed) annual number of scientific publications, while explicitly accounting for persistence in university output through the inclusion of a lagged dependent variable.

Table 2 presents the results from the dynamic fixed effects (FE) panel regressions of university publication output on key institutional inputs (number of all university employees

and total university expenditures), using both basic and fully controlled specifications. Across all model variants, the lagged dependent variable (number of academic papers) is positive and highly significant, with coefficients ranging from 0.225 to 0.331 ($p < 0.01$), indicating substantial persistence in publication activity over time. This highlights the dynamic character of academic output and suggests that past research performance is an important predictor of current productivity.

Both total personnel and total expenditures exhibit positive and significant effects on publication output. In the baseline specification (1), the elasticity with respect to the number of universities employees is estimated at 0.361 (SE = 0.049), while the elasticity with respect to total expenditures is 0.585 (SE = 0.048), both significant at the 1% level. This implies that a 1% increase in the number of employees or in institutional spending is associated with an approximate 0.36% and 0.59% increase in publication output, respectively.

After the inclusion of year dummies (2), these elasticities decline to 0.184 for total personnel and 0.319 for total expenditures, though both remain highly significant. The coefficients are stable when further controlling for research institution status, doctoral intensity, and field of study (3 and 4), with the elasticity of total personnel in the fully controlled model estimated at 0.195 (SE = 0.050) and total expenditures at 0.337 (SE = 0.052). These results confirm the central role of human resources and financial capacity as determinants of research productivity but also suggest diminishing returns to scale at the institutional level.

Overall, the models explain between 27% and 33% of within-university variation in publication output, as indicated by the R-squared statistics. The estimation sample comprises approximately 6,000 university-year observations, with between 756 and 814 unique universities included, depending on the specification of models.

These results are robust to the inclusion of additional controls and alternative specifications. The strong and consistent effect of lagged output underscores the importance of dynamic modelling in the analysis of academic productivity, while the evidence of diminishing returns suggests that simply increasing staff or expenditures is unlikely to generate proportionate gains in research output.

Tab. 2 – Dynamic fixed effects panel regressions. Source: own research

	(1)	(2)	(3)	(4)
	One-way effects	Two-way effects	Controlled One-way effects	Controlled Two-way effects
$\ln(Publications_{t-1})$	0.331*** (0.0130)	0.227*** (0.0134)	0.321*** (0.0134)	0.225*** (0.0138)
$\ln(total\ emp)$	0.361*** (0.0488)	0.184*** (0.0478)	0.388*** (0.0504)	0.195*** (0.0496)
$\ln(total\ exp)$	0.585*** (0.0478)	0.319*** (0.0497)	0.602*** (0.0498)	0.337*** (0.0521)
Constant	-9.777*** (0.701)	-3.002*** (0.779)	-10.48*** (0.742)	-3.495*** (0.835)
Time fixed effects	No	Yes	No	Yes

Control variables	No	No	Yes	Yes
Observations	5,994	5,994	5,681	5,681
R-squared	0.271	0.331	0.277	0.333
Number of ID	814	814	756	756
Standard errors in parentheses				
*** p<0.01, ** p<0.05, * p<0.1				

Table 3 presents the main results from the dynamic panel estimation of university publication output using the Arellano–Bond GMM approach, alongside the corresponding fixed effects estimates in Table 2 for comparison. Results from both estimation strategies provide evidence of a strong and persistent relationship in research productivity, as reflected in the highly significant coefficient on the lagged dependent variable presented in Figure 1. The magnitude of the persistence is notably higher in the GMM two-step specification (0.49) compared to the FE model (0.23), reflecting the ability of the dynamic estimator to account for feedback effects and unobserved heterogeneity in academic output.

Turning to the core institutional inputs, both total personnel and total expenditures emerge as positive and statistically significant predictors of publication output in all model variants. In the FE specifications, the estimated elasticities of total personnel and total expenditures are approximately 0.18–0.36 and 0.32–0.58, respectively, depending on the inclusion of additional controls. The GMM results yield comparable estimates: in the two-step model, the elasticity with respect to personnel is 0.19 ($p < 0.05$), while that for expenditures is 0.28 ($p < 0.01$). These findings are highly consistent across methods, underscoring the robustness of the observed relationships.

Tab. 3 – Arellano–Bond GMM approach. Source: own research

	(1)	(2)
	GMM One-step	GMM Two-step
$\ln (Publications_{t-1})$	0.322***	0.486***
	(0.0488)	(0.0531)
$\ln (total\ emp)$	0.197**	0.192**
	(0.0896)	(0.0813)
$\ln (total\ exp)$	0.289***	0.274***
	(0.0960)	(0.0716)
Constant	-4.002**	-4.494***
	(1.673)	(1.348)
Observations	3,955	3,955
Number of ID	688	688
Standard errors in parentheses		
*** p<0.01, ** p<0.05, * p<0.1		

Importantly, in both approaches, the estimated elasticities remain well below unity, indicating diminishing returns to scale: increasing university resources leads to higher publication output,

but at a decreasing rate. This result holds even after addressing potential endogeneity and dynamic feedback in the GMM framework.

Diagnostic checks further validate the GMM estimates. The Sargan test of overidentifying restrictions does not reject the null hypothesis of instrument validity ($p = 0.73$, one-step; $p = 0.22$, two-step), and the Arellano–Bond test for second-order serial correlation in the differenced residuals is not significant ($p = 0.52$), confirming the appropriateness of the estimator.

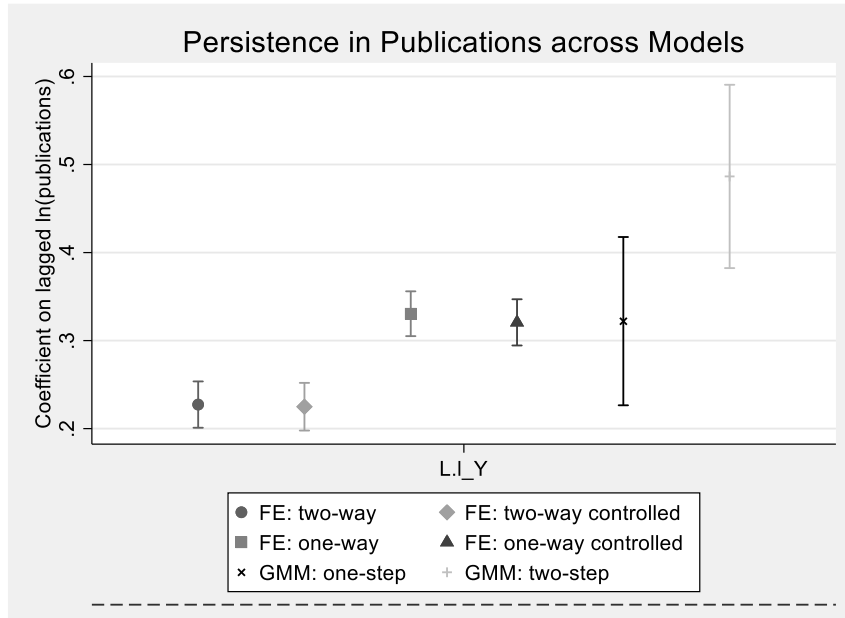


Fig. 1 – Persistence in Publications across Models. Source: own calculations

Overall, the dynamic panel results reinforce and strengthen the conclusions from the FE models. Both methods point to substantial persistence in academic performance and highlight the central roles of human and financial resources for knowledge production in European universities, while consistently revealing diminishing returns to scale.

5 DISCUSSION

The empirical analysis presented in this study provides evidence on the determinants of publication productivity in European universities. Across both fixed effects and dynamic panel models, the results consistently demonstrate that human (personnel) and financial (total expenditures) resources—measured by the total number of university employees and total expenditures—are positively associated with research output. This finding aligns with the predictions of the knowledge production function (Griliches, 1979) and supports a substantial body of literature emphasizing the role of institutional capacity in fostering academic productivity (Bonaccorsi et al., 2017; Aghion et al., 2010; Lee & Graff, 2018).

A notable contribution of this study lies in the explicit modelling of persistence in research output. The Arellano–Bond GMM results show that past publication activity strongly predicts future output, with a persistence coefficient close to 0.5. This is consistent with recent findings on cumulative advantage and reputational effects in higher education (Abramo & D’Angelo, 2017; Carayol & Lanoë, 2017), but to our knowledge this is one of the first studies to confirm these dynamics in a Europe-wide panel of universities.

At the same time, the estimated elasticities of both personnel and expenditures inputs remain well below unity, regardless of model specification. This indicates diminishing returns to scale: while increasing staff or funding does enhance publication output, the incremental gains become progressively smaller. This provides novel comparative evidence across higher education systems with very different governance and funding models.

From a policy perspective, these results imply that investment in human and financial resources remains essential for sustaining research productivity, but “more is not proportionally better.” Policy strategies should therefore combine resource allocation with measures that increase efficiency, foster collaboration, and strengthen research culture. In addition, the strong persistence in productivity underscores the importance of long-term and stable support.

Finally, future research could build on these findings by investigating the mechanisms underlying diminishing returns, such as differences in governance, research focus, or collaborative networks. Further exploration of heterogeneity across countries, institutional types, and scientific fields may also provide more insights into the determinants of academic productivity within the European context.

6 CONCLUSION

This paper investigates the determinants of publication productivity in European universities using a unique panel dataset that combines bibliometric and institutional data from 2011 to 2020. Applying both fixed effects and dynamic panel data methods, the analysis provides consistent evidence that human and financial resources—specifically, the number of university employees and total expenditures—play a central role in driving scientific output. The results consistently show positive and significant elasticities for both inputs, but these effects are subject to diminishing returns, indicating that simply increasing staff or institutional spending yields progressively smaller gains in research output.

A key contribution of this study is the explicit modelling of dynamic effects in university productivity. The significant coefficient on the lagged dependent variable highlights strong persistence in publication activity: universities with established research profiles tend to maintain their output over time. These findings underscore the cumulative and path-dependent nature of academic performance and emphasize the importance of stable, long-term support for research institutions.

Overall, the results reinforce the relevance of the knowledge production function framework in the context of European higher education. While adequate investment in personnel and resources remains essential, policymakers and university leaders should also consider strategies that enhance efficiency and foster innovation to maximize research productivity. Future research could extend this analysis by exploring the roles of institutional governance, collaboration networks, and field-specific factors in shaping academic outcomes.

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THE IMPACT OF FINTECH ON OPERATIONAL PERFORMANCE OF COMMERCIAL BANKS IN VIETNAM

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Abstract

The study is situated within the context of the FinTech boom in Southeast Asia, with a particular focus on Vietnam - a rapidly expanding market supported by policy frameworks promoting digital payments and regulatory sandbox initiatives. Its novelty lies in integrating the innovation diffusion framework with transaction cost theory to explain the underlying mechanisms of impact. Using panel data from 24 commercial banks over the period 2015-2023, and applying OLS, FE, RE, and FGLS estimations, the analysis ensures methodological robustness. The findings indicate that FinTech adoption significantly enhances both ROA and ROE; bank size (SIZE) and capital adequacy (CAP) contribute positively to performance, whereas the cost-to-income ratio (CIR) and inflation exert a detrimental effect. The study emphasizes that lower transaction costs-achieved through process automation, reduced processing times, and the elimination of intermediaries-constitute the key channel amplifying performance gains. Policy implications include accelerating digital platform development, expanding open APIs, leveraging AI/ML in credit assessment, and refining the sandbox framework in parallel with strengthened data security measures.

Keywords: *Fintech, commercial banks, operational performance, Vietnam*

1 INTRODUCTION

Fintech, a term that describes the intersection of finance and technology, is reshaping the structure and operations of the banking sector by applying digital technologies, including online payments, digital lending, and insurtech. In Vietnam, Fintech is considered a key driver of banking modernization, contributing to improved service quality, cost reduction, and broader financial inclusion for individuals and businesses. Within the frameworks of innovation diffusion and transaction cost theory, Fintech development is also shown to influence cost structure, information distribution, and competition among financial institutions. Amid the Fourth Industrial Revolution and Vietnam's national digital transformation strategy, the country's fintech ecosystem has witnessed explosive growth, with 260 companies established by 2022, up from 115 in 2020. Decision No. 2545/QĐ-TTg, which promoted non-cash payments from 2016 to 2020, significantly boosted online transactions, especially during the COVID-19 pandemic. This accelerated the shift to QR code-based payments, resulting in nearly 183 million transactions by the end of 2023. Concurrently, electronic wallets, peer-to-peer (P2P) lending, and insurtech have become increasingly prevalent, altering customer expectations and compelling traditional banks to restructure their business models. Vietnam currently ranks second in Asia, after Singapore, in terms of Fintech market growth, reflecting the sector's significant appeal and potential. The rapid emergence of Fintech firms has also placed substantial pressure on commercial banks to expedite digital transformation. According to Do (2022), Fintech not only facilitates convenient payment solutions but also promotes the adoption of artificial intelligence (AI), machine learning, and big data analytics, which help automate credit appraisal processes, reduce transaction costs, and expand service reach to rural and remote areas. Claessens et al. (2018) found that Fintech lending enhances access to credit for underserved groups while increasing competition and diversifying traditional credit channels. Although several studies provide overviews of Fintech, most focus on developed

markets or the construction of composite indices and lack quantitative analysis of Fintech's effects on Vietnamese commercial banks. The period from 2015 to 2023 experienced both a Fintech boom and the disruptive impacts of the COVID-19 pandemic, necessitating a multi-dimensional analysis to clarify mechanisms of influence. The use of panel data from 24 listed banks allows for controlling institution-specific heterogeneity, thereby enabling an accurate assessment of Fintech's effect on ROA. The findings aim to contribute to the theoretical discourse on innovation diffusion and transaction cost economics by providing empirical insights into the role of Fintech in the Vietnamese context. On a practical level, this study provides a scientific basis for the State Bank of Vietnam and commercial banks to develop structured digital transformation strategies, refine Fintech sandbox regulations, and enhance collaboration between banks and technology firms. It also proposes a multidimensional Fintech measurement index, encompassing API integration level, digital transaction ratio, and service quality, to evaluate the effectiveness of financial technology adoption comprehensively. These recommendations support public policy formulation and technology investment decisions, while helping optimise costs and sustainably enhance bank profitability.

2 LITERATURE REVIEW

The term Fintech emerged after the 2008 financial crisis, when new service providers began leveraging technology to enhance processes and increase efficiency. Fintech, a combination of “financial” and “technology,” encompasses digital-based financial solutions, products, and business models. Arner et al. (2015) define Fintech as the extension of traditional financial services into digital platforms. Rupeika-Apoga et al. (2020) emphasise that Fintech focuses on developing technology-driven financial services to optimise user experience.

Fintech is a key catalyst for digital finance and the digital economy, serving as a new driver of high-quality, sustainable economic growth. According to Allied Market Research (2023), the global market for online banking and mobile platforms was valued at USD 110.57 billion in 2020 and is projected to reach USD 698.48 billion by 2030, with a compound annual growth rate (CAGR) of 20.3% from 2021 to 2030. Fintech not only enhances labour quality, optimises business processes, and broadens access to financial services, but also improves user convenience through digital channels such as banking, credit cards, and POS terminals. However, it also presents accessibility challenges for populations lacking digital infrastructure. Ernst & Young (2017) highlighted the pronounced impact of Fintech on developing economies, such as China and India, where it compelled traditional institutions to adapt their strategies. Additionally, Gobble (2018) underscored that digitalization and electronification have allowed Fintech to penetrate daily economic transactions deeply.

Vietnam is actively promoting financial digital transformation through its roadmap for cashless payments, a FinTech sandbox framework, a high mobile penetration rate, and the development of e-wallet/QR code ecosystems. The banking market, while competitive, remains moderately concentrated, enabling collaborative FinTech-Bank partnerships under a platform-based model. Such an environment fosters innovation, accelerates service integration, and expands financial accessibility across diverse customer segments.

In recent years, Fintech has made significant strides amid the digital transformation wave, offering benefits to businesses such as increased efficiency, reduced risk, and lower labour costs. The Fourth Industrial Revolution has also expanded the reach of digital financial services via traditional banking channels. The Vietnamese government has issued Decision No. 241/QĐ-TTg (2018-2020) and Decree No. 52/2024/NĐ-CP to promote cashless payments. As a result, non-cash transactions in 2022 rose by 86% in volume and 31.39% in value, with nearly 183 million QR code transactions recorded by the end of 2023. Vietnam currently ranks second

in Asia in terms of Fintech growth, after Singapore, with flagship products including ZaloPay, QR codes, eKYC, and 24/7 instant money transfers.

In Vietnam, Pham et al. (2024) used balanced panel data from 24 banks during 2015-2023 and a multivariate regression model to confirm that Fintech enhances ROA. In contrast, Dinh and Nguyen (2021) found a negative impact using a Fixed Effects approach. Tang My Sang (2023) and Nguyen & Nguyen (2024) reported that Fintech improves both ROA and Z-score, thus enhancing risk resilience.

Do (2022) affirms that the application of AI-ML has contributed to reducing loan appraisal time by 30%. From a strategic perspective, the case study on Sacombank by Nogalski et al (2023), along with the analysis of the platform banking model by Tran (2025), both indicate that Fintech serves as a powerful driver for banking system restructuring. As of 2022, the number of Fintech enterprises in Vietnam reached 260 (Vo, 2024), further underscoring the necessity of regulatory sandboxes, as recommended by the CGFS-FSB (2017), and aligning with Kania's (2023) perspective on a long-term strategic investment orientation.

Internationally, Claessens et al. (2018) used multivariate regression on a sample of 63 countries and concluded that Fintech reduces transaction costs and improves performance. Na Song & Isaac Appiah-Otoo (2022), using IV-GMM, confirmed a bidirectional relationship between Fintech and China's economic growth. William C. Dudley & Klaas Knot (2017) analysed Fintech's role in financial stability, while Qiao Jiang et al. (2023), employing text mining to construct a Fintech index, verified its positive impact on ROA.

Chen et al. (2019) demonstrate that Fintech enables U.S banks to achieve higher market valuations, while Phan et al. (2023) show that Fintech simultaneously expands financial inclusion and increases risk tolerance across 31 emerging markets. The comprehensive review by Gomber et al. (2018) identifies three pillars of innovation as big data, cloud computing, and mobility as guiding principles for digital transformation in the banking sector.

3 METHODOLOGY

This paper employs a combination of qualitative and quantitative synthesis methods to analyze the impact of Fintech on the performance of 24 Vietnamese commercial banks during the period from 2015 to 2023. The qualitative synthesis method includes theoretical consolidation and expert surveys in the fields of banking and Fintech to clarify potential impacts. The quantitative method utilizes panel data from the annual financial statements of banks and macroeconomic indicators (GDP, CPI) sourced from the World Bank. The data is cleaned and statistically described. The quantitative model is constructed using ROA as the dependent variable and FT (log of the number of new Fintech companies) as the primary explanatory variable, alongside control variables. The model is estimated using pooled OLS, Fixed Effects, and Random Effects methods, with Hausman tests applied; finally, GLS/FGLS is used to correct for autocorrelation and heteroskedasticity. The estimation is conducted using Stata 17.0 to ensure accuracy.

$$ROA_{i,t} = \beta_0 + \beta_1 * FT + \beta_2 * SIZE_{i,t} + \beta_3 * CAP_{i,t} + \beta_4 * NPL_{i,t} + \beta_5 * LDR_{i,t} + \beta_6 * LLP_{i,t} + \beta_7 * CIR_{i,t} + \beta_8 * INF_{i,t} + \beta_9 * GDP_{i,t} + \epsilon_{i,t} \quad (1)$$

$$ROE_{i,t} = \beta_0 + \beta_1 * FT + \beta_2 * SIZE_{i,t} + \beta_3 * CAP_{i,t} + \beta_4 * NPL_{i,t} + \beta_5 * LDR_{i,t} + \beta_6 * LLP_{i,t} + \beta_7 * CIR_{i,t} + \beta_8 * INF_{i,t} + \beta_9 * GDP_{i,t} + \epsilon_{i,t} \quad (2)$$

Where:

i: list of commercial banks in Vietnam

t: from 2015 to 2023

β_0 : intercept

$\beta_1, \beta_2, \dots, \beta_9$: coefficients of the respective independent variables

ε : residual

The theoretical framework is constructed to clarify the mechanism through which Fintech development influences financial performance, with a focus on internal factors. The research investigates two indicators of bank performance: ROA and ROE. Two regression models are established, using ROA and ROE as dependent variables, and FT as the main independent variable, along with a set of control variables (SIZE, CAP, NPL, LDR, LLP, CIR, INF, GDP). The theoretical basis is derived from literature and empirical findings of prominent international studies.

Firstly, the FinTech development variable (FT): Measured by the number of new FinTech firms established each year, it is expected to exert a positive impact on performance. Claessens et al. (2018) found that the FinTech credit market helps reduce transaction costs and promotes innovation in banking business models, thereby improving ROA and ROE. Similarly, Jiang et al. (2023) provided evidence of a positive and statistically significant relationship between the FinTech index and the return on assets of commercial banks in China. Accordingly, the following hypotheses are proposed:

$$FT_t = \text{Ln}(\text{Total number of FinTech companies})_t$$

H1a: FT has a positive effect on ROA.

H1b: FT has a positive effect on ROE.

Bank size (SIZE): Measured by the natural logarithm of total assets, the economies of scale theory suggests that larger banks can take advantage of lower funding costs and better risk diversification (Cull et al., 2018). Berger & Bouwman (2013) also noted that larger size enhances both ROA and ROE due to better technological investment capabilities. Thus, we propose:

$$SIZE_t = \text{Ln}(\text{Total assets})_t \quad (3)$$

H2a: SIZE has a positive effect on ROA;

H2b: SIZE has a positive effect on ROE.

Equity ratio (CAP): Measured as the ratio of equity to total assets, reflecting a bank's financial capacity. Studies by Arner et al. (2015) and Berger & Bouwman (2013) confirm that higher capitalization reduces funding costs and facilitates investment in FinTech technologies, thereby increasing profitability. Therefore:

$$CAP_t = \frac{\text{Equity}_t}{\text{Total assets}_t} \quad (4)$$

H3a: CAP has a positive effect on ROA.

H3b: CAP has a positive effect on ROE.

Non-performing loan ratio (NPL) and loan loss provisions ratio (LLP): Both are expected to have negative impacts. Demirgüç-Kunt & Huizinga (2010) found that higher NPLs increase provisioning costs, reduce net interest margins, and depress both ROA and ROE. Jiang et al. (2023) also reported that higher LLPs correspond to increased operating costs, which negatively affect profitability. Accordingly:

$$NPL_t = \frac{\text{Total non – performing loans}_t}{\text{Total outstanding loans}_t} \quad (5)$$

H4a: NPL has a negative effect on ROA.

H4b: NPL has a negative effect on ROE.

$$LLP_t = \frac{\text{Loan loss provisions}_t}{\text{Total outstanding loans}_t} \quad (6)$$

H5a: LLP has a negative effect on ROA.

H5b: LLP has a negative effect on ROE.

Loan-to-deposit ratio (LDR) and cost-to-income ratio (CIR): These reflect funding structure and cost management efficiency. Bourke (1989) and Berrospide & Edge (2010) suggest that a moderate LDR improves net interest margins, but exceeding the threshold increases liquidity risk and funding costs, leading to adverse effects. DeYoung & Rice (2004) demonstrated that a high CIR indicates inefficient cost management, which reduces both ROA and ROE. Therefore: Total deposits

$$LDR_t = \frac{\text{Total loans outstanding}_t}{\text{Total deposits}_t} \quad (7)$$

H6a: LDR has a nonlinear effect on ROA.

H6b: LDR has a nonlinear effect on ROE.

$$CIR_t = \frac{\text{Total operating expenses}_t}{\text{Total operating income}_t} \quad (8)$$

H7a: CIR has a negative effect on ROA.

H7b: CIR has a negative effect on ROE.

Finally, macroeconomic factors, including inflation (INF) and GDP growth rate (GDP), are considered. Boyd, Hu & Jagannathan (2005) argue that high inflation increases funding costs, reduces net interest margins, and lowers bank profitability. Conversely, positive GDP growth is associated with increased demand for credit and banking services, thereby improving ROA and ROE (Demirgüç-Kunt & Detragiache, 1998; Sufian, 2011; Na Song & Appiah-Otoo, 2022). Hence:

$$INF_t = \text{Inflation rate as published by the government} \quad (9)$$

H8a: INF has a negative effect on ROA.

H8b: INF has a negative effect on ROE.

H9a: GDP has a positive effect on ROA.

H9b: GDP has a positive effect on ROE.

The study utilizes publicly available secondary data sources. The key variables are defined and measured as follows:

Dependent Variable (ROA): Return on Assets, calculated as the ratio of pre-tax profit to average total assets per year. This indicator reflects the bank's profitability, consistent with the approach of Claessens et al. (2018).

Main Independent Variable (FT): Fintech development level, measured by the number of newly established Fintech companies each year. This data is compiled from reports by the State Bank of Vietnam and other credible sources, using a text mining method similar to that of Jiang et al. (2023).). In addition to the number of newly established companies, alternative measures of FinTech development could include market capitalization, transaction volume, digital payment value, the number of monthly active users (MAU), or the degree of API integration. These indicators may capture different dimensions of FinTech activity, potentially providing a more comprehensive assessment of its impact on banking performance.

Control Variables

SIZE: Bank size, calculated as the natural logarithm of total assets ($\log(TA)$). The log transformation helps reduce data skewness and control for size effects.

CAP: The ratio of equity to total assets (Equity/Total Assets), which reflects a bank's financial strength and its capacity to absorb risks.

NPL: Non-Performing Loan Ratio, calculated as the ratio of total non-performing loans to total loans, commonly used to assess credit quality and liquidity risk.

LDR: Loans to Deposits Ratio, measuring the bank's ability to mobilize and utilize capital, affecting liquidity and interest margins.

LLP: Loan Loss Provision Ratio, indicates the buffer a bank sets aside in advance to absorb potential credit losses.

CIR: Cost-to-Income Ratio, calculated as operating expenses over total income, reflecting efficiency in cost management.

INF: Inflation rate, using the Consumer Price Index (CPI), sourced from the World Bank.

GDP: Vietnam's economic growth rate, calculated as the annual percentage change in real GDP, also sourced from the World Bank.

4 RESULTS

The descriptive statistical analysis presented in Table 5.1 aims to summarize the distributional characteristics and volatility levels of each research variable prior to conducting further tests. The dataset comprises 243 observations, corresponding to the panel data of 24 commercial banks during the 2015-2023 period, after excluding missing and outlier observations.

Tab. 1 – Descriptive Statistics Analysis. Source: own research

Variables	Observations	Mean	Standard Deviation	Minimum value	Maximum Value
ROA	243	0.009253	0.00713	-0.006957	0.03238
ROE	243	0.109679	0.071397	-0.131423	0.263876
NIM	243	0.037164	0.01608	0.007289	0.111625
INF	243	2.735579	0.895694	0.631201	3.539628
SIZE	243	32.80959	1.119176	30.50734	35.37206
CIR	243	0.505101	0.1678898	0.2271	1.7225
LDR	243	0.61363	0.086027	0.2635	0.7881
LLP	243	0.012922	0.004158	0.0076	0.0312
NPL	243	0.020368	0.023371	0	0.3035
FT	243	4.747396	0.467098	3.663562	5.231109
CAP	243	0.0846965	0.0306528	0.0406177	0.1910526

Table 1 provides an overview of the diverse financial landscape of 24 Vietnamese commercial banks over the 2015-2023 period, based on 243 observations. First, in terms of profitability, the average return on assets (ROA) is recorded at 0.93% ($\sigma = 0.71\%$), but the range from -0.70% to 3.24% indicates the coexistence of loss-making banks and highly efficient ones. The average ROE of 10.97% with a standard deviation of 7.14% further highlights the disparity in capital utilization strategies. The net interest margin (NIM) averages 3.72% , with a maximum value of 11.16% , suggesting that some banks leverage high pricing or focus on riskier lending segments.

In terms of cost efficiency, the average CIR is 50.5% , yet the maximum value reaches 172% , raising concerns about the operational burden in banks with limited digitalization; this underscores the need for streamlining manual processes. Liquidity appears relatively stable, with an average LDR of 61% ; however, the minimum of 26% reflects excess liquidity in certain banks, while the 79% maximum signals funding pressures during tense periods. Asset quality is generally healthy, with a non-performing loan (NPL) ratio averaging 2.04% , though an outlier of 30.35% indicates the need for closer supervision of smaller-scale banks. Accordingly, the loan loss provision ratio (LLP) averages 1.29% , but its variation up to 3.12% implies differing provisioning policies.

Recommendations: (i) Set a KPI to reduce the cost-to-income ratio (CIR) by 5-10% through process automation and post-transaction verification; (ii) implement open APIs and AI/ML-based credit scoring systems; (iii) enhance data governance and security in line with international standards; and (iv) expand FinTech partnerships based on specific use cases (e.g., payments, digital identity verification, digital lending) with pilot programs that include performance measurement mechanisms.

The Fintech variable (FT, measured as the logarithm of the number of Fintech firms) averages 4.75, with a maximum of 5.23, confirming the surge in Fintech development. Meanwhile, the average CAP is 8.47%, reflecting a relatively safe capital buffer; however, its wide range (4.06%-19.11%) may lead to varying levels of risk tolerance. These divergences suggest the need to adjust for heteroskedasticity and account for potential bank-specific effects when estimating the model.

Tab. 2 – Correlation Matrix. Source: own research

	ROA	ROE	GDP	INF	SIZE	CIR	LDR	LLP	NPL	FT	CAP
ROA	1.0000										
ROE	0.8697	1.0000									
GDP	-0.1166	-0.1138	1.0000								
INF	0.1622	0.1869	0.1198	1.0000							
SIZE	0.5063	0.6467	-0.1265	0.1382	1.0000						
CIR	-0.6960	-0.7321	0.1604	0.0959	-0.5773	1.0000					
LDR	0.1103	0.2071	-0.0444	0.1810	0.2857	-0.2020	1.0000				
LLP	0.2601	0.2691	-0.1122	0.0154	0.5572	-0.3310	0.0488	1.0000			
NPL	-0.1864	-0.2987	0.0004	0.0639	-0.0902	0.4321	-0.0778	0.2281	1.0000		
FT	0.3875	0.3791	-0.2961	0.6605	0.3014	-0.3086	0.2524	0.2409	0.0988	1.0000	
ETA	0.3788	-0.0194	-0.0025	0.0739	-0.2332	-0.1909	-0.0249	-0.0220	0.0105	0.0069	1.0000

The correlation matrix reflects the degree of linear association between variables, enabling the identification of both positive (FT-ROA) and negative (CIR-ROA) relationships. These results serve as a basis for variable selection and for refining an appropriate regression model. As shown in Table 4.2, ROA and ROE exhibit a strong positive correlation (0.8697), affirming the consistency between the two performance indicators. CIR exhibits a strong negative correlation with both ROA (−0.6960) and ROE (−0.7321), suggesting that higher operating costs have a detrimental impact on profitability. The level of Fintech development (FT) is positively correlated with ROA (0.3875) and ROE (0.3791), suggesting that Fintech contributes to improving performance. Meanwhile, GDP, NPL, and CAP show relatively weak correlation.

Tab. 3 - VIF Test. Source: *Author's calculation based on processed data*

Variable	VIF	1/VIF
FT	2.85	0.350701
CIR	2.69	0.372370
SIZE	2.58	0.387457
INF	2.34	0.428053
LLP	1.80	0.557028
NPL	1.67	0.600586
GDP	1.37	0.730203
ETA	1.36	0.736175
LDR	1.16	0.860775
Mean VIF	1.98	

The VIF test (Mean VIF = 1.98; maximum VIF = 2.85 for FT) confirms the absence of serious multicollinearity among the variables. This result reinforces the reliability of the correlation matrix in Table 2 and ensures the explanatory validity of the variable selection in the regression model.

The author employs three estimation methods - Pooled Ordinary Least Squares (Pooled OLS), Fixed Effects (FE), and Random Effects (RE) - to examine the impact of macroeconomic factors, bank-specific characteristics, and the level of Fintech development on the operational performance (measured by ROA) of 24 Vietnamese joint-stock commercial banks during the period 2015-2023. This sample includes major state-owned banks such as Vietcombank, BIDV, VietinBank, and Agribank, as well as prominent private banks like Techcombank, ACB, and VPBank.

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Tab. 4 – Summary of Regression Models with ROA as the Dependent Variable. Source: own research

Variable	OLS		FEM		REM	
	coefficient β	P-value	coefficient β	P-value	Coefficient β	P-value
GDP	0.000	1.43	0.000**	2.12	0.000**	2.11
INF	-0.000	-1.07	-0.001**	-2.45	-0.001**	-2.34
SIZE	0.003***	7.14	0.002*	1.93	0.002***	3.99

CIR	-0.017***	-6.36	-0.014***	-5.50	-0.014***	-5.93
LDR	-0.010***	-3.08	0.007	1.47	0.003	0.73
LLP	-0.270***	-3.10	-0.257***	-3.64	-0.264***	-3.83
NPL	0.007	0.48	0.004	0.35	0.006	0.49
FT	0.004***	4.05	0.004***	3.62	0.004***	5.09
CAP	0.091***	8.89	0.065***	5.25	0.072***	6.54
Constant	-0.090***	-6.53	-0.081**	-2.42	-0.086***	-4.61
R ² / Wald χ^2	0.667		0.651			
df_r / Obs.	233.000		207.000			
Note: Significance levels are denoted by ***, **, *, and . corresponding to 0.1%, 1%, 5%, and 10%, respectively.						

Table 4 presents the estimation results of three models - Pooled OLS, Fixed Effects (FE), and Random Effects (RE) - using ROA as the dependent variable. The Fintech variable (FT) maintains a positive coefficient of approximately 0.004, statistically significant at the 1% level across all three models. This suggests that a 1% increase in the number of Fintech firms is associated with an average increase of 0.004 points in ROA. Bank size (SIZE) also exhibits a positive and significant effect, reaffirming that economies of scale contribute to enhanced asset utilization efficiency. Conversely, both the Cost-to-Income Ratio (CIR) and Loan Loss Provisions (LLP) exhibit strong negative coefficients, significant at the 1% level, indicating that high operating costs and increased credit risk provisioning negatively impact profitability. Regarding macroeconomic variables: GDP has no significant impact in the OLS model and only shows a minimal effect at the 5% level in the FE/RE models. Inflation (INF) consistently has a negative and statistically significant effect at the 5% level in the panel models. The Loans-to-Deposits Ratio (LDR) is only significant in the OLS model and changes sign in the FE/RE models, indicating an unstable effect. The Non-Performing Loan ratio (NPL) is found to be statistically insignificant. The Capital Adequacy Ratio (CAP) demonstrates a positive and significant coefficient across all three models, highlighting the importance of capital buffers in improving ROA. The models explain approximately 65% of the variation in ROA (with $R^2 \approx 0.667$ for OLS and 0.651 for FE/RE), indicating a strong explanatory power of the selected variables.

Tab. 5– Summary of Regression Models with ROE as the Dependent variable. Source: own research

Variable	OLS		FE		RE	
	coefficient β	P-value	coefficient β	P-value	Coefficient β	P-value
GDP	0.002	1.46	0.003**	2.26	0.003**	2.22
INF	-0.004	-0.88	-0.008**	-2.17	-0.007**	-2.10
SIZE	0.025***	6.25	0.023*	1.95	0.022***	3.68
CIR	-0.218***	-8.03	-0.200***	-7.67	-0.205***	-8.20

LDR	-0.036	-1.04	0.096**	2.03	0.060	1.44
LLP	-2.611***	-2.92	-2.926***	-3.94	-3.001***	-4.14
NPL	-0.086	-0.56	0.048	0.39	0.051	0.42
FT	0.032***	3.17	0.034***	2.67	0.035***	4.04
CAP	-0.082	-0.78	-0.465***	-3.55	-0.359***	-3.12
Constant	-0.688***	-4.86	-0.682*	-1.93	-0.646***	-3.41
R ² / Wald χ^2	0.648		0.627			
df_r / Obs.	233.000		207.000			
Note: Significance levels are denoted by ***, **, *, and . corresponding to 0.1%, 1%, 5%, and 10%, respectively.						

Table 5 presents the regression results using ROE as the dependent variable across the Pooled OLS, Fixed Effects (FE), and Random Effects (RE) models. The Fintech variable (FT) shows a positive coefficient, ranging from 0.032 to 0.035, statistically significant at the 1% level, reaffirming its positive influence on ROE. Bank size (SIZE) exhibits a coefficient of approximately 0.022, also significant at the 1% level, reflecting economies of scale. Inflation (INF) exerts a negative impact ($\beta \approx -0.007$ to -0.008), significant at the 5% level, while GDP growth has only a modest positive effect ($\beta \approx 0.002$ – 0.003), albeit statistically significant at 1%. Both operating costs (CIR) and loan loss provisions (LLP) negatively affect ROE, whereas the non-performing loan ratio (NPL) remains insignificant. The loan-to-deposit ratio (LDR) is only significant under the FE model. Meanwhile, the capital adequacy ratio (CAP) reverses its effect under FE/RE models, suggesting that capital cost pressures may undermine ROE. The models explain approximately 62%–65% of the variation in ROE ($R^2 \approx 0.627$ – 0.648), indicating strong explanatory power of the selected variables.

The regression findings indicate that Fintech development (FT) consistently shows a positive and highly significant impact (1%) on both asset efficiency (ROA) with $\beta \approx 0.004$ and return on equity (ROE) with β ranging from 0.032 to 0.035 across all three estimation models (Pooled OLS, FE, RE). This demonstrates that a 1% increase in the number of Fintech firms is associated with a statistically meaningful improvement in bank performance, affirming the role of technology in reducing transaction costs, enhancing process automation, and expanding digital distribution channels. Bank size (SIZE) also exhibits a positive and significant impact, reinforcing the idea that economies of scale contribute to better asset and capital optimization.

On the other hand, Cost-to-Income Ratio (CIR) and Loan Loss Provisions (LLP) both show strong negative and significant coefficients (1%), indicating that operational expenses and credit risk provisions remain critical constraints on profitability. Inflation (INF) consistently exerts a negative effect at the 5% significance level. At the same time, GDP growth shows no meaningful influence, suggesting that this macroeconomic variable is not a primary driver of performance during the research period. The Capital Adequacy Ratio (CAP) has a positive impact on ROA but reverses direction with ROE, implying that capital costs and complex financial structures may offset returns on equity. The insignificant effect of NPL and the inconsistent influence of LDR highlight the need for further research into credit risk management and lending structures in the digital transformation context. Overall, the results support innovation diffusion theory and transaction cost theory, confirming that Fintech serves as a critical catalyst for enhancing the operational efficiency of Vietnamese commercial banks.

5 DISCUSSION

This study confirms that Fintech development has a significant impact on the performance of Vietnamese commercial banks. The Fintech variable (FT) shows a consistently positive and statistically significant effect on both ROA ($\beta \approx 0.004$) and ROE ($\beta \approx 0.032\text{--}0.035$) across all models, aligning with innovation diffusion and transaction cost theories. These findings are consistent with Claessens et al. (2018) and Chen et al. (2019), who highlight Fintech's role in reducing transaction costs and improving financial efficiency. In Vietnam, the Fintech ecosystem's rapid growth, reaching 260 firms by 2022 (Vo, 2024), and policies such as Decision No. 2545/QĐ-TTg have further strengthened this impact.

Bank size (SIZE) has a positive influence on performance, suggesting that larger banks benefit more from digital investments, which supports the results from Pham et al. (2024). In contrast, high operating costs (CIR) and credit risk provisions (LLP) significantly reduce profitability, especially in banks lacking automation (Do, 2022). Despite advancements like AI-based credit scoring, LLP variation (up to 3.12%) reveals inconsistent risk management practices.

GDP growth was not significant, possibly due to pandemic disruptions, while inflation (INF) negatively impacted performance, consistent with findings by Na Song and Isaac Appiah-Otoo (2022). CAP positively influenced ROA but reduced ROE, reflecting a trade-off between capital buffers and shareholder returns (Tran, 2025). NPL was insignificant, although some small banks exhibited high outliers, highlighting concerns about credit risk.

From a policy perspective, the results support strengthening Vietnam's Fintech sandbox (Committee on the Global Financial System and Financial Stability Board, 2017) and promoting deeper collaboration between banks and technology firms, as in the Sacombank case (Nogalski, Dang, and Nguyen, 2023). Investing in AI and digital infrastructure, as recommended by Gomber, Kauffman, Parker, and Weber (2018), can improve efficiency. A standardized Fintech index could guide technology adoption and regulatory strategy.

In conclusion, fintech plays a key role in driving banking performance in Vietnam. However, controlling operational costs, managing credit risk, and ensuring regulatory readiness remain essential to maximise its benefits.

6 CONCLUSION

This study concludes that, based on panel data from 24 Vietnamese commercial banks during 2015-2023, Fintech development plays a central role in improving bank performance as measured by ROA. Specifically, a 1% increase in the Fintech index corresponds to an average increase of 0.004 in ROA. Bank size (SIZE) also contributes positively, whereas operating costs (CIR) and credit risk provisions (LLP) have a negative impact on profitability. Inflation has a detrimental impact, while GDP growth is statistically insignificant. The econometric tests, including Pooled OLS, Fixed Effects, Random Effects, FGLS, as well as tests for cross-sectional dependence, stationarity, and endogeneity, ensure the consistency and reliability of the results.

From a scientific perspective, the research extends the analytical framework of the Fintech banking relationship using panel data methods and proposes a Fintech index tailored to the Vietnamese context. From a practical perspective, the findings suggest that banks should invest more heavily in digital infrastructure, automate processes, and collaborate closely with regulatory authorities to optimise costs, develop innovative products, and enhance competitiveness in the digital era.

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THE RELATIONSHIP BETWEEN JOB SATISFACTION, EMPLOYEE TURNOVER INTENTION, AND INNOVATIVE BEHAVIOUR

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Abstract

Job satisfaction represents a key determinant of organisational performance, influencing not only employees' motivation and retention but also their innovative behaviour. This study aimed to explore the relationships between three core constructs: job satisfaction, turnover intention, and innovative behaviour. Data were collected through a structured employee survey, complemented by qualitative interviews, and analysed using Spearman's correlation coefficient. The results confirmed a positive correlation between job satisfaction and innovative behaviour, a negative correlation between job satisfaction and turnover intention, and a negative correlation between turnover intention and innovative behaviour. These findings highlight the strategic role of job satisfaction in reducing turnover risk while simultaneously fostering innovative behaviour, offering valuable insights for human resource management practices in dynamic organisational contexts.

Keywords: *job satisfaction, innovative behaviour, turnover intention, well-being at work, employee engagement*

1 INTRODUCTION

In today's environment, which is changing all the time, there is an increasing realisation that employee job satisfaction and well-being are strategic resources that can help to shape organisational competitiveness. It has been suggested that both constructs may have a significant influence on employee performance, creativity, and the organisation's capacity to adapt to frequent changes (Robbins & Judge, 2015; Harter, Schmidt, & Keyes, 2003). Beyond immediate performance outcomes, it has been suggested that employee well-being and satisfaction may be closely linked to resilience, motivation, loyalty, and long-term retention (Tang et al., 2021).

It is important to note that the role of job satisfaction extends beyond individual affective states. Research suggests that employees who are satisfied with their job are more engaged, more innovative, and less likely to leave their organisations (Moslehpour et al., 2023; Daneshmandi et al., 2023). Conversely, it has been suggested that dissatisfaction may be associated with burnout, absenteeism, decreased productivity, and increased turnover intention (Schwepker, 2001; Kundi et al., 2021). It is interesting to note that these findings underline the importance of job satisfaction not only as an outcome, but also as a key predictor of organisational success.

It is important to acknowledge the contemporary challenges in the labour market, such as talent shortages, high turnover rates, burnout, and declining employee loyalty. These challenges are forcing organisations to implement practical and evidence-based measures aimed at retaining motivated and engaged employees (Berber et al., 2022; McNall, Masuda, & Nicklin, 2009). One approach that shows promise is the development of systems that are designed to strengthen job satisfaction and support employee well-being. This could be a way to create a climate that reduces turnover intention and fosters innovative behaviour.

Against this backdrop, the present article aims to examine the relationships between job satisfaction, turnover intention, and innovative behaviour. The study is based on empirical research conducted in a selected company as part of a master's thesis project. By analysing the

interconnections between these constructs, the study provides insights into how organisations can improve employee stability, retain valuable talent, and stimulate innovative behaviours that support organisational adaptability in dynamic environments.

2 LITERATURE REVIEW

To better understand the context, it is important to clarify the meaning of the terms job satisfaction and tendency to leave. In addition, understanding the meaning of innovative behaviour is key to a comprehensive overview.

2.1 Job satisfaction

Job satisfaction and employee engagement are closely linked to well-being. Physical, mental, and emotional well-being directly affect how employees feel at work and how they engage with it. Satisfied employees are generally more engaged, motivated, and loyal to their organization. On the other hand, a lack of support for well-being at work can lead to stress, burnout, and lower productivity, which hurts the company's performance. (Clifton, J., & Harter, J., 2021)

Job satisfaction is the overall emotional state of employees when faced with challenges related to their work environment. Job satisfaction occurs when employees feel joyful or positive emotions about their work, which stems from their work experience and the characteristics of their job. It is, therefore, a subjective emotional response of an individual to their work, which is influenced by many factors. Job satisfaction is not only about emotional reactions but also about the conscious evaluation of working conditions (salary, benefits, career growth opportunities, fairness, relationships). It is therefore a process of comparing reality with expectations. If an employee has positive feelings about their work, this is job satisfaction, but if the opposite is true, i.e., they have negative feelings about their work, this is job dissatisfaction. It is therefore the employee's general attitude towards their work, which employees express through their attitudes towards their work and the company. (Robbins et al., 2015; Tang, Shao, Chen & Ma 2021)

According to Vorina et al. (2017), job satisfaction is a positive emotional state that comes from one's job position and job content. Employee satisfaction, along with low absenteeism, turnover, and workplace accidents, influences organizational success. Many studies confirm that job satisfaction has an inverse relationship with turnover. Satisfied employees are less likely to leave, especially if they appreciate their work environment, compensation, career opportunities, and the meaningfulness of their tasks (Alam and Asim, 2019).

Several factors influence job satisfaction, including internal and external motivators, management quality, social relationships, and success at work (Armstrong, 2007, cited in Horváthová et al., 2016). Authors Rosser (2021), Damestani (2024), and Wang (2024) highlight factors such as fair pay and benefits, recognition and appreciation, the quality of the work environment, corporate culture and interpersonal relationships, opportunities for career growth, meaningful work, shared values and visions, leadership styles, and work-life balance.

Redmond and McGuinness (2019) note gender differences in job satisfaction, with women often reporting higher levels of satisfaction despite facing discrimination or receiving lower wages. However, these differences tend to disappear when the job aligns with individual preferences.

Job satisfaction can be measured using structured questionnaires, interviews with employees, or a mix of both methods (Horváthová et al., 2016). Nortje (2021) also suggests conducting interviews with supervisors.

2.2 Turnover intention

The tendency to leave is closely related to the quality of working life. According to Killham (2023), Michaels (2024), and Clifton and Harter (2021), low job satisfaction, insufficient feedback, and weak leadership are the most common reasons for employee turnover.

Based on social exchange theory, it can be argued, according to Blau (2017), that employees who are cared for by companies show loyalty and commitment to the company and also perform activities that are beneficial to the company. Conversely, if employees lose trust in the company, their commitment and loyalty decline, feelings of discouragement follow, and the gap between employee expectations and reality widens, resulting in a search for other job opportunities. If several employees decide to leave, this can lead to an operational crisis for the company. Szilagyi (1979) emphasizes that the level of job satisfaction can significantly influence employees' intention to leave. Karsh et al. (2005) found that the work environment and organizational conditions directly affect employee satisfaction, while low loyalty and satisfaction negatively affect the tendency of employees to leave. Based on social exchange theory, it can therefore be argued that if a company cares for and supports its employees, this results in high levels of job satisfaction and employee loyalty. Employees therefore perceive the magnitude of the loss for both parties if they decide to leave a company worthy of their trust and loyalty. (Tang, Shao, Chen & Ma 2021)

We can also discuss the relationship between the tendency to leave and the degree of innovative behaviour. Employees who are not engaged and are even considering leaving the company lose interest in bringing new ideas and solutions to the table. Active support for job satisfaction and employee well-being plays a preventive role not only in combating employee turnover but also in maintaining or strengthening the level of innovative behaviour among employees. Choi & Park (2025)

2.3 Innovative employee behaviour

The main competitive advantage in today's business world is the innovative behaviour of employees. For this reason, it is in the interest of every company to pay attention to organizational innovation, i.e., to inspire employees to develop their creativity and motivation to implement it. Innovative ideas are essential for a company to increase work efficiency and improve business performance. Innovative employee behaviour is a comprehensive behavioural process of searching for, generating, realizing, and implementing ideas for new techniques, processes, and products with the aim of transforming them into useful and effective ones. (Yuan a Woodman, 2010; Anderson a kol., 2014; Tang, Shao, Chen & Ma 2021)

Innovative behaviour includes three steps. First, it means generating new ideas and methods. Second, it involves sharing and promoting these concepts. Third, individuals participate in implementing them. Research by Mitchell (2018), Pradhan and Hati (2019) and Clifton and Harter (2021) shows that a supportive work environment helps employees feel safe, competent, and recognized, which boosts creativity and innovative behaviour. Constructive feedback, encouragement of autonomy and independence, teamwork, and transformational leadership are also crucial. However, according to Edmondson and Lei (2014), a culture that focuses too much on psychological safety can reduce the tension needed to achieve the company's performance goals, limit constructive conflict, and unintentionally promote complacency. Therefore, it is important to find a balance, which can be achieved through structured processes, feedback, and criticism that promote healthy discussions and create an atmosphere of trust. Job satisfaction and employee well-being at work can either hinder or encourage innovative behaviour.

3 METHODOLOGY

The research took place from 2024 to 2025 at a selected manufacturing company in the Czech Republic. This company has 282 staff members across various professional categories, including production, administration, and management. The research design used both quantitative and qualitative methods to better understand the relationships among job satisfaction, innovative behaviour, and turnover intention.

A total of 42 respondents took part in the questionnaire survey, representing about 15% of the overall workforce. Of these, 71% were men and 29% were women. The younger age group (18-34) accounted for 36%, the middle age group (35-44) accounted for 31%, and the older age group (45+) accounted for 34%. Employees accounted for 48%, production workers for 40%, and 2% were represented by other/prefer not to say. Of this distribution, 19% of respondents were in management positions. Participation was voluntary, and all responses were collected anonymously. Participants included employees from different departments and levels of hierarchy. Although this Sample does not fully represent the entire organization, it offers valuable insights into key employee attitudes and the perceived relationships among the variables studied. This limitation is acknowledged and discussed further in the final section of the article.

The questionnaire was created after reviewing relevant literature. It included scale items covering three main areas:

- Job satisfaction g (e.g., satisfaction with work-life balance, relationships, and benefits).
- Innovative behaviour (e.g., initiative, proposing improvements, problem-solving).
- Turnover intention (e.g., thoughts about leaving, desire to remain in the organization).

The collected data were analysed using descriptive statistics and correlational analysis, including Spearman's correlation coefficient.

The research included semi-structured interviews with employees from various departments and company leadership. The interviews were analysed using thematic coding, which helped identify recurring patterns related to perceptions of job satisfaction, innovation, and employee retention.

The data collection process followed principles of voluntariness, anonymity, and informed consent. No personal or identifiable information was collected or stored.

Most studies agree that job satisfaction correlates significantly with willingness to work. (Tsai and Wu, 2010; Park et al., 2014; Jehanzeb and Mohanty, 2018; Shah et al., 2020). Schwepker (2001) and Karsh et al. (2005) pointed out in their research the negative impact of job satisfaction on the tendency to leave. Also, Moslehpour et al. (2023) and Kundi et al. (2021) documented the robust inverse association between job satisfaction and turnover intention. Based on this, hypothesis No. 1 was formulated:

H1: There is a correlation between job satisfaction and turnover intention.

Empirical research has pointed to a significant connection between job satisfaction and employees' innovative work behaviour. Daneshmandi et al. (2023) confirmed that job satisfaction positively predicts individual innovative behaviour across all of its components, including idea generation, idea promotion, and idea implementation. Similarly, Grolleau et al. (2022) showed that employees working in innovation-oriented organisations report higher job satisfaction, reinforcing the argument that satisfaction and innovative behaviour are mutually reinforcing. Based on this, hypothesis No. 2 was formulated:

H2: There is a correlation between job satisfaction and innovative behaviour.

The relationship between innovative behaviour and intention to leave the organisation has been examined with mixed results. For example, Kamarudin et al. (2021) found that employees in the Malaysian hospitality industry with higher levels of innovation and creativity demonstrated lower turnover intention, suggesting a protective effect of innovation on retention. However, Shih and Susanto (2011) identified a potential 'dark side' to innovative behaviour, showing that employees engaged in high levels of innovation may also experience greater conflict with colleagues. These contrasting findings emphasise the importance of organisational context in shaping the relationship between innovative behaviour and turnover intention. Based on this, hypothesis No. 3 was formulated:

H3: There is a correlation between innovative behaviour and turnover intention.

Based on the literature review, three research hypotheses (H1–H3) were formulated. These hypotheses represent expected relationships between the variables as identified in previous studies.

4 RESULTS

Within the scope of this article, three hypotheses were tested based on data from research conducted as part of a thesis. The results of the hypotheses were supported by semi-structured interviews.

For the purpose of statistical testing, each research hypothesis (H1–H3) was translated into a null hypothesis (H_0), assuming no significant relationship between the variables, and an alternative hypothesis (H_1), assuming the existence of such a relationship. The hypotheses were tested using Spearman's correlation coefficient.

4.1 Job satisfaction and Innovative Behaviour

Data analysis showed a positive link between employee job satisfaction and innovative behaviour. Employees who felt satisfied with their working conditions, relationships, and work-life balance also reported engaging more in taking initiative, suggesting improvements, and actively solving problems. Statistical analysis confirmed a clear positive relationship between these factors, supporting Hypothesis H1:

Null hypothesis (H_0): There is no statistically significant relationship between job satisfaction levels and employees' innovative behaviour.

Alternative hypothesis (H_1): There is a statistically significant positive relationship between job satisfaction levels and employees' innovative behaviour.

Spearman's Correlations

Variable		Job satisfaction	Innovative behaviour
1. Job satisfaction	Spearman's rho	—	
	p-value	—	
2. Innovative behaviour	Spearman's rho	0.370	—
	p-value	0.041	—

Fig. 1 – Verification of hypothesis no. 1 – Job satisfaction and innovative behaviour. Source: own research

The relationship between job satisfaction and employees' innovative behaviour was tested using Spearman's correlation coefficient (Figure 2). The coefficient of $\rho = 0.370$ indicates a weak to moderate positive association, suggesting that higher job satisfaction is related to more frequent engagement in innovative behaviour. The result is statistically significant ($p = 0.041 < 0.05$), although the p-value is close to the threshold of significance. Therefore, while the null hypothesis can be rejected in favour of the alternative. Nevertheless, the result aligns with existing theoretical perspectives and prior empirical evidence linking job satisfaction to innovative behaviour.

4.2 Job satisfaction and Turnover Intention

A negative link was found between job satisfaction and turnover intention. Respondents who expressed dissatisfaction with their work environment, management, and benefits were more likely to think about leaving the organisation. These findings support Hypothesis H2:

Null hypothesis (H0): There is no statistically significant relationship between job satisfaction levels and employees' turnover intention.

Alternative hypothesis (H1): There is a statistically significant negative relationship between job satisfaction levels and employees' turnover intention.

Spearman's Correlations

Variable		Job satisfaction	Turnover intention
1. Job satisfaction	Spearman's rho	—	
	p-value	—	
2. Turnover intention	Spearman's rho	-0.790	—
	p-value	0.011	—

Fig. 2 – Verification of hypothesis no. 2 – Job satisfaction and turnover intention. Source: own research

The Spearman correlation coefficient shown in Figure 1 takes the value -0.790, which represents a strong negative correlation between job satisfaction and the tendency to leave. The fact that the value is close to -1 indicates a strong indirect relationship, suggesting that higher job satisfaction among employees is associated with a lower tendency to leave. Based on the fact that the p-value is lower than alpha, we reject the null hypothesis in favour of the alternative. Spearman's correlation revealed that there is a statistically significant negative relationship between job satisfaction and the tendency to leave.

4.3 Turnover Intention and Innovative Behaviour

The results also showed a negative relationship between turnover intention and innovative behaviour. Employees thinking about leaving the organisation tended to engage less in innovation-related activities or suggest new solutions. This suggests that employees who are emotionally or psychologically disengaged are less likely to actively contribute to innovation. Hypothesis H3:

Null hypothesis (H0): There is no statistically significant relationship between employees' turnover intention and their innovative behaviour.

Alternative hypothesis (H1): There is a statistically significant negative relationship between employees' turnover intention and their innovative behaviour.

Spearman's Correlations

Variable		Innovative behaviour	Turnover intention
1. Innovative behaviour	Spearman's rho	—	
	p-value	—	
2. Turnover intention	Spearman's rho	-0.396	—
	p-value	0.027	—

Fig. 3 – Verification of hypothesis no. 3 – Turnover intention and innovative behaviour. Source: own research

Figure 3 shows the relationship between innovative behaviour and the tendency to leave. Spearman's correlation coefficient is -0.396, which indicates a negative relationship between the two variables. The p-value (0.027) is lower than alpha (0.05), which means that we reject the null hypothesis in favour of the alternative and thus that employees who exhibit innovative behaviour have a lower tendency to leave the company.

4.4 Insights from Interviews

Semi-structured interviews backed up the findings from the quantitative analysis and offered a practical context. Respondents highlighted the importance of relationships, leadership style, career growth opportunities, and flexibility as key factors that affect their job satisfaction and well-being. Many mentioned that support from both colleagues and management motivated them to share ideas and improvements. Moreover, a lack of feedback and formal chances to join in decision-making were noted as discouraging factors, especially among employees already considering leaving the organisation.

5 DISCUSSION

The results show that job satisfaction is not just a subjective feeling, but has a significant impact on behaviour, performance, and workforce stability. Promoting job satisfaction can not only reduce turnover but also strengthen the innovative potential of employees and, in turn, the entire company.

The findings of this study suggest that job satisfaction plays a significant role in shaping employee attitudes and behaviours, though they also highlight the complexity of these relationships. It is encouraging to note that all three proposed hypotheses were supported, although the strength and nature of these associations would be best understood by examining them in more detail against the broader literature.

Firstly, the positive relationship between job satisfaction and innovative behaviour appears to be consistent with prior studies indicating that satisfied employees may be more creative, proactive, and willing to engage in problem-solving (Mitchell, 2018; Pradhan & Hati, 2019; Clifton & Harter, 2021). It is also worth noting that Tang, Shao and Chen (2019) suggested that job satisfaction and organisational commitment could potentially act as mediators of psychological capital in predicting innovative work behaviour. However, it should be noted that the strength of these effects varies across studies. For example, Zhang et al. (2022) observed that job satisfaction can be a contributing factor to innovative behaviour, however, its impact is often indirect and dependent on mediating factors such as work engagement or organisational climate. It seems that while our findings align with the general consensus, the effect of satisfaction on innovation may be context-dependent.

Secondly, it is worth noting that there appears to be an inverse correlation between job satisfaction and turnover intention, a correlation that has been well documented. Our results align with those of Schwepker (2001), Tett and Meyer (1993), and Moslehpour et al. (2023), who have documented that employees experiencing dissatisfaction are more likely to consider leaving. In contrast, Killham (2023) and Michaels (2024) further posit that a lack of recognition and managerial support can potentially compound the existing risks. However, some meta-analyses (for example, Park & Min, 2020) suggest that while satisfaction is a strong predictor of turnover intention, other variables – such as career opportunities, compensation, and cultural factors – can moderate this relationship. It is possible that this subtle difference may shed light on why our respondents, despite experiencing varying degrees of job satisfaction, did not all express a definitive opinion.

Thirdly, the negative link between turnover intention and innovative behaviour is also supported, but the literature highlights both positive and negative perspectives. Our data suggested that employees with weaker ties to the organisation and those with higher turnover intention appeared less motivated to propose new ideas. This finding aligns with the observations made by Kamarudin et al. (2021), who noted that innovative and creative employees in the hospitality sector exhibited a reduced tendency to consider leaving their positions. However, Shih and Susanto (2011) revealed the opposite dynamic: employees who engage intensively in innovative behaviour may also experience conflict with co-workers, increasing their turnover intention, especially when distributive fairness is perceived as low. This tension could be seen as pointing to the dual nature of innovative behaviour, which has the potential to both anchor employees through meaningful engagement and, conversely, push them away when organisational support is lacking.

The qualitative findings suggest that leadership, fairness, and collegial relationships may have a protective effect. It is interesting to note that respondents frequently cited these elements as contributing to a reduction in dissatisfaction and turnover intentions. Similar arguments have been made by Harter, Schmidt, and Keyes (2003), who emphasised that supportive leadership and a positive climate can transform job satisfaction into engagement and loyalty.

Taken together, the results suggest that job satisfaction may be more than just a subjective feeling; it could be a critical determinant of behaviour, performance, and organisational stability. However, it is important to consider the limitations of our findings and to approach them with a degree of caution. While the dominant view that job satisfaction reduces turnover and fosters innovation is supported by the evidence, the contrasting results in the literature highlight the importance of contextual factors, such as leadership style, organisational culture, and perceptions of fairness. It would be very helpful for future research to examine these moderating conditions more closely, in order to determine under what circumstances satisfaction most effectively translates.

6 RESEARCH LIMITATIONS

The results of the research revealed interesting findings about the relationships between job satisfaction, turnover, and innovative behaviour. However, it is necessary to take into account certain limitations that affect the interpretation and generalization of the results.

1. Sample size and selection

The research sample included 42 respondents out of a total of 282 employees. Although this provides some insight into the attitudes of employees in the organization, the sample is not statistically representative. Participation in the research was voluntary, which could have led to selection bias, i.e., more active and engaged employees participated in the research.

2. One company, specific environment

The research was conducted in one specific manufacturing company, which limits the possibility of generalizing the results to other types of organizations (e.g., public administration, IT sector). Company culture, management approaches, and organizational specifics also had a significant impact on the research results.

3. Subjectivity of measurement

The questionnaire used carries the risk of social desirability, i.e., respondents may have answered as they thought they should. The qualitative part of the research partially offsets this aspect, but it is not possible to completely exclude subjectivity.

4. Correlational research design

The results express relationships between variables, but not causality. Although correlations have been confirmed, there may be deeper and more complex relationships and realities.

7 CONCLUSION

The research findings confirm that job satisfaction and employee well-being significantly influence their behaviour, including their innovative efforts and their likelihood to stay with the company. The support for the three hypotheses shows a clear connection between job satisfaction, turnover, and innovation. This has important implications for human resource management.

The results indicate that investing in job satisfaction and employee well-being is more than just a way to care for staff. It should mainly be seen as a strategy for boosting the company's potential. Organizations that consistently promote employee well-being, such as through benefits, fair management, mental health support, or work-life balance, lower turnover rates and create a better atmosphere for innovation.

Key recommendations include regularly monitoring job satisfaction and well-being at work through anonymous surveys or feedback interviews. It also involves strengthening relationships among coworkers by fostering teamwork and a culture of recognition. Additionally, creating opportunities for employee initiatives, such as innovative workshops, brainstorming sessions, and suggestion boxes, is essential. Supporting work-life balance and providing training for managers are also crucial.

These findings offer a valuable framework for companies that understand that sustainable growth depends not only on performance but also on employee satisfaction and mental health. In the future, it would be beneficial to expand the research to other organizations and sectors, while also implementing long-term monitoring of changes over time.

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