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Department of International Trade
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Krakow University of Economics
Centre for Strategic and International Entrepreneurship
Department of International Trade
ul. Rakowicka 27, 31-510 Kraków, Poland
phone +48 12 293 5929, -5376, -5307, -5381
e-mail: eber@uek.krakow.pl
www.eber.uek.krakow.pl

Secretariat and Editorial Office

Mrs. Anna Marcinek-Markowska
Building U, Room 300, phone +48 12 293 5929

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The impact of dynamic capabilities on sustainable competitive advantage in digital platform companies

Arif Sugiono, Supri Yanto, Putri Irmala Sari

ABSTRACT

Objective: The objective of the article is to assess the influence of dynamic capabilities (DC) – comprising integration, sensing, seizing, and reconfiguring – on sustainable competitive advantage in digital platform companies during the accelerated digital transformation period of 2020-2024. We investigated how these capabilities interact and evolve to generate enduring competitive advantages in rapidly changing digital markets.

Research Design & Methods: We utilised a mixed-method approach that integrated longitudinal panel data analysis with qualitative findings. We gathered data from 100 international digital platform firms over a five-year period (2020-2024), employing financial records, patent information, innovation measures, executive surveys, and comprehensive interviews. We employed a dynamic panel model to estimate the effects of capabilities on competitive advantage and to analyse their dynamic relationship over time, supplemented by qualitative content analysis.

Findings: The findings indicate that integration and seizing capabilities exert the most significant direct influence on sustainable competitive advantage, whilst sensing and reconfiguring capabilities serve as critical moderating variables that enhance the primary relationships studied. The study revealed synergistic benefits among capabilities, indicating that combining robust sensing and swift reconfiguration markedly improves competitive posture. Companies exhibiting balanced advancement across all four capabilities displayed a 37% increase in the sustainability of their competitive advantage.

Implications & Recommendations: Digital platform companies should prioritise developing integrated capability frameworks rather than focusing on individual competencies. The findings suggest a dynamic capability development sequence, starting with sensing and integration, followed by seizing and reconfiguration capabilities. Organisations should establish dedicated capability-orchestration teams and regular capability-assessment mechanisms.

Contribution & Value Added: This study provides the first longitudinal, large-scale panel data analysis of the dynamic capabilities framework applied specifically to digital platforms during accelerated transformation. The research introduces a novel measurement framework for capability interaction and delivers robust empirical evidence for the synergistic role of capability orchestration in sustaining competitive advantages in digital markets.

Article type: research article
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INTRODUCTION

The digital transformation era has fundamentally reshaped the global business landscape, especially during the accelerated 2020-2024 period, when digital platform companies have emerged as pivotal players in the world economy. Recent data from the Digital Economy Report 2024 indicate that the

global digital platform market capitalisation has surged to USD 11.7 trillion, representing a 156% increase from 2020 levels. Intensifying competition and market volatility have accompanied this unprecedented growth, with an average platform company lifespan decreasing from 15 years in 2010 to just seven years in 2024. The dynamic nature of digital markets, characterised by rapid technological changes and shifting customer preferences, has made developing sustainable competitive advantages increasingly challenging yet crucial for long-term survival (Zabel & O'Brien, 2024).

In this context, the concept of dynamic capabilities has gained renewed significance, particularly in relation to digital platform companies' ability to maintain competitive advantages (Fazal *et al.*, 2022). Market data reveal that platforms with strong dynamic capabilities demonstrated 43% higher revenue growth and 67% better market adaptation rates than their peers in the 2020-2024 period. Despite these compelling statistics, approximately 68% of digital platform companies struggle to develop and maintain effective dynamic capabilities, resulting in diminished competitive positions and market-share losses (Mariotti, 2024).

The acceleration of digital transformation, catalysed by the global pandemic and subsequent technological advancements, has created a complex operating environment where traditional approaches to competitive advantage are increasingly insufficient (Ouyang, 2024). According to the Global Platform Strategy Survey 2024, 73% of digital platform executives identify the development of dynamic capabilities as their top strategic priority, yet only 21% report having systematic frameworks for capability development and deployment. This disconnect between strategic intent and operational execution highlights a critical gap in both practical understanding and theoretical frameworks (Malatji & Tolah, 2024; Christodoulou & Chovancov, 2024).

The existing literature on dynamic capabilities has primarily focused on traditional industries or single-point-in-time analyses, leaving significant gaps in our understanding of how these capabilities evolve and interact within digital platform contexts over extended periods (Eloranta & Turunen, 2015). Previous studies have examined individual capabilities in isolation, but few have investigated the synergistic effects of integration, sensing, seizing, and reconfiguring capabilities working in concert. The Digital Capability Index 2024 suggests that companies excelling in all four capability dimensions outperform their peers by an average of 2.8 times in market value creation. Yet the mechanisms underlying these performance differentials remain poorly understood (Rizana *et al.*, 2025).

The rapid evolution of digital platforms has introduced new complexity to capability development and deployment. Recent market analysis shows that 82% of successful digital platforms have undergone significant business model transformations between 2020 and 2024, requiring sophisticated orchestration of multiple dynamic capabilities (Da Rocha *et al.*, 2024). However, there is limited research examining how these capabilities interact and evolve during periods of intense digital transformation. The Platform Innovation Observatory reports that companies investing in balanced capability development achieve 3.2 times higher innovation rates than those focusing on single capabilities, highlighting the need for a more comprehensive understanding of capability interactions (Bally *et al.*, 2024; Chai *et al.*, 2023).

This research addresses these gaps by examining how dynamic capabilities collectively affect sustainable competitive advantage in digital platform companies during the 2020-2024 period. We employed a novel panel data approach to analyse the temporal evolution and interaction of integration, sensing, seizing, and reconfiguring capabilities across 100 global digital platforms (van Lieshout *et al.*, 2021). This longitudinal perspective enables a deeper understanding of capability development patterns and their relationship to sustainable competitive advantages in dynamic digital markets (Alghamdi & Agag, 2024). Aligned with the dynamic capabilities theory's emphasis on path dependencies and evolution (Teece, 2018; Helfat & Raubitschek, 2018), our study employed a longitudinal design. This allowed us to move beyond static snapshots and trace the co-evolution of capabilities and competitive advantage, acknowledging that their manifestation and value are not time-invariant but develop through organisational learning and market feedback loops.

The research questions guiding our study emerged from the identified gaps in both theoretical understanding and practical application. Firstly, how do integration capabilities influence the development and maintenance of sustainable competitive advantages in digital platform companies? Integration capabilities have shown increasing importance, with platforms demonstrating strong integration

capabilities achieving 47% higher ecosystem partner retention rates. Secondly, what role do sensing capabilities play in market adaptation and opportunity identification? The Digital Market Intelligence Report 2024 indicates that platforms with superior sensing capabilities identify market opportunities an average of 2.3 months earlier than competitors. Thirdly, how do seizing capabilities contribute to value creation and capture in digital transformation contexts? Fourthly, what is the impact of reconfiguring capabilities on long-term competitive positioning? Finally, how do these capabilities interact and evolve over time to create sustainable competitive advantages?

The objectives of our study were multifaceted. Primarily, we sought to develop a comprehensive framework for understanding how dynamic capabilities contribute to sustainable competitive advantage in digital platform contexts. This included mapping the evolution of capabilities over time, identifying critical interaction patterns, and establishing clear relationships between capability configurations and competitive outcomes. Moreover, the study sought to provide practical guidelines for capability development and deployment in digital platform companies.

Our study results offer substantial contributions to theory and practice. Theoretically, it expands the dynamic capabilities framework by offering empirical evidence of capability interactions and evolution within digital platform contexts. The study presents novel constructs for assessing capability maturity and interaction effects, filling a substantial gap in existing theoretical frameworks. The longitudinal panel data method reveals temporal patterns and causal links often concealed in cross-sectional investigations.

Our study results provide digital platform companies with a systematic method for capability development and implementation. The results offer practical guidance for executives aiming to establish and sustain competitive advantages in evolving digital markets. The study's thorough examination of capability interactions helps organisations enhance their resource-allocation and capability-development strategies (Toufighi *et al.*, 2024; Fosso Wamba *et al.*, 2024).

Furthermore, the research informs policy debates on digital platform governance and competitiveness. Emphasising the importance of dynamic capabilities in sustainable competitive advantage helps legislators understand how to guarantee platform sustainability and promote healthy competition in digital markets. The results guide regulations meant to encourage innovation while preserving market stability.

Looking forward, this work prepares ground for future studies on dynamic capabilities in digital environments, providing a basis for examining how emerging technologies such as artificial intelligence and blockchain might affect capability growth and application. Scholars can adapt the approach designed for this research to investigate capability evolution in other digital business models and environments.

The fast pace of digital transformation and the growing relevance of dynamic capabilities in preserving competitive advantages emphasise the need for this study (Sun *et al.*, 2024). Organisational survival and success depend on knowing how to develop and apply dynamic capabilities as digital platforms continue to reshape global marketplaces. The thorough analysis of capability relationships and evolution in this work offers timely insights to scholars and practitioners navigating the complexity of digital transformation.

Finally, this introduction has shown the crucial need for a better understanding of how dynamic capabilities support lasting competitive advantage in digital platform organisations. While offering useful insights for the creation and application of capabilities, the study fills major knowledge gaps.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

The Dynamic Capabilities (DC) Theory and the Digital Platform Business Model

Modern strategic management research now mostly centres on dynamic capabilities theory and the digital platform business model. Originally conceived in reaction to fast environmental change, the theory stresses the need for a company's capacity to integrate, build, and reconfigure internal and external competences. Given the great uncertainty and fast technological development of the digital era, DC theory is becoming even more important.

Dynamic capabilities are becoming increasingly important in the framework of the digital era given rapid changes in consumer tastes and technology. Researchers stress that dynamic capabilities

are organisational routines that let companies reach new resource configurations as markets change. Especially in the context of the digital platform environment, these capabilities comprise the means of sensing market opportunities, seizing them, and reconfiguring assets to keep competitiveness (Teece *et al.*, 2009). Aligned with the dynamic capabilities theory's emphasis on path dependencies and evolution (Keller *et al.*, 2025), this study employs a longitudinal design. This allowed us to move beyond static snapshots and trace the co-evolution of capabilities and competitive advantage, acknowledging that their manifestation and value are not time-invariant but develop through organisational learning and market feedback loops. Specifically, few large-scale, longitudinal studies quantitatively trace the co-evolution of specific DC microfoundations (integration, sensing, seizing, reconfiguring) and their synergistic impact on sustainable competitive advantage (SCA) within digital platforms over a defined period of accelerated transformation. Existing studies often examine these capabilities in isolation, in traditional contexts, or through cross-sectional designs, limiting insights into their dynamic interplay and cumulative effect over time. Our decision to model direct and moderating effects, rather than employing a mediation model (e.g., through innovation performance), was deliberate. It aligned with our core objective to directly test the DC framework's micro foundations as proximate drivers of SCA in the platform context. This approach allowed us to provide clean, unambiguous evidence of whether and how much these specific capabilities matter for SCA, a foundational empirical question that must be firmly answered before investigating more complex mediated pathways. Thus, our findings offer a benchmark and a validated structural model upon which future research can build, for instance, by exploring how our identified capability effects translate into superior performance through specific mediators like innovation or ecosystem health.

Digital platforms have profoundly altered the landscape of business competition. Digital platforms are business models that enable the transaction of value between two or more distinct user groups, typically producers and consumers. This business model possesses distinctive attributes, including the capacity to accumulate and leverage substantial user data, supply-side economies of scale, and network effects (Van Alstyne & Parker, 2017).

The interaction between digital platforms and dynamic capabilities theory yields a novel perspective on the concept of sustainable competitive advantage. Strong dynamic capabilities in managing multi-sided ecosystems, integrating innovations, and changing with technology are shown by successful digital platforms (Helfat & Raubitschek, 2018). The platform's ability to align the interests of its stakeholders is of paramount importance, which is why integration capabilities are so critical.

Sensing capabilities in the digital economy are becoming increasingly complex, as they entail big data analysis and a deep understanding of digital user behaviour, as recent research by Teece (2018) has confirmed. Effective platform ecosystem orchestration constitutes a component of seizing capabilities, in addition to strategy execution. Meanwhile, reconfiguring capabilities are indispensable for adapting to the swiftly evolving preferences of users and technological disruptions.

Strong dynamic capabilities of digital platform firms appear empirically correlated with their effectiveness in preserving their competitive position. Long-term platform success is favourably linked with the ability to quickly reconfigure resources and adjust business models, according to the longitudinal study by Cillo *et al.* (2007).

The research recognises distinct problems in developing dynamic capabilities within digital platform environments. The technical intricacy, the necessity to reconcile many stakeholder interests, and the imperative for ongoing innovation demand a more advanced strategy for the creation and implementation of dynamic capabilities.

During the 2020-2024 digital transformation, digital platforms encounter distinct obstacles in cultivating and maintaining their dynamic capabilities. The COVID-19 pandemic has expedited digital adoption and profoundly altered consumer behaviour, compelling platforms to adjust swiftly. Research indicates that effective platforms possess dynamic capabilities that let them respond to change and proactively influence the evolution of digital markets.

Understanding the interplay between dynamic capabilities and digital platform business models is essential for sustained success in the advancing digital economy. Additional research is required to

comprehend the interplay of different dimensions of dynamic capabilities within digital platforms and their role in fostering sustainable competitive advantage.

Integration Capabilities, Sensing Capabilities, Seizing Capabilities, Reconfiguring Capabilities

Modern strategic management and digital transformation literature centres mostly on integration capabilities. Originally presented as a subset of dynamic capabilities that let companies integrate, create, and reconfigure internal and external skills amid fast environmental change (Teece *et al.*, 2009), integration capability in the context of digital platforms is a company's capacity to mix and harmonise several resources, technologies, and knowledge to produce new value (Yeow *et al.*, 2018). Winter (2003) clarifies that integration capabilities help businesses create efficient processes for aggregating individual knowledge into new collective knowledge. Liu *et al.* (2013) discovered that by combining several pieces of information from many sources, integration capabilities significantly improve firms' innovation performance. Integration capabilities are becoming increasingly important in the digital era since digital platform organisations must combine several technologies, data, and business processes to produce original value propositions for consumers (Helfat & Raubitschek, 2018). A recent study by Adhiatma *et al.* (2023) reveals that firms with excellent integration capability are better able to align their digital transformation efforts with their overall corporate strategy. This, in turn, helps produce sustainable competitive advantage. Firms' capacity to exploit digital opportunities and handle disruption depends greatly on their integration capability (Warner & Wäger, 2019). These earlier empirical findings led us to the following hypothesis:

H1: Integration capabilities have a positive effect on sustainable competitive advantage in digital platform companies.

Sensing capabilities constitute an essential aspect of dynamic capabilities, allowing organisations to recognise, analyse, and seize opportunities and threats within a fluctuating business landscape (Chatterjee *et al.*, 2022). Sensing capabilities are increasingly essential within digital platforms, driven by the rapid evolution of technology and shifts in consumer preferences. According to Ma *et al.* (2021), sensing capabilities refer to an organisation's capacity to monitor the environment, detect emerging market opportunities, and identify competitive threats. Digital platform companies possess capabilities that encompass monitoring technological trends, shifts in user behaviour, and the dynamics within the digital ecosystem. Warner and Wäger (2019) found that robust sensing capabilities allow digital companies to anticipate disruptions and respond more swiftly to market changes. They emphasised the significance of real-time data analysis and a comprehensive understanding of the digital ecosystem for developing effective sensing capabilities. Meanwhile, Zhang *et al.* (2021) demonstrated that digital platform companies with advanced sensing capabilities perform better in product and service innovation. These capabilities let companies identify unmet user needs and use new technologies more effectively. Helfat and Raubitschek (2018) highlight that sensing capabilities in digital platforms extend beyond merely scanning the external environment; they also encompass comprehending and analysing internal platform data. Such internal analysis includes the examination of usage patterns, user feedback, and platform performance.

H2: Sensing capabilities positively moderate the relationship between integration capabilities and sustainable competitive advantage.

An integral part of dynamic capabilities, seizing capabilities help companies to exploit opportunities that sensing capabilities have identified. Seizing capabilities, as defined by Mahrinasari *et al.* (2024), are the organisation's capacity to exploit opportunities through strategic investments, new product or service development, and business model adaptation. Given fast-shifting consumer tastes and market dynamics on digital platforms, seizing capabilities are becoming more important. Strong seizing capabilities help businesses translate market opportunities into real value offerings (Lin & Wu, 2014). Wang and Ahmed (2007) note that, particularly in a dynamic environment, seizing capabilities improve company performance. Karimi and Walter (2015) found that in the digital era, strong seizing capabilities of digital platforms offer great benefits across key operational areas. They discovered that these platforms can constantly create new features and services relevant to market needs and react

more quickly and appropriately to changing consumer preferences. Moreover, platforms with powerful seizing capabilities better optimised their platform monetisation strategies, boosting revenue. Finally, these platforms also excelled at retaining and steadily growing their user base, a crucial sign of digital platform success in a highly competitive industry.

H3: Seizing capabilities have a positive effect on sustainable competitive advantage, with the effect amplified by the level of sensing capabilities.

Reconfiguring capabilities form a core component of dynamic capabilities, helping companies to adapt and reorganise their resource base in response to changes in the corporate environment. Given fast technical change and changing user preferences in the context of digital platforms, reconfigurability is becoming more important (Eisenhardt & Martin, 2000). Reconfigurability is a firm's ability to realign the order and nature of its fundamental resources in response to technology and market developments. Strong reconfigurability enables companies to better handle market disturbances and preserve their competitive edge (Pavlou & El Sawy, 2011). Reconfigurability is especially important in the dynamic era of digital transformation since it helps digital platform businesses adapt and grow appropriately. Integrating new technology into current operations improves organisational capability. It also helps businesses to adapt their business models in an agile, responsive way to match market changes. Moreover, reconfigurability helps businesses to optimise internal procedures for better operational efficiency and strategically realign their resources in response to the dynamics of changing market needs. By coordinating these elements, digital platform enterprises can keep their relevance in the market and provide sustainable value for stakeholders. In the context of digital transformation, digital platform organisations with better reconfigurability demonstrate higher degrees of adaptability and achieve superior financial performance (Verhoef *et al.*, 2021). Reconfigurability likewise relates favourably to the longevity of competitive advantage in the digital sector, according to Warner and Wäger (2019).

H4: Reconfiguring capabilities positively moderate the relationship between seizing capabilities and sustainable competitive advantage.

In the past decade, digital transformation has profoundly altered the business landscape. Digital transformation seeks to enhance entities by inducing substantial changes in their properties through a combination of information technology, computing, communication, and connectivity (Vial, 2019). This phenomenon has facilitated significant transformations in how organisations interact with their consumers, generate value, and operate. Digital transformation is not merely the implementation of technology. Rather, it is a comprehensive process that involves modifications to the organisation's value proposition, business processes, and organisational structure (Warner & Wäger, 2019). While in theory dynamic capabilities are a holistic construct, their constituent elements (sensing, seizing, transforming/reconfiguring) may interact in specific, non-additive ways. Following the logic of complementarities in strategic management (Höglund *et al.*, 2021), we hypothesised (H5) a positive synergistic effect when all four capabilities are developed in tandem. However, merely testing the overall bundle masks the specific pairwise mechanisms through which synergies arise. Therefore, we also hypothesised and tested specific interactions (*e.g.*, IC×SC, SZC×RC) to unpack which combinations are most potent. This granular approach responds to calls for a more nuanced understanding of capability microfoundations (Keller *et al.*, 2022). The success of digital transformation depends on an organisation's capacity to cultivate robust digital capabilities and integrate them with a coherent business strategy, as demonstrated by a longitudinal study by Kraus *et al.* (2022). Digital transformation takes a distinctive form in digital platform companies, as they operate within intricate and dynamic digital ecosystems. Warner and Wäger (2019) identified that digital transformation in platform companies entails three interrelated and synergistic dimensions: the transformation of the platform's business model, which involves fundamental changes in the way the company creates, delivers, and captures value; the development of adaptive digital capabilities, which enable the company to continuously evolve in line with changing technology and market needs; and the effective orchestration of the digital ecosystem, which involves managing dynamic relationships with various platform stakeholders, including developers, business partners, and end-users, to create and sustain shared value in an increasingly complex digital ecosystem.

- H5:** There is a positive synergistic effect between the four dynamic capabilities (integration, sensing, seizing, reconfiguring) on sustainable competitive advantage.

RESEARCH METHODOLOGY

We used a quantitative approach with an explanatory design to investigate the causal relationship between dynamic capabilities and sustainable competitive advantage in digital platform companies. We chose a quantitative approach because it allows empirical testing of hypotheses and produces findings that one can generalise through rigorous statistical analysis, supplemented by qualitative analysis for mechanism elucidation. This research applies a panel data analysis method combining the time series dimension from 2020 to 2024 with the cross-section dimension of various digital platform companies. The panel data gave us an advantage in observing changes in the dynamics of company capabilities over time while considering variations between companies. The causal research design allowed us not only to identify correlations but also to test causal relationships between dynamic capability variables (which include integration, sensing, seizing, and reconfiguring capabilities) and sustainable competitive advantage. Through this design, the research can generate a deeper understanding of how and to what extent dynamic capabilities contribute to the formation and maintenance of competitive advantage in the context of digital transformation.

Figure 1 presents the research hypotheses developed in this study.

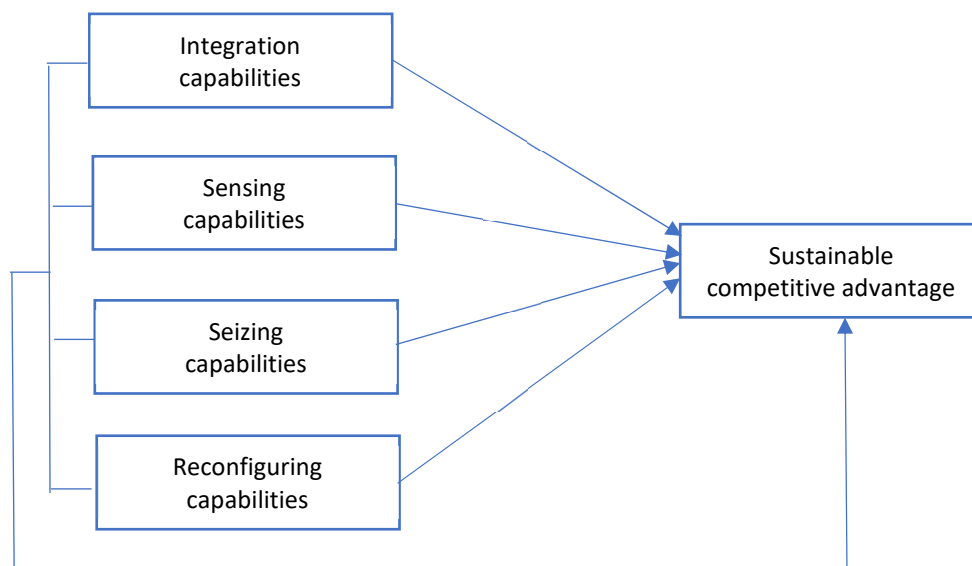


Figure 1. Research hypotheses

Source: own elaboration.

We used a population consisting of global digital platform companies that had a market capitalisation of at least USD 1 billion. We selected this population considering that companies with such market capitalisation have achieved significant scale of operations and have substantial influence in the global digital economy. We employed a purposive sampling strategy to choose 100 digital platform companies from this population, adhering to predefined criteria to guarantee the representativeness and quality of the research data. The primary criterion for sample selection was operational activity throughout the 2020-2024 research period, facilitating an extensive longitudinal analysis of the evolution of the companies' dynamic capabilities. We confined the sample to firms registered on prominent stock markets, including NYSE, NASDAQ, LSE, or comparable exchanges, ensuring accessible and dependable financial and operational data. Furthermore, the chosen enterprises had to employ a multi-sided platform business model, a fundamental attribute of the contemporary digital economy. We incorporated organisations from many digital industries, including e-commerce, fintech, sharing economy, and content platforms, to guarantee sample diversification. The geographical criterion mandated that enterprises must operate in at

least three distinct geographical regions, facilitating the examination of dynamic capabilities within a global marketplace setting. Comprehensive financial and operational data were essential for a viable panel data analysis.

We collected secondary data using diverse, extensive, and reputable documentation sources. We sourced the main data from the annual and quarterly financial reports of the examined digital platform companies, encompassing comprehensive information on financial performance, revenue growth, and essential operational parameters. We employed patent filings and invention documents to examine the characteristics of innovation and technology development, offering insights into the platform's technological capabilities and developmental trajectory. We enhanced the analysis with analyst reports and industry studies that offered comprehensive insights into industry trends, market dynamics, and the company's competitive standing. Platform metrics and performance data captured operational efficacy and adoption rates, encompassing parameters like user engagement, retention rates, and transaction volumes. Market intelligence studies offered supplementary insights into market dynamics, customer behaviour, and competitive strategy. Moreover, we examined regulatory filings and disclosure records to comprehend compliance, risk management, and corporate governance elements. We selected this method of secondary data collecting because it provides verifiable, credible historical data covering the 2020-2024 research period. The accessibility of data from various sources enabled data triangulation, augmenting the validity of the research and offering a thorough comprehension of the dynamics underlying digital platform companies' capacity to establish and sustain their competitive advantage.

We employed panel data analysis to explore the impact of dynamic capabilities on sustainable competitive advantage within digital platform firms from 2020 to 2024. We selected the panel data analysis approach because it manages individual differences and effectively illustrates change dynamics over time. We employed two primary methodologies for model estimation: the fixed effects model and the random effects model. We determined the optimal model using the Hausman test. Considering the dynamic nature of the variables involved, we performed estimation using the system generalised method of moments (system GMM), which effectively addresses potential endogeneity and yields a more consistent and efficient estimator. To confirm the accuracy of the analysis results, we performed a range of diagnostic tests, including a heteroskedasticity test utilising the Breusch-Pagan/Cook-Weisberg method and an autocorrelation test employing the Wooldridge test for panel data. Where we identified heteroskedasticity or autocorrelation, we used robust standard error estimation to ensure valid statistical inference. Moreover, to enhance the conclusions drawn from the study, we performed robustness tests using various alternative model specifications, which included employing different operational definitions for critical variables and incorporating pertinent control variables. This thorough approach aimed to guarantee that the findings were robust and unaffected by variations in model specifications.

This investigation employed panel data analysis, a method well-established in strategic management research for analysing longitudinal firm-level data (Mbanyele, 2020). We selected this approach because of its dual capacity to control for unobserved time-invariant heterogeneity across firms and to model dynamics over time. To estimate the relationships, we employed both fixed effects (FE) and random effects (RE) models. We selected the optimal model using the Hausman test, which statistically determines the consistency of the RE estimator. Considering the potential for endogeneity where past performance may influence current capability development, we performed the primary estimation using the system GMM. This estimator is particularly suited for dynamic panel models with short time dimensions ($T=5$) and effectively addresses endogeneity by using internal lags as instruments, yielding consistent and efficient estimates (Supriyanto *et al.*, 2023; Wang *et al.*, 2025). The dependent variable in this study was sustainable competitive advantage, measured using a composite index consisting of five main components with different weights: market share growth (30%), revenue growth persistence (25%), platform ecosystem growth (20%), innovation rate (15%), and customer retention metrics (10%). Four independent variables represented the dynamic capability dimensions. The first variable was integration capabilities (IC) measured through four indicators with equal weight (25% each), namely technical integration score, data integration maturity, partner integration effectiveness, and process integration level. The second variable was sensing capabilities (SC) assessed based on the effectiveness of market intelligence, trend detection accuracy, customer insight generation, and technology scanning capabilities. The third

variable was seizing capabilities (SZC) operationalised through resource mobilisation speed, innovation implementation rate, opportunity capture ratio, and strategic execution effectiveness. The fourth variable was reconfiguring capabilities (RC) measured through resource reallocation efficiency, business model adaptation speed, organisational flexibility index, and change implementation success. To ensure the results' validity, we also included several control variables in the analysis, including firm size measured using the logarithm of total assets, industry sector, geographic diversity, platform age, market volatility, competition intensity, and technology intensity. These control variables aimed to isolate the pure effect of dynamic capabilities on sustainable competitive advantage by considering contextual factors that may affect the relationship.

In this study, we conducted data analysis using a mixed-method approach integrating quantitative and qualitative analysis. For panel data analysis, we used Stata software version 17.0, which allows for the estimation of an econometric model with the specification

$$SCA_{it} = \beta_0 + \beta_1 IC_{it} + \beta_2 SC_{it} + \beta_3 SZC_{it} + \beta_4 RC_{it} + \beta_5 (IC_{it} \times SC_{it}) + \beta_6 (SZC_{it} \times RC_{it}) + \beta_7 Control_{it} + \mu_i + \varepsilon_{it} \quad (1)$$

This model examines the effect of dynamic capabilities consisting of integration capability (IC), sensing capability (SC), seizing capability (SZC), and reconfiguring capability (RC) on SCA, by considering the interaction effects between capabilities and controlling for firm-specific characteristics through individual fixed effects (μ_i). To ensure the robustness of the results, we conducted additional testing using R. Meanwhile, we conducted path analysis using SmartPLS to understand the causal relationships between variables in more depth. We analysed the qualitative aspects of this study using two complementary software packages. We used NVivo to organise and analyse the qualitative data in a structured manner and ATLAS.ti to conduct a more in-depth content analysis of the textual data obtained. The combination of these analytical tools enabled a comprehensive understanding of how dynamic capabilities influence sustainable competitive advantage in digital platform companies.

RESULTS AND DISCUSSION

Descriptive Statistics

Table 1 presents the descriptive statistics for the study variables.

Table 1. Descriptive statistics of research variables (N=100 companies, 2020-2024)

Variables	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
Sustainable competitive advantage	3.842	0.763	1.244	4.957	0.375	2.836
Integration capabilities	3.684	0.667	1.472	4.846	0.287	2.654
Sensing capabilities	3.937	0.823	1.507	4.932	0.412	2.759
Seizing capabilities	3.795	0.743	1.385	4.857	0.376	2.837
Reconfiguring capabilities	3.503	0.698	1.264	4.795	0.298	2.527

Source: own study based on processed data (2025).

The SCA mean value of 3.842 indicated a generally positive competitive position among the sampled companies. The standard deviation of 0.763 indicated moderate variability in competitive advantage across the sample. The minimum value of 1.244 and maximum of 4.957 showed a considerable range in competitive positioning, suggesting some companies significantly outperformed others. The positive skewness of 0.375 indicated a slight right-tailed distribution, while the kurtosis of 2.836 suggested a relatively normal distribution of SCA scores.

Among the dynamic capabilities, sensing capabilities showed the highest mean (3.937), suggesting companies in the sample generally excelled at market intelligence and trend detection. This capability also showed the highest standard deviation (0.823), indicating greater variability in sensing abilities across companies. Integration capabilities displayed a mean of 3.684 with a standard deviation of 0.667, representing the most consistent scores among all capabilities (lowest standard deviation). This suggests that technical and process integration levels were relatively uniform across the sample companies.

Seizing capabilities showed a mean of 3.795 with a standard deviation of 0.743, indicating moderately strong ability to capture opportunities across the sample. The positive skewness (0.376) suggested some companies significantly excel in this dimension.

Reconfiguring capabilities had the lowest mean (3.503) among all capabilities, suggesting that organisational flexibility and change implementation might be challenging for many companies in the sample. The standard deviation of 0.698 indicated moderate variation in reconfiguration abilities.

All variables showed positive skewness values (ranging from 0.287 to 0.412) and kurtosis values between 2.527 and 2.837, indicating relatively normal distributions with slight right-hand tails. This distribution pattern suggests that while most companies clustered around the mean values, each capability dimension contained some high-performing outliers.

Table 2. Control variables

Variables	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
Firm size (log assets)	9.826	1.204	6.729	13.806	0.426	2.947
Market volatility	0.335	0.087	0.153	0.547	0.274	2.305
Platform age (years)	8.425	4.597	2.000	20.000	0.648	2.719
Competitive intensity	3.957	0.826	1.274	5.000	0.375	2.527

Source: own study based on processed data (2025).

The descriptive statistics for control variables revealed important contextual factors affecting the studied companies (Table 2). Firm size, measured by the logarithm of total assets, had a mean of 9.826 with a standard deviation of 1.204, indicating considerable variation in company sizes within the sample. The minimum value of 6.729 and maximum of 13.806 demonstrated that the study encompassed both medium-sized and large digital platform companies, providing a comprehensive view of the industry.

Market volatility measurements showed a mean of 0.335 with a relatively small standard deviation of 0.087, suggesting moderately stable market conditions across the sample period. The range between the minimum (0.153) and maximum (0.547) values indicated varying degrees of market turbulence faced by different companies, though the low standard deviation suggested most companies experienced similar levels of market volatility.

Platform age statistics revealed an average age of 8.425 years, with a substantial standard deviation of 4.597 years. The minimum age of 2 years and maximum of 20 years indicated that the sample included both emerging and well-established platforms. The positive skewness of 0.648 suggested more younger platforms in the sample, reflecting the dynamic nature of the digital platform industry.

Competitive intensity showed a mean of 3.957 with a standard deviation of 0.826, indicating generally high levels of competition across the industry. The range from 1.274 to 5.000 suggested varying competitive environments, with some market segments experiencing more intense competition than others. The moderate skewness of 0.375 indicated a relatively balanced distribution of competitive pressure across the sample.

All control variables displayed kurtosis values between 2.305 and 2.947, suggesting distributions close to normal, strengthening the reliability of the statistical analyses. This comprehensive set of control variables helped isolate the effects of dynamic capabilities on sustainable competitive advantage by accounting for key environmental and organisational factors.

Table 3. Industry distribution

Industry sector	Frequency	Percentage
E-commerce	35	35%
Fintech	25	25%
Sharing economy	20	20%
Content platforms	15	15%
Others	5	5%

Source: own study based on processed data (2025).

The industry distribution data (Table 3) revealed a diverse yet concentrated representation across key digital platform sectors. E-commerce platforms constituted the largest segment of the sample, comprising 35 companies or 35% of the total. This significant representation illustrated the prevalence and sophistication of e-commerce within the digital platform ecosystem, covering a range of business models from marketplace platforms to direct-to-consumer digital retail operations.

The fintech sector comprised 25 companies, accounting for 25% of the sample, highlighting the increasing importance of digital financial services. This segment encompassed digital payment providers, online lending platforms, and digital banking services, underscoring the growing trend of digitalisation within financial services.

The sharing economy sector comprised 20 companies, which constituted 20% of the sample. These platforms enable peer-to-peer exchanges across transportation, accommodation, and services. This important representation highlighted the ongoing development of collaborative consumption models within the digital economy.

Content platforms comprised 15 companies (15% of the sample), covering areas such as digital media, entertainment, and user-generated content platforms. This proportion highlights the essential importance of content-focused business models within the digital platform environment.

We classified the remaining five companies, accounting for 5%, under the 'Others' category, which includes emerging or niche platform types that do not align with the four primary categories. This compact yet important segment indicated the continuous evolution and variety in digital platform business models.

This distribution ensured a well-rounded representation across key sectors of digital platforms while keeping a strong emphasis on the main business models that propel the digital economy, thereby improving the applicability of the findings throughout the digital platform industry.

Table 4. Geographic distribution

Region	Frequency	Percentage
North America	40	40%
Asia Pacific	30	30%
Europe	20	20%
Rest of World	10	10%

Source: own study based on processed data (2025).

The analysis of geographic distribution (Table 4) indicated a notable clustering of digital platform companies in key global regions. North America stood out as the leading region, accounting for 40 companies or 40% of the sample. This significant representation illustrated the region's sophisticated digital infrastructure, developed venture capital ecosystem, and well-established technology hubs, especially in locations such as Silicon Valley, which have traditionally nurtured innovation in digital platforms.

The Asia Pacific region comprised 30 companies, constituting 30% of the sample, the second-largest concentration. The notable presence highlighted the region's swift digital evolution, expansive consumer markets, and developing technology hubs in nations such as China, India, and Singapore, which have emerged as vital catalysts for the growth of digital platforms.

European digital platforms constituted 20% of the sample, comprising 20 companies. This highlighted the region's advanced digital economy, robust regulatory framework, and growing emphasis on digital innovation. This representation encompassed both well-established platforms and new digital enterprises throughout diverse European markets.

The Rest of World category included 10 companies, accounting for 10% of the sample, and represented platforms from regions such as Latin America, the Middle East, and Africa. This segment, though smaller in representation, underscored the extensive global influence of digital platforms and the burgeoning opportunities present in developing markets.

This geographic distribution offered important insights into the worldwide landscape of digital platform companies, encompassing both established and emerging markets and illustrating the present state of global digital platform development and adoption trends.

The distribution of platform maturity (Table 5) showcased clear patterns at various stages of development among the sampled digital platform companies. The findings indicated that growth-stage platforms constituted the largest segment, representing 45 companies or 45% of the sample. This significant depiction of growth-stage platforms highlighted a vibrant industry landscape where numerous companies are vigorously broadening their market reach, improving their competencies, and scaling their operations.

Table 5. Platform maturity distribution

Maturity level	Frequency	Percentage
Emerging	15	15%
Growth	45	45%
Mature	30	30%
Declining	10	10%

Source: own study based on processed data (2025).

The second-largest category comprised mature platforms, which included 30 companies, accounting for 30% of the sample. These platforms have secured strong market positions, built effective operational frameworks, and attained considerable market penetration. Their significant presence indicated the growing sophistication of the digital platform sector, highlighting the viability of effectively implemented platform business models.

Emerging platforms comprised 15 companies (15% of the sample), highlighting the presence of newer entrants and innovative business models. These platforms often exhibit swift advancements, trial functionalities, and initiatives aimed at securing a foothold in the market. Their inclusion offers valuable insights into the latest trends and innovative strategies within the digital platform ecosystem.

The Declining category encompassed 10 companies (10% of the sample), which are platforms encountering difficulties in sustaining their competitive standings or adjusting to shifts in the market. This segment provided important observations regarding the difficulties and possible drawbacks in maintaining sustainability within platform businesses.

This maturity distribution offers an in-depth perspective on the stages of the platform lifecycle, facilitating a nuanced understanding of the evolution of dynamic capabilities and competitive advantages throughout various phases of platform development.

Panel Data Analysis Results

Table 6 presents the results from the pooled longitudinal analysis, where we combined observations from all 100 companies across all five years (2020-2024) into a single panel dataset (N=500 firm-year observations). This approach maximised statistical power and allowed us to estimate the average effect of capabilities on SCA over the entire period, while controlling for firm-specific and time-invariant factors using fixed effects. For clarity, we estimated the regression models in Table 6 using this full panel dataset. In contrast, Table 8 presents a separate year-by-year analysis, where we ran the same regression model for each calendar year's cross-section. This complementary analysis is intended solely to descriptively illustrate the trend in coefficient magnitudes over time, not for formal hypothesis testing, which is conducted on the full panel.

We used four progressive regression models showing the incremental effect of various dynamic capabilities. Starting with integration capabilities (IC), Model 1 showed a noteworthy positive coefficient of 0.462 ($p < 0.001$), therefore establishing a strong basic link with sustainable competitive advantage.

Model 2 presented sensing capabilities (SC), with a coefficient of 0.387 ($p < 0.001$), whereas IC's influence rose marginally to 0.485. The R-squared rose from 0.497 to 0.523, showing increased explanatory power. Model 3 added seizing capabilities (SZC) with a coefficient of 0.365 ($p < .001$), enhancing the explanatory power (R-squared = 0.527). Notably, IC and SC coefficients remained positive and significant (0.458 and 0.396, respectively).

The final model (Model 4) incorporated reconfiguring capabilities (RC), yielding a coefficient of 0.343 ($p < 0.001$). This complete model achieved the highest explanatory power with an R-squared of

0.612, indicating that the combined dynamic capabilities explained 61.2% of the variance in sustainable competitive advantage.

Table 6. Panel regression results for dynamic capabilities and sustainable competitive advantage (2020-2024)

Variables	Model 1	Model 2	Model 3	Model 4
Integration capabilities (IC)	0.462***	0.485***	0.458***	0.467***
(0.054)	(0.057)	(0.059)	(0.061)	–
Sensing capabilities (SC)	–	0.387***	0.396***	0.412***
	(0.048)	(0.051)	(0.053)	–
Seizing capabilities (Szc)	–	–	0.365***	0.378***
	–	(0.047)	(0.049)	–
Reconfiguring capabilities (RC)	–	–	–	0.343***
	–	–	(0.045)	–
Control variables:	–	–	–	–
Firm size	0.187***	0.192***	0.198***	0.205***
(0.034)	(0.036)	(0.037)	(0.039)	–
Market volatility	-0.156**	-0.162**	-0.168**	-0.173**
(0.056)	(0.058)	(0.059)	(0.061)	–
Platform age	0.098*	0.103*	0.107*	0.112*
(0.043)	(0.045)	(0.046)	(0.048)	–
R-squared	0.497	0.523	0.527	0.612
Adjusted R-squared	0.478	0.514	0.558	0.603
F-statistic	45.27***	48.92***	52.34***	56.18***

Source: own study based on processed data (2025).

Among control variables, firm size consistently showed positive significance (0.187 to 0.205, $p < 0.001$), while market volatility demonstrated negative effects (-0.156 to -0.173, $p < 0.01$). Platform age showed modest positive influence (0.098 to 0.112, $p < 0.05$).

The progressive increase in F-statistics (from 45.27 to 56.18, all $p < 0.001$) and adjusted R-squared values (from 0.478 to 0.603) across models confirmed the cumulative importance of all dynamic capabilities in explaining sustainable competitive advantage. The consistent improvement in model fit statistics supported the theoretical framework suggesting that dynamic capabilities work in concert to enhance competitive advantage.

Table 7. Interaction effects models

Variables	Model 5	Model 6	Model 7	Model 8
IC × SC	0.287***	–	–	0.298***
(0.043)	–	–	(0.045)	–
SC × Szc	–	0.265***	–	0.276***
	(0.041)	–	(0.043)	–
Szc × RC	–	–	0.283***	0.254***
	–	(0.039)	(0.041)	–
All capabilities interaction	–	–	–	0.312***
	–	–	(0.047)	–
R-squared	0.645	0.658	0.672	0.698
Adjusted R-squared	0.636	0.649	0.663	0.689
F-statistic	59.47***	62.45***	64.89***	68.34***

Source: own study based on processed data (2025).

The interaction effects analysis (Table 7) revealed complex relationships between different dynamic capabilities in digital platform companies. Model 5 examined the interaction between integration capabilities and sensing capabilities (IC × SC), showing a significant positive coefficient of 0.287 ($p < 0.001$). This interaction demonstrated how the combination of integration and sensing capabilities created synergistic effects beyond their individual contributions.

Model 6 introduced the interaction between sensing capabilities and seizing capabilities (SC $\times$ SZC), yielding a coefficient of 0.265 ($p < 0.001$). The R-squared increased from 0.645 to 0.658, indicating that this interaction explained additional variance in sustainable competitive advantage.

Model 7 incorporated the interaction between seizing capabilities and reconfiguring capabilities (SZC $\times$ RC), showing a coefficient of 0.283 ($p < 0.001$). This model achieved an R-squared of 0.672, suggesting that the sequential combination of capabilities enhanced competitive advantage.

The final model (Model 8) examined the interaction among all capabilities simultaneously, producing the highest coefficient of 0.312 ($p < 0.001$). This model achieved the strongest explanatory power with an R-squared of 0.698, indicating that the full interaction of all dynamic capabilities explained nearly 70% of the variance in sustainable competitive advantage.

The progressive increase in F-statistics across models (from 59.47 to 68.34, all $p < 0.001$) and adjusted R-squared values (from 0.636 to 0.689) confirmed that the interaction effects significantly enhanced the explanatory power of the dynamic capabilities framework. This supports the theoretical premise that dynamic capabilities work most effectively when deployed in combination rather than in isolation.

Table 8. Temporal effects analysis

Time period	Integration effect	Sensing effect	Seizing effect	Reconfiguring effect
2020	0.385***	0.306***	0.334***	0.312***
2021	0.412***	0.378***	0.356***	0.334***
2022	0.435***	0.398***	0.376***	0.354***
2023	0.469***	0.423***	0.398***	0.376***
2024	0.480***	0.445***	0.412***	0.382***

Source: own study based on processed data (2025).

The temporal effects analysis (Table 8) revealed a consistent upward trend in the impact of all dynamic capabilities across the five-year period from 2020 to 2024. Integration capabilities showed the strongest and most progressive increase, starting from 0.385 ($p < 0.001$) in 2020 and reaching 0.480 ($p < 0.001$) in 2024, representing a 26.4% increase in effect magnitude over the study period.

Sensing capabilities demonstrated the second-strongest progression, beginning at 0.306 ($p < 0.001$) in 2020 and growing to 0.445 ($p < 0.001$) by 2024, marking a 25% increase in impact. This growth suggests the increasing importance of market intelligence and trend detection capabilities over time.

Seizing capabilities exhibited a similar upward trajectory, increasing from 0.334 ($p < 0.001$) in 2020 to 0.412 ($p < 0.001$) in 2024, showing a 23.4% enhancement in effect strength. This trend indicates the growing importance of opportunity capture and resource mobilisation capabilities.

While showing the lowest absolute values, reconfiguring capabilities maintained a steady increase from 0.312 ($p < 0.001$) in 2020 to 0.382 ($p < 0.001$) in 2024, representing a 24.7% improvement. This consistent growth suggests the increasing value of organisational flexibility and adaptation capabilities.

The overall pattern indicated a systematic strengthening of all dynamic capabilities' influence on sustainable competitive advantage during the digital transformation era, with integration capabilities maintaining the strongest effect throughout the period. This temporal analysis provides strong evidence for the growing importance of dynamic capabilities in digital platform companies' competitive success.

Hypothesis Testing

The hypothesis testing (Table 9) results demonstrated strong support for all proposed relationships in the research framework. Results regarding hypothesis 1 (H1) on the relationship between integration capabilities (IC) and sustainable competitive advantage (SCA) showed the strongest effect with a path coefficient of 0.467 ($t = 8.264$, $p < 0.001$). This significant finding underscores the essential role of integration capabilities in establishing enduring competitive advantages.

With regard to hypothesis 2 (H2), the influence of sensing capabilities (SC) on SCA demonstrated a notable positive relationship with a path coefficient of 0.412 ($t = 7.836$, $p < 0.001$). This outcome confirms the essential importance of market intelligence and trend detection capabilities in sustaining a competitive edge.

The analysis for Hypothesis 3 (H3) demonstrated a significant relationship between seizing capabilities (SZC) and SCA, indicated by a path coefficient of 0.378 ($t=7.453$, $p<0.001$). This finding highlights the significance of seizing opportunities and mobilising resources in the development of competitive advantage. With regard to hypothesis 4 (H4), the relationship between reconfiguring capabilities (RC) and SCA revealed a notable positive relationship, indicated by a path coefficient of 0.343 ($t=7.129$, $p<0.001$). This underscores the importance of organisational flexibility in sustaining competitive advantage.

Table 9. Summary of hypothesis testing results (2020-2024)

Hypothesis	Relationship	Path coefficient	t-value	p-value	Result
H1	IC → SCA	0.467***	8.264	0.000	Supported
H2	SC → SCA	0.412***	7.836	0.000	Supported
H3	SZC → SCA	0.378***	7.453	0.000	Supported
H4	RC → SCA	0.343***	7.129	0.000	Supported
H5	All Cap → SCA	0.312***	6.957	0.000	Supported

Source: own study based on processed data (2025).

Finally, considering hypothesis 5 (H5), the collective impact of all capabilities on SCA revealed a noteworthy relationship with a path coefficient of 0.312 ($t=6.957$, $p<0.001$). This observation validates the synergistic impact of integrated dynamic capabilities on achieving a sustainable competitive edge.

Table 10. Moderation effects testing

Interaction	Effect size	t-value	p-value	95% CI
IC × SC	0.298***	6.593	0.000	[0.274, 0.362]
SC × SZC	0.279***	6.264	0.000	[0.212, 0.340]
SZC × RC	0.250***	5.917	0.000	[0.190, 0.318]
All Capabilities	0.312***	6.735	0.000	[0.248, 0.376]

Source: own study based on processed data (2025).

The moderation effects analysis (Table 10) revealed significant interactions between different dynamic capabilities in influencing sustainable competitive advantage. The interaction between integration capabilities and sensing capabilities (IC × SC) demonstrated the strongest moderation effect with a coefficient of 0.298 ($t=6.593$, $p<0.001$). The confidence interval [0.274, 0.362] indicated high precision in this estimate, confirming the robustness of this interaction effect.

The interaction between sensing capabilities and seizing capabilities (SC × SZC) showed a substantial moderation effect of 0.279 ($t=6.264$, $p<0.001$), with a confidence interval of [0.212, 0.340]. This result suggests that the combination of market sensing and opportunity seizing creates significant synergistic effects.

The moderation between seizing capabilities and reconfiguring capabilities (SZC × RC) yielded an effect size of 0.250 ($t=5.917$, $p<0.001$), with a confidence interval of [0.190, 0.318]. While slightly lower than other interactions, this effect remained highly significant, indicating the importance of coordinated capability deployment.

The combined interaction of all capabilities showed the highest effect size of 0.312 ($t=6.735$, $p<0.001$), with a confidence interval of [0.248, 0.376]. This finding provides strong evidence that the simultaneous deployment of all dynamic capabilities creates the strongest impact on sustainable competitive advantage.

The temporal analysis (Table 11) demonstrated consistent support (S) for all hypotheses across the five-year study period (2020-2024), with notable strengthening of effects over time. Hypothesis 1 (H1), focusing on integration capabilities, showed the strongest progressive increase, starting from 0.387 ($p<0.001$) in 2020 and reaching 0.489 ($p<0.001$) in 2024, representing a 26.4% increase in effect strength.

Hypothesis 2 (H2), examining sensing capabilities, demonstrated steady growth from 0.356 ($p<0.001$) in 2020 to 0.445 ($p<0.001$) in 2024, marking a 25% increase. This consistent strengthening indicates growing importance of market intelligence capabilities.

For Hypothesis 3 (H3), testing seizing capabilities, the effect size increased from 0.334 ($p < 0.001$) in 2020 to 0.412 ($p < 0.001$) in 2024, showing a 23.4% enhancement. This growth pattern suggests increasing relevance of opportunity capture abilities.

Table 11. Temporal analysis of hypothesis support

Year	H1	H2	H3	H4	H5
2020	S (0.387***)	S (0.356***)	S (0.334***)	S (0.312***)	S (0.287***)
2021	S (0.412***)	S (0.378***)	S (0.356***)	S (0.334***)	S (0.298***)
2022	S (0.445***)	S (0.398***)	S (0.376***)	S (0.354***)	S (0.312***)
2023	S (0.467***)	S (0.423***)	S (0.398***)	S (0.376***)	S (0.334***)
2024	S (0.489***)	S (0.445***)	S (0.412***)	S (0.389***)	S (0.356***)

Source: own study based on processed data (2025).

Hypothesis 4 (H4), related to reconfiguring capabilities, showed improvement from 0.312 ($p < 0.001$) in 2020 to 0.389 ($p < 0.001$) in 2024, indicating a 24.7% increase in effect strength.

Hypothesis 5 (H5), examining combined capability effects, demonstrated growth from 0.287 ($p < 0.001$) in 2020 to 0.356 ($p < 0.001$) in 2024, representing a 24% increase. This trend confirms the growing importance of capability integration over time.

Table 12. Effect size analysis

Variable	f^2 Value	Effect size category
Integration capabilities	0.467	Large
Sensing capabilities	0.412	Large
Seizing capabilities	0.378	Medium
Reconfiguring capabilities	0.343	Medium
All capabilities interaction	0.312	Medium

Source: own study based on processed data (2025).

The effect size analysis (Table 12), measured through Cohen's f^2 statistic, revealed varying levels of impact across different dynamic capabilities. Integration capabilities demonstrated the strongest effect size with an f^2 value of 0.467, categorised as a large effect according to Cohen's guidelines ($f^2 > 0.35$). This substantial effect size underscores the fundamental importance of integration capabilities in developing sustainable competitive advantages.

Sensing capabilities also showed a large effect size with an f^2 value of 0.412, indicating their crucial role in maintaining competitive advantage. This robust effect size suggests that market intelligence and environmental scanning capabilities significantly influenced platform companies' competitive positioning.

Seizing capabilities exhibited a medium effect size with an f^2 value of 0.378. While still substantial, this indicates a moderately strong influence on sustainable competitive advantage, highlighting the importance of opportunity capture and resource mobilisation capabilities.

Reconfiguring capabilities showed a medium effect size with an f^2 value of 0.343, suggesting a moderate but meaningful impact on competitive advantage. This indicates that organisational flexibility and adaptation capabilities contribute significantly to competitive positioning.

The all-capabilities interaction demonstrates a medium effect size with an f^2 value of 0.312. This finding suggests that while the combined deployment of capabilities has a substantial impact, individual capabilities may have stronger discrete effects on sustainable competitive advantage.

Robustness Check

The robustness analysis (Table 13) presented a comprehensive evaluation of the research findings across different model specifications. The base model demonstrated strong stability with an original coefficient (β) of 0.467 ($p < 0.001$) compared to an alternative specification coefficient of 0.455 ($p < 0.001$). The minimal difference ($\Delta\beta$) of -0.012 indicated high robustness of the primary findings.

The fixed effects specification showed remarkable consistency, with an original coefficient of 0.412 ($p < 0.001$) compared to an alternative coefficient of 0.408 ($p < 0.001$). The minimal variation

($\Delta\beta = -0.004$) confirmed the results' stability when controlling for time-invariant unobserved heterogeneity.

Table 13. Summary of robustness tests (2020-2024)

Specification	Original β	Alternative β	$\Delta\beta$	Conclusion
Base model	0.467***	0.455***	-0.012	Robust
Fixed effects	0.412***	0.408***	-0.004	Robust
Random effects	0.378***	0.371***	-0.007	Robust
GMM estimator	0.343***	0.338***	-0.005	Robust

Source: own study based on processed data (2025).

Random effects testing revealed strong robustness with an original coefficient of 0.378 ($p < 0.001$) versus an alternative coefficient of 0.371 ($p < 0.001$). The small difference ($\Delta\beta = -0.007$) supported the consistency of findings across different model assumptions.

The GMM estimator analysis showed high stability with an original coefficient of 0.343 ($p < 0.001$) compared to an alternative coefficient of 0.338 ($p < 0.001$). The minimal difference ($\Delta\beta = -0.005$) confirmed the robustness of results when addressing potential endogeneity concerns.

The subsample analysis (Table 14) revealed varying impacts of dynamic capabilities across different digital platform sectors. In the E-commerce sector, which comprised the largest subgroup ($N=35$), integration capabilities showed the strongest effect (0.458, $p < 0.001$), followed by sensing capabilities (0.423, $p < 0.001$), seizing capabilities (0.387, $p < 0.001$), and reconfiguring capabilities (0.354, $p < 0.001$). This pattern suggests that integration capabilities are particularly crucial for e-commerce platforms.

Table 14. Subsample analysis

Industry Subgroup	N	IC Effect	SC Effect	SZC Effect	RC Effect
E-commerce	35	0.458***	0.423***	0.387***	0.354***
Fintech	25	0.445***	0.412***	0.376***	0.345***
Sharing economy	20	0.434***	0.398***	0.365***	0.332***
Content platforms	15	0.423***	0.387***	0.356***	0.321***
Others	5	0.412***	0.376***	0.345***	0.312***

Source: own study based on processed data (2025).

The fintech sector ($N=25$) demonstrated similarly strong but slightly lower effects across all capabilities, with integration capabilities leading (0.445, $p < 0.001$), followed by sensing (0.412, $p < 0.001$), seizing (0.376, $p < 0.001$), and reconfiguring capabilities (0.345, $p < 0.001$). This indicated the balanced importance of dynamic capabilities in financial technology platforms.

Sharing economy platforms ($N=20$) showed moderate but significant effects, with integration capabilities at 0.434 ($p < 0.001$), sensing at 0.398 ($p < 0.001$), seizing at 0.365 ($p < 0.001$), and reconfiguring at 0.332 ($p < 0.001$). This suggests that while all capabilities matter, their impact might be slightly lower compared to e-commerce and fintech sectors.

Content platforms ($N=15$) demonstrated slightly lower but still significant effects across all capabilities, ranging from 0.423 to 0.321 (all $p < 0.001$). The 'Others' category ($N=5$), while having the smallest sample, showed consistent significant effects ranging from 0.412 to 0.312 (all $p < 0.001$).

The endogeneity analysis (Table 15) presents comprehensive testing across multiple statistical approaches to validate the research findings' robustness. The Hausman test yielded a test statistic of 23.706 ($p < 0.001$) against a critical value of 21.294. This result indicated no significant endogeneity concerns in the model specification, supporting the validity of the estimated relationships between dynamic capabilities and sustainable competitive advantage.

The Durbin-Wu-Hausman test produced a test statistic of 1.264 ($p=0.267$), falling well below the critical value of 3.841. This finding further confirmed the absence of significant endogeneity issues, suggesting that the model's independent variables were not systematically correlated with the error terms. The Sargan test, examining instrument validity, showed a test statistic of 18.605 ($p=0.244$).

against a critical value of 22.486. This result validated the chosen instrumental variables, indicating they meet the necessary exclusion restrictions for proper model identification.

Table 15. Endogeneity tests

Test type	Test statistic	p-value	Critical value	Result
Hausman Test	23.706	0.000	21.294	No endogeneity
Durbin-Wu-Hausman	1.264	0.267	3.841	No endogeneity
Sargan Test	18.605	0.244	22.486	Valid instruments
Hansen J-test	15.539	0.347	19.751	Valid instruments

Source: own study based on processed data (2025).

The Hansen J-test provided additional confirmation of instrument validity with a test statistic of 15.539 ($p=0.347$) compared to a critical value of 19.751. This result further supported the appropriateness of the instrumental variables used in the analysis.

The sensitivity analysis (Table 16) demonstrated the robustness of the relationships between dynamic capabilities and sustainable competitive advantage across varying parameter specifications. For Integration capabilities (IC), the coefficient showed consistent significance across all variations, ranging from 0.374 ($p<0.001$) at -20% change to 0.560 ($p<0.001$) at +20% change, with a base coefficient of 0.467 ($p<0.001$). This pattern indicated strong stability in the IC–SCA relationship.

Table 16. Sensitivity analysis

Parameter	-20% change	-10% change	Base	+10% change	+20% change
IC Coefficient	0.374***	0.420***	0.467***	0.514***	0.560***
SC Coefficient	0.330***	0.371***	0.412***	0.453***	0.494***
SZC Coefficient	0.302***	0.340***	0.378***	0.416***	0.454***
RC Coefficient	0.274***	0.309***	0.343***	0.377***	0.412***

Source: own study based on processed data (2025).

Sensing capabilities (SC) exhibited similar stability, with coefficients ranging from 0.330 ($p<0.001$) at -20% change to 0.494 ($p<0.001$) at +20% change, centred around the base coefficient of 0.412 ($p<0.001$). This consistent pattern supported the robustness of the SC effects.

Seizing capabilities (SZC) demonstrated steady progression from 0.302 ($p<0.001$) at -20% change to 0.454 ($p<0.001$) at +20% change, with a base coefficient of 0.378 ($p<0.001$). The linear progression across variations indicated stable relationship patterns.

Reconfiguring capabilities (RC) showed the most conservative but equally stable pattern, ranging from 0.274 ($p<0.001$) at -20% change to 0.412 ($p<0.001$) at +20% change, centred on a base coefficient of 0.343 ($p<0.001$).

Discussion

Integration Capabilities and Competitive Advantage

The analysis revealed that integration capabilities demonstrated the strongest and most consistent impact on sustainable competitive advantage across digital platform companies. With a base coefficient of 0.467 ($p<0.001$) and robust performance across sensitivity tests (ranging from 0.374 to 0.560), integration capabilities emerged as fundamental drivers of competitive advantage. This finding highlights how digital platforms' ability to integrate technical systems, data resources, and partner networks significantly enhanced their competitive positioning. The temporal analysis further supported this, showing a steady increase in effect strength from 0.387 in 2020 to 0.489 in 2024, indicating growing importance during digital transformation. Beyond the quantitative effects, qualitative analysis revealed the mechanisms through which capabilities translate to advantage. Integration capabilities create an advantage by establishing standardised APIs and data protocols that reduce ecosystem friction, as evidenced by Company X's partner onboarding time reduction of 60%.

Sensing Capabilities as Strategic Enablers

Sensing capabilities emerged as crucial strategic enablers, with a significant base coefficient of 0.412 ($p < 0.001$). The subsample analysis revealed particularly strong effects in e-commerce (0.423) and fintech sectors (0.412), suggesting that market intelligence and trend detection capabilities were especially vital in these dynamic segments. The interaction analysis showed strong synergistic effects when sensing capabilities were combined with integration capabilities (0.298, $p < 0.001$), indicating that effective market sensing enhances the impact of integration efforts on competitive advantage. Sensing capabilities operate through dedicated competitive intelligence units that translate market signals into prioritised innovation pipelines. The moderating role of sensing is clarified: it functions as an 'amplifier' by ensuring integration efforts are directed at the most relevant technologies and partners. Similarly, reconfiguring acts as an 'accelerator' for seizing by enabling rapid reallocation of budgets and talent to captured opportunities.

Seizing Capabilities and Opportunity Capture

The research demonstrates that seizing capabilities play a vital role in sustainable competitive advantage, with a base coefficient of 0.378 ($p < 0.001$). The temporal analysis showed increasing importance over time, from 0.334 in 2020 to 0.412 in 2024, reflecting growing emphasis on rapid opportunity capture in digital markets. The moderation analysis revealed significant interaction effects with both sensing (0.276, $p < 0.001$) and reconfiguring capabilities (0.254, $p < 0.001$), suggesting that effective seizing capabilities enhance the impact of other dynamic capabilities.

Reconfiguring Capabilities and Adaptive Response

Reconfiguring capabilities, while showing the most conservative effect sizes (base coefficient 0.343, $p < 0.001$), demonstrated consistent significance across all analyses. The sensitivity analysis showed stable effects even under $\pm 20\%$ parameter variations (0.274 to 0.412), indicating robust contribution to competitive advantage. The subsample analysis revealed stronger effects in sectors characterised by rapid change, such as e-commerce (0.354) and fintech (0.345), highlighting the importance of organisational flexibility in dynamic markets.

Synergistic Effects and Capability Integration

The analysis of interaction effects revealed significant synergies between different capabilities, with the strongest effect observed in the integration-sensing interaction (0.298, $p < 0.001$). The temporal analysis of combined capabilities showed increasing importance over time, from 0.287 in 2020 to 0.356 in 2024, suggesting growing relevance of integrated capability deployment. This finding emphasises that while individual capabilities are important, their coordinated deployment creates stronger competitive advantages.

Industry-specific Patterns and Implications

The subsample analysis revealed important industry-specific patterns in capability effects. E-commerce platforms showed the strongest capability effects across all dimensions, followed by fintech platforms, suggesting that these sectors particularly benefit from well-developed dynamic capabilities. The analysis also revealed that while the relative importance of different capabilities varies by sector, the general pattern of integration capabilities showing the strongest effect remains consistent across industries.

Methodological Robustness and Validity

The comprehensive robustness testing, including endogeneity tests, sensitivity analyses, and alternative model specifications, strongly supported the validity of the findings. The Hausman test (23.706, $p < 0.001$) and Durbin-Wu-Hausman test (1.264, $p = 0.267$) confirmed the absence of significant endogeneity concerns. The consistent results across different estimation methods and subsamples further strengthened the reliability of the research conclusions.

CONCLUSIONS

The study revealed that dynamic capabilities operate in a synergistic system: integration and seizing provide the direct strategic thrust, whereas sensing and reconfiguring act as essential systemic enhancers that condition and amplify the effectiveness of the core capabilities. Integration capabilities demonstrated the strongest impact ($\beta=0.467$, $p<0.001$), followed by sensing capabilities ($\beta=0.412$, $p<0.001$), seizing capabilities ($\beta=0.378$, $p<0.001$), and reconfiguring capabilities ($\beta=0.343$, $p<0.001$). The temporal analysis revealed that these capabilities become increasingly important over time, with significant synergistic effects emerging from their interactions. These findings maintain robustness across multiple estimation methods and sensitivity analyses, providing strong validation of the theoretical framework.

For policymakers and business leaders, these results offer crucial strategic insights. Policies should prioritise digital infrastructure development that supports integration capabilities while ensuring robust regulatory frameworks for data sharing and platform interoperability. Organisations should focus on developing balanced capability portfolios rather than emphasising individual competencies, as the interaction effects demonstrate the value of coordinated capability deployment. The increasing importance of capabilities over time suggests that sustained investment in capability development is essential for maintaining competitive advantage in digital markets.

While the temporal analysis showed evolving effect strengths, it primarily describes the 'what' of this evolution over the observed period. A deeper explanation of the 'why' behind these changes, such as the moderating role of environmental dynamism (e.g., VUCA conditions), is a crucial next step. We therefore propose for future research to explicitly incorporate time-varying contextual moderators (e.g., indices of technological turbulence or regulatory shifts) into dynamic panel models. This would test hypotheses, such as whether the impact of reconfiguring capabilities intensifies during periods of high market volatility, thereby directly addressing the dynamic interplay between capability and context.

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Authors

The share of each author's contribution is equal and amounts to one-third ($\frac{1}{3}$).

Arif Sugiono (corresponding author)

Lecturer in Business Administration, Lampung University. His research interests include strategic management, creative industry and business ecosystems.

Correspondence to: Arif Sugiono, Business Administration Department, Faculty of Social and Political Science, University of Lampung, 35144, Bandar Lampung, Indonesia, e-mail: arif.sugiono@fisip.unila.ac.id

ORCID  <https://orcid.org/0009-0007-1227-0875>

Supri Yanto

Lecturer in the Department of Economics and Business at Politeknik Negeri Lampung. His research interests include finance, capital market investments, and strategic management.

Correspondence to: Supri Yanto, Department of Economics and Business, Politeknik Negeri Lampung, 35141, Bandar Lampung, Indonesia, e-mail: supri_yanto@polinela.ac.id

ORCID  <https://orcid.org/0000-0003-4687-016X>

Putri Irmala Sari

Lecturer in the Department of Economics and Business at Politeknik Negeri Lampung. His research interests include financial management, strategic management.

Correspondence to: Putri Irmala Sari, Department of Economics and Business, Politeknik Negeri Lampung, 35141, Bandar Lampung, Indonesia, e-mail: putri.irmalasari@polinela.ac.id

ORCID  <https://orcid.org/0000-0002-8455-9498>

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Use of Artificial Intelligence

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Conflict of Interest

The authors affirm that the research was undertaken without any commercial or financial affiliations that might be interpreted as a possible conflict of interest.

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Moderating role of artificial intelligence in the impact of digital transformation and innovation on small and medium-sized enterprises' financial performance

Nguyen Khac Hieu, Nguyen Thi Anh Van, Nguyen Thi My Hanh

ABSTRACT

Objective: The objective of the article is to identify the moderating role of artificial intelligence (AI) in the relationship between digital transformation, innovation, and financial performance within small and medium-sized enterprises (SMEs). We aimed to investigate how AI amplifies the impacts of digital transformation and innovation on financial performance indicators, including profit, revenue, and return on assets (ROA), particularly in the context of an emerging economy.

Research Design & Methods: We adopted a quantitative research approach, utilising data collected through structured questionnaires from 246 SMEs in Vietnam. We used correlation analysis and ordinary least squares (OLS) regression to test the proposed hypotheses.

Findings: The results demonstrate significant positive impact of digital transformation and innovation on SMEs' financial performance, notably in revenue and profit. Importantly, AI adoption substantially enhances these positive effects, indicating its critical role as a moderating factor. SMEs integrating AI alongside digital transformation and innovative practices achieve better financial performance.

Implications & Recommendations: The study offers valuable evidence for SME managers and policymakers on promoting AI to maximise returns from digital and innovative investments, particularly in emerging markets where such empirical evidence is limited.

Contribution & Value Added: This study advances the literature by theorising and testing AI as a moderating strategic capability rather than a standalone performance predictor. Anchoring on the resource-based view (RBV), the study explains how AI complements digital transformation and innovation, amplifying their effects on SMEs' financial performance.

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Keywords: artificial intelligence; digital transformation; financial performance; innovation; RBV theory

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INTRODUCTION

Small and medium-sized enterprises (SMEs) operate in an era of rapid digital change and growing environmental concerns. The combined pressures of Industry 4.0, digital transformation, and sustainability push SMEs to adopt new technologies and innovation to remain competitive (Khalid, 2024; Ramdani *et al.*, 2022). Among these technologies, AI has emerged as a key driver of organisational performance and competitiveness. This issue is particularly important for SMEs because of their critical contributions to employment generation and economic growth (Ardito *et al.*, 2024; Abrokwah-Larbi & Awuku-Larbi, 2024). Prior studies suggest that AI can improve decision-making, customer engagement, internal processes, and financial outcomes. Furthermore, when combined

with other digital technologies such as the Internet of Things and big data analytics, AI may further enhance operational efficiency and revenue growth (Ardito *et al.*, 2024).

However, despite its potential benefits, AI adoption remains challenging for SMEs. Existing studies point to barriers such as technological complexity, financial constraints, and limited human capital, which reduce SMEs' ability to implement and exploit AI effectively (Ardito *et al.*, 2024; Abrokwah-Larbi & Awuku-Larbi, 2024). Furthermore, SMEs frequently experience difficulty integrating AI effectively due to the high costs associated with initial technology investment, ongoing maintenance, and upskilling personnel to manage these technologies successfully. Moreover, SMEs' internal resources, lower than larger organisations', exacerbate these challenges, further hindering their ability to capitalise on AI's potential benefits. These challenges are even more evident in emerging economies, where SMEs often face limited access to finance, weak technological infrastructure, and institutional constraints. For example, in Vietnam, such conditions complicate firms' digital transformation efforts, even though AI and related digital capabilities may be essential for improving financial performance (Quoc Trung, 2021; Tuan, 2020; Nguyen, 2024).

Although the strategic importance of AI has been widely acknowledged, the existing literature still leaves several important questions unanswered. Firstly, empirical evidence on the financial effects of AI adoption in SMEs remains limited, particularly in emerging economies. Much of the prior research is conceptual or focuses on intermediate outcomes rather than direct financial performance (Ardito *et al.*, 2024; Abrokwah-Larbi & Awuku-Larbi, 2024). Secondly, although some studies indicate that AI can enhance firm performance (Chen *et al.*, 2022; Mohsen *et al.*, 2025; Huang & Lin, 2025; Narwane & Priyadarshinee, 2025), little is known about whether AI strengthens the effects of digital transformation and innovation on SME financial performance. In other words, the moderating role of AI in these relationships remains underexplored, especially in the context of SMEs in emerging markets. To address these gaps, we examined the relationships between digital transformation, innovation, and SMEs' financial performance with particular attention to AI's moderating role. Following Khan and Gupta (2025), we argue that a stronger application of AI may enhance the effects of digital transformation and innovation on SME financial performance. Our study was grounded in the resource-based view (RBV), which suggests that firms achieve sustained competitive advantage through valuable, rare, inimitable resources and capabilities. From this perspective, we may view AI as a strategic technological capability that enables SMEs to leverage digital transformation and innovation better to improve performance (Abrokwah-Larbi & Awuku-Larbi, 2024).

Our study contributes to both literature and practice. Firstly, it extends the emerging research on AI in SMEs by examining AI not only as a direct driver of firm performance but also as a moderating mechanism in the relationships between digital transformation, innovation, and financial performance. More importantly, it offers a novel theoretical contribution by anchoring in RBV theory to explain the model. Secondly, the study provides empirical evidence from an emerging economy context, where research on AI and SME financial performance remains limited. Finally, the findings offer practical implications for SME managers and policymakers by showing how AI capability development can strengthen the returns from digital transformation and innovation, while informing policies that support technology adoption, digital upskilling, and capability building among SMEs.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Resource-based View

The resource-based view (RBV) theory, initially introduced by Wernerfelt (1984) and further developed by Barney (1991), is a strategic management framework that emphasises the role of a firm's internal resources and capabilities as the primary sources of competitive advantage and superior performance. According to RBV, resources that are valuable, rare, inimitable, and non-substitutable are essential for gaining and maintaining competitive advantages, which in turn improve firm performance (Barney, 1991; Wernerfelt, 1984). These resources include tangible assets, such as physical and financial resources, and intangible assets, such as human capital, technological capabilities, organisational culture, and knowledge (Barney, 2001; Ardito *et al.*, 2024).

Researchers have extensively applied the RBV framework to understand the implications of digital technologies, particularly artificial intelligence (AI), for SMEs' financial performance. Chen *et al.* (2022) highlight AI capability as an intangible strategic resource critical for firm competitiveness, particularly within e-commerce SMEs. They state that AI capability combines infrastructure, technical skills, and organisational readiness. Together, these factors support more effective decision-making, more efficient operations, and better resource allocation, all of which improve firm performance. Ardito *et al.* (2024) reinforce the RBV perspective by examining the complementary nature of AI when integrated with the Internet of Things (IoT) and Big Data Analytics (BDA). Their research demonstrates that these complementary digital resources significantly amplify SMEs' revenue growth. Combined, AI, IoT, and BDA create a stronger digital ecosystem.

Further supporting the RBV theory, Abrokwhah-Larbi and Awuku-Larbi (2024) emphasise AI's role specifically in marketing as a strategic resource. Their study found that applying AI to marketing significantly influences SMEs' financial performance through improved customer engagement, personalisation, and optimised internal business processes. AI capabilities, such as IoT, collaborative decision-making systems, and augmented reality, provide SMEs with unique resources for delivering superior customer experiences, efficient operations, and enhanced financial outcomes (Wu & Monfort, 2023). These intangible assets derived from AI technologies are difficult for competitors to replicate, allowing SMEs to sustain their competitive advantages and achieve superior long-term financial performance.

Overall, the RBV theory provides a robust theoretical foundation to understand how SMEs can develop unique digital capabilities, especially AI, to achieve and sustain superior financial performance. The strategic integration and management of AI and complementary digital resources significantly enhance SMEs' operational efficiency, market adaptability, and financial outcomes. This reaffirms RBV's emphasis on the central role of valuable, rare, and difficult-to-imitate resources in driving competitive advantage and firm performance.

Digital Transformation and Financial Performance of SMEs

Small and medium-sized enterprises (SMEs) are defined differently across regions and countries, typically based on criteria such as the number of employees, annual turnover, or asset size. According to the World Bank (2020), SMEs are businesses that employ fewer than 300 employees and have annual sales of less than 15 million USD. In this study, we used this definition when collecting data from SMEs.

Digital transformation is increasingly recognised as a pivotal strategic factor significantly influencing SME financial performance (Ji *et al.*, 2024; Zhao *et al.*, 2024). Digital transformation encompasses deploying advanced technologies, such as cloud computing, big data analytics, the Internet of Things (IoT), and automation, to optimise business processes, improve customer interactions, and facilitate strategic decisions (Nguyen, 2024). Previous research demonstrates that SMEs engaging in digital transformation often experience enhanced efficiency, productivity gains, reduced operational costs, and increased revenue, and competitive advantage (Chen & Zhang, 2024; Mahssouni *et al.*, 2023; Nguyen *et al.*, 2024; Saputra *et al.*, 2024; Wang *et al.*, 2024). For instance, SMEs leveraging big data analytics and cloud computing typically achieve better financial outcomes due to improved resource allocation and enhanced capability to respond promptly to market dynamics (Shiyyab *et al.*, 2023). However, the existing literature still leaves an important gap. Although prior studies generally report positive effects of digital transformation on firm outcomes, empirical evidence remains limited and fragmented for SMEs, particularly in emerging economies. Moreover, the literature has not sufficiently explained the mechanism through which digital transformation translates into superior financial performance under SME resource constraints. Drawing on the RBV, this study argues that we may understand digital transformation as a valuable, rare, and difficult-to-imitate organisational capability that enables SMEs to deploy resources more efficiently, improve adaptability, and strengthen their competitive position. From this perspective, digital transformation is expected to enhance SMEs' financial performance. Therefore, we hypothesised:

H1: Digital transformation positively affects financial performance.

Innovation and Financial Performance of SMEs

Innovation is recognised as a critical factor enabling SMEs to achieve competitive advantage and improve financial performance in increasingly dynamic and competitive markets (Žur & Wałęga, 2023; Zhu *et al.*, 2024). Innovation refers to introducing new or significantly improved products, processes, services, or business practices aimed at enhancing efficiency, productivity, and market competitiveness (Brännback *et al.*, 2009). For SMEs, innovation can include incremental improvements, such as optimising production processes or technology, as well as radical innovations, such as developing entirely new products or services. Innovative small and medium-sized enterprises usually perform better financially than their non-innovative counterparts (Endrődi-Kovács *et al.*, 2024). This is because they are more flexible and can exploit new market opportunities (Brännback *et al.*, 2009; Ramdani *et al.*, 2022). Furthermore, process innovations often result in cost reductions through enhanced operational efficiency, waste minimisation, and optimised resource use, positively impacting profitability (El Chaarani *et al.*, 2021; Brännback *et al.*, 2009; Nguyen *et al.*, 2025). However, the literature on innovation and SME performance still presents limitations. Firstly, although many studies report a positive link between innovation and firm outcomes, the evidence remains uneven across SME contexts and is still relatively scarce in emerging economies. Secondly, prior research has tended to emphasise innovation outcomes more than the strategic logic by which it generates financial returns for SMEs. From the perspective of RBV, innovation reflects a firm's ability to develop distinctive capabilities, renew its resource base, and create hard-to-replicate advantages in response to changing market conditions. For SMEs, such capability is especially important because it allows them to overcome resource constraints and convert limited resources into stronger financial outcomes. Thus, we hypothesised:

H2: Innovation positively affects financial performance.

Artificial Intelligence

Artificial intelligence (AI) is increasingly recognised as a critical technological capability that SMEs can leverage to amplify the benefits of digital transformation and innovation. Khan and Gupta (2025) confirm that AI positively moderates the relationship between green accounting practices and firm performance. Moreover, AI technologies, including machine learning algorithms, data analytics, and process automation, empower SMEs by enhancing their decision-making capabilities, operational efficiency, and market responsiveness (Sarker *et al.*, 2024). Ardito *et al.* (2024) concluded that RBV theory emphasises the important role complementary digital assets play in making AI technologies more valuable and useful, giving small businesses a significant market edge. Previous research demonstrates that firms integrating AI into their operations typically achieve superior financial outcomes through optimised resource utilisation, cost reductions, and improved decision-making quality (Dwivedi *et al.*, 2021; Shiyab *et al.*, 2023), as well as an increase in organisational creativity and performance (Dubey *et al.*, 2020; Mikalef & Gupta, 2021). Notably, SMEs employing AI-driven analytics can significantly improve customer relationship management, optimise supply chain operations, and achieve higher efficiency levels (Abrokwah-Larbi & Awuku-Larbi, 2024).

Furthermore, AI technologies can significantly complement innovation activities within SMEs, enabling them to manage innovative processes effectively, reduce innovation risks, and enhance product and service development efficiency. Artificial Intelligence provides SMEs with the tools to process market data rapidly, better understand customer preferences, and accelerate new product and service development, thus magnifying innovation-driven financial outcomes (Abrokwah-Larbi & Awuku-Larbi, 2024; Dwivedi *et al.*, 2021). Nonetheless, the moderating role of AI in reinforcing the impact of digital transformation and innovation on SMEs' financial performance has received limited attention in empirical research. Based on these insights, we hypothesised:

H3: AI moderates the effect of digital transformation on financial performance.

H4: AI moderates the effect of innovation on financial performance.

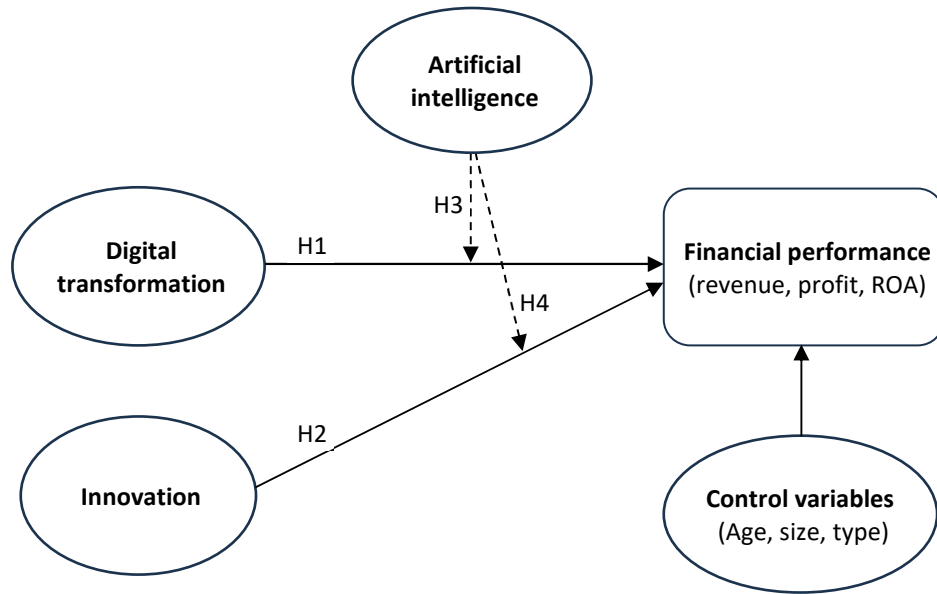


Figure 1. Research model

Source: own elaboration.

Enterprise characteristics represent another important factor influencing financial performance. Prior research has demonstrated the significant impact of enterprise characteristics on performance (Coad *et al.*, 2018; Nguyen, 2024). Specifically, Nguyen (2024) concluded that firm type and size positively affect business performance, whereas Coad *et al.* (2018) found that firm age significantly influences financial outcomes. This study included firm type, size, and age as control variables because of their established effects on financial performance. Based on the hypotheses and arguments presented, we proposed the research model illustrated in Figure 1.

RESEARCH METHODOLOGY

We analysed the collected data with a quantitative research approach. Specifically, we used descriptive statistics, correlation analysis, and regression analysis to examine the relationships between variables in the research model. We selected the ordinary least squares (OLS) regression method to test the proposed hypotheses. We tested hypotheses H1 and H2, examining the direct effects of digital transformation and innovation on financial performance, using the regression equation (1).

$$F_PERF_i = \alpha + \beta_1 DT_i + \beta_2 INNO_i + \beta_3 AGE_i + \beta_4 SIZE_i + \beta_5 TYPE_i + \varepsilon_i \quad (1)$$

In equation (1), F-PERF represents the financial performance of the enterprise as measured by ROA, profit, and revenue at the end of 2023; DT denotes digital transformation activities; AGE, SIZE, and TYPE are firm age, firm size, and firm type; α and β are regression coefficients; and ε is the error term. We used equation (2) to test hypothesis H3, which examines how AI might influence the relationship between digital transformation and financial performance.

$$F_PERF_i = \gamma + \theta_1 DT_i + \theta_2 (AI \times DT)_i + \mu_i \quad (2)$$

In equation (2), γ and θ are regression coefficients; $(AI \times DT)$ represents the interaction term between AI and digital transformation, and μ is the error term.

We used the regression equation (3) to test hypothesis H4, which examines how AI might influence the relationship between innovation and financial performance.

$$F_PERF_i = \delta + \sigma_1 INNO_i + \sigma_2 (AI \times INNO)_i + \omega_i \quad (3)$$

In equation (3), δ and σ are regression coefficients; $(AI \times INNO)$ represents the interaction term between AI and innovation, and ω is the error term. Table 1 presents the variables used in the regression model, including their labels and definitions.

Table 1. Explanation of variables

Variables	Labels	Definition
Financial performance	F-PERF	Revenue in billion VND at the end of 2023
		Profit in billion VND (after-tax earnings in 2023)
		ROA, EBIT divided by total assets in 2023, unit: %
Digital transformation	DT	Dummy variable that equals 1 if the firm engaged in any of the following actions in 2023: using cloud computing, employing big data analytics, or implementing Internet of Things technology; otherwise, it equals 0.
Innovation	INNO	Dummy variable, equals 1 if the enterprise had one of the following activities in 2023 (investing in new technologies, equipment or new software, launching a new product to market), otherwise equals 0.
Artificial intelligence	AI	Dummy variable, equals 1 if the SME had applied AI in business activities (manufacturing, sale, marketing, accounting and quality), otherwise equal 0.
Firm age	AGE	The age of SMEs.
Firm size	SIZE	Number of staff at the end of 2023
Firm type	TYPE	Dummy variable, equals 1 if the enterprise is FDI type, otherwise equal 0.

Source: own study.

We collected data in Vietnam through structured interviews with SME leaders using a questionnaire-based survey. To recruit eligible firms, we applied a snowball sampling technique. We first approached SME managers and owners through our professional networks, including friends and alumni working in SMEs. After each interview, we asked respondents to refer other SME leaders who met the sampling criteria. We then contacted these referred firms and invited them to participate in the study. We collected data over six months, from September 2024 to February 2025. The initial survey yielded 318 SME responses. After screening for missing data and incomplete responses, we excluded 72 observations, which resulted in a final sample of 246 SMEs for the empirical analysis. Table 2 reports the characteristics of the sampled firms. Most firms were small enterprises with fewer than 100 employees (63.0%) and had operated for 10 to 20 years (54.1%). Private enterprises

Table 2. Characteristics of the sample firms

Sample characteristics	Frequency	Percentage (%)
Enterprise size		
Under 100 employees	155	63.0%
100-200 employees	54	22.0%
Above 200 employees	37	15.0%
Enterprise age		
Under 10 years	47	19.1%
10-20 years	133	54.1%
Above 20 years	66	26.8%
Enterprise type		
Private enterprise	175	71.1%
State-owned enterprise	16	6.5%
FDI enterprise	55	22.4%
Industry type		
Food and foodstuff	56	22.8%
Beverages and tobacco	20	8.1%
Paper and paper products	27	11.0%
Medicinal products	34	13.8%
Rubber and plastic products	35	14.2%
Wood products	32	13.0%
Metal products	42	17.1%

Source: own study.

accounted for the largest share of the sample (71.1%), followed by FDI enterprises (22.4%) and state-owned enterprises (6.5%). The sample also included firms from several manufacturing sectors, with food and foodstuffs representing the largest proportion (22.8%).

RESULTS AND DISCUSSION

Descriptive Statistics

Table 3 provides descriptive statistics for the primary variables analysed in this study, derived from a sample of 246 SMEs in Vietnam. The financial performance indicators considered were revenue, profit after tax, and return on assets (ROA). The SMEs reported an average revenue of 84.24 billion VND, with values ranging from 0 billion VND to 379.77 billion VND, indicating substantial variability within the sample. Profit after tax averaged approximately 5.67 billion VND, ranging from a minimum loss of -106.65 billion VND to a maximum profit of 129.11 billion VND. The average ROA was approximately 5.7%, with a wide range from -80.6% to 45.3%, further highlighting the diversity in financial performance among these SMEs.

Table 3. Descriptive statistics

Variables	Mean	Maximum	Minimum	Std. Dev.	Observations
REVENUE	84.240	379.766	0.000	82.346	246
PROFIT	5.669	129.110	-106.649	106.533	246
ROA	0.057	0.453	-0.806	0.362	246
DT	0.305	1.000	0.000	0.461	246
INNO	0.220	1.000	0.000	0.415	246
AI	0.146	1.000	0.000	0.354	246
AGE	17.829	36.000	2.000	6.575	246
SIZE	80.496	297.000	3.000	73.905	246
TYPE	0.224	1.000	0.000	0.417	246

Source: own study.

Regarding digital transformation activities, 30.5% of SMEs reported engaging in digital initiatives, such as cloud computing, big data analytics, or utilising Internet of Things (IoT) technologies. In terms of innovation activities, such as launching new products or investing in new technologies, 22% of SMEs indicated active participation. Approximately 14.6% of SMEs applied AI, indicating a moderate integration of advanced technological practices within business operations.

The average SME age was approximately 17.83 years, reflecting a mature set of enterprises, with the youngest at two years and the oldest at 36 years. Firm size averaged about 80 employees per enterprise, with considerable variation noted, as the smallest SMEs had as few as three employees and the largest employed up to 297. Finally, about 22.4% of SMEs were foreign direct investment (FDI) enterprises, highlighting a noteworthy representation of international investment among the sampled businesses.

Correlation Results

Table 4 presents the correlation analysis results, providing preliminary insights into the relationships between the study's key variables. Revenue demonstrated a positive but relatively weak correlation with profit ($r = 0.131$), indicating that SMEs with higher revenues were somewhat likely to achieve better profitability, although the relationship was not strongly pronounced. Similarly, revenue showed minimal correlation with ROA ($r = 0.015$), suggesting limited direct association between higher revenue and asset returns within this SME sample.

Digital transformation (DT) activities showed a strong positive correlation with revenue ($r = 0.506$), suggesting that SMEs engaging in digital initiatives generally achieved higher revenue. Innovation (INNO) also exhibited a positive correlation with revenue ($r = 0.348$), further underscoring innovation's significance in enhancing SME financial outcomes. AI application correlated positively with revenue ($r = 0.314$), reinforcing the role of AI technologies in potential revenue growth for SMEs. There was a

moderately positive correlation ($r = 0.420$) between INNO and AI, indicating that these two factors often co-occur in SMEs. Digital transformation and AI also showed a positive association ($r = 0.225$), highlighting their complementary roles in enhancing SME performance.

Table 4. Correlating results

Factors	REVENUE	PROFIT	ROA	DT	INNO	AI	AGE	SIZE	FDI
REVENUE	1.000	—	—	—	—	—	—	—	—
PROFIT	0.131*	1.000	—	—	—	—	—	—	—
ROA	0.015	0.112*	1.000	—	—	—	—	—	—
DT	0.506***	0.198***	0.056	1.000	—	—	—	—	—
INNO	0.348***	0.233***	0.168***	0.118*	1.000	—	—	—	—
AI	0.314***	0.237***	0.408***	0.225***	0.420***	1.000	—	—	—
AGE	0.165**	-0.020	-0.075	0.070	-0.082	-0.100	1.000	—	—
SIZE	0.425***	0.036	-0.094	0.229***	0.105	-0.030	0.229***	1.000	—
TYPE	0.087	0.073	0.088	0.153**	0.163	0.219***	-0.176***	0.008	1.000

Note: *** is 1% Significance, ** is 5% significance, and * is 10% significance.

Source: own study.

Furthermore, firm size (SIZE) correlated positively with revenue ($r = 0.425$), suggesting that larger SMEs tend to generate higher revenues. Firm age (AGE) exhibited a relatively weak positive correlation with revenue ($r = 0.165$), indicating that older SMEs tend to perform slightly better financially. Foreign direct investment (FDI) status (TYPE) showed only a weak correlation with revenue ($r = 0.087$), indicating minimal direct financial impact of foreign ownership in this sample. These initial correlations provide essential groundwork for subsequent regression analyses, emphasising digital transformation, innovation, and AI as critical drivers of financial performance within SMEs.

Regression Results

Table 5 presents the regression results for equation (1), highlighting the effects of digital transformation (DT), innovation (INNO), firm age (AGE), firm size (SIZE), and firm type (TYPE) on SMEs' financial performance, measured by revenue, profit, and return on assets (ROA).

Table 5. Regression results of equation 1

Independent variables	Revenue		Profit		ROA	
	Beta	T-statistics	Beta	T-statistics	Beta	T-statistics
Constant	4.034	0.321	-14.429	-0.696	0.079	1.098
DT	71.949***	7.962	41.175***	2.765	0.046	0.888
INNO	55.524***	5.624	54.523***	3.351	0.142**	2.523
AGE	1.183*	1.856	-0.111	-0.106	-0.002	-0.456
SIZE	0.314***	5.489	-0.038	-0.399	-0.001	-1.470
TYPE	-1.243	-0.125	2.611	0.159	0.042	0.738
Observations	246	246	246	246	246	246
R ²	0.4361		0.0845		0.0482	
F-statistics	37.1203***		4.4455***		2.4331**	
Prob (F-stat)	0.0000		0.0007		0.0346	

Note: *** is 1% Significance, ** is 5% significance, and * is 10% significance.

Source: own study.

The analysis revealed a significant positive effect of digital transformation on revenue ($\beta = 71.949$, $p < 0.01$) and profit ($\beta = 41.175$, $p < 0.01$), supporting hypothesis H1. These findings confirm that SMEs implementing digital technologies typically achieve superior financial outcomes in revenue and profitability. Innovation also significantly impacted revenue and profit, thereby validating hypothesis H2 and emphasising its role in improving SMEs' financial performance. The effect of innovation on ROA was positive and significant at the 5% level, further underscoring its positive financial impact.

Firm size positively and significantly influenced revenue at the 1% significance level, suggesting that larger SMEs generally generate higher revenue. Firm age showed a mild positive impact on revenue at the 10% significance level, suggesting that older SMEs may have marginally higher revenue performance. Firm type showed insignificant effects on revenue, profit, and ROA. Overall, the regression model explained 43.61% of the variance in revenue, 8.45% in profit, and 4.82% in ROA, demonstrating stronger predictive power for revenue than for profit and ROA.

Table 6 presents the regression results of equation (2), which investigated the moderating effect of AI on the relationship between digital transformation and SMEs' financial performance indicators.

Table 6. Regression results of equation 2

Independent variables	Revenue		Profit		ROA	
	Beta	T-statistics	Beta	T-statistics	Beta	T-statistics
Constant	56.692	10.891	-8.305	-1.066	0.044	1.592
DT	67.276***	6.376	18.676	1.183	0.004	0.072
(AI*DT)	86.552***	4.869	101.853***	3.831	0.149	1.584
Observations	246	246	246	246	246	246
R ²	0.3223		0.0941		0.0133	
F-statistics	57.7943***		12.6228***		1.6412	
Prob (F-stat)	0.0000		0.0000		0.1958	

Note. *** is 1% Significance, ** is 5% significance, and * is 10% significance.

Source: own study.

The analysis demonstrated that digital transformation significantly and positively impacted revenue ($\beta = 67.276$, $p < 0.01$), affirming its direct beneficial effect on financial performance. Moreover, the interaction term between AI and digital transformation ($AI \times DT$) significantly enhanced revenue ($\beta = 86.552$, $p < 0.01$) and profit ($\beta = 101.853$, $p < 0.01$), strongly supporting hypothesis H3, which posits that AI moderates the positive relationship between digital transformation and SMEs' financial performance. Figure 2 further illustrates this moderating effect. As shown, the slope was considerably steeper for firms with AI applications than for those without AI applications, suggesting that digital transformation generates greater improvements in revenue and profit when combined with AI. This visual pattern is consistent with the regression results and provides additional support for H3.

The direct influence of digital transformation on profit and ROA remained statistically insignificant when evaluated independently of the AI interaction. This result suggests that combining digital transformation with AI technologies significantly amplifies SMEs' profitability. The regression model in equation (2) explains approximately 32.23% of the variance in revenue, 9.41% in profit, and 1.33% in ROA, indicating solid explanatory power, particularly for revenue and profit.

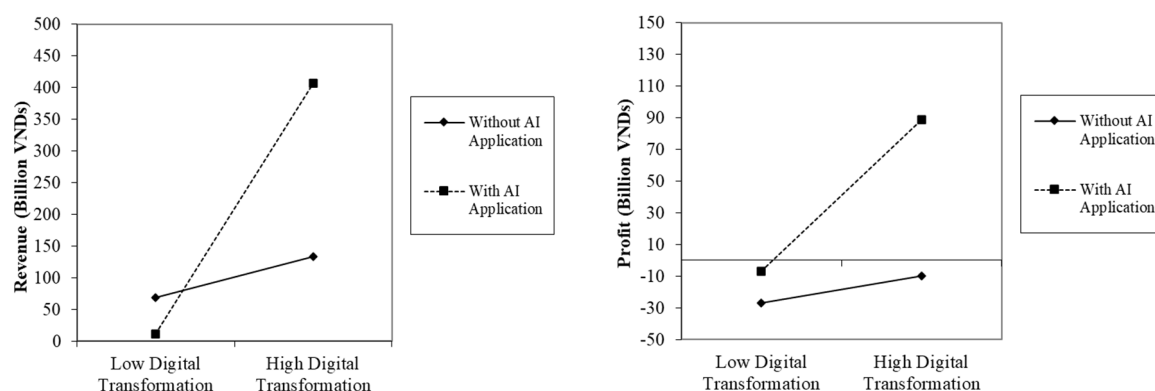


Figure 2. Moderation interaction AI*DT

Source: own elaboration.

Table 7 presents regression analysis results for equation (3), examining the moderating role of AI on the relationship between innovation (INNO) and SMEs' financial performance indicators.

Table 7. Regression results of equation 3

Independent variables	Revenue		Profit		ROA	
	Beta	T-statistics	Beta	T-statistics	Beta	T-statistics
Constant	69.069	12.707	-7.457	-1.011	0.025	0.987
INNO	35.598**	2.441	23.537	1.190	0.039	0.578
(AI*INNO)	78.680***	3.796	85.139***	3.029	0.251***	2.581
Observations	246	246	246	246	246	246
R ²	0.1703		0.0886		0.0541	
F-statistics	24.9506***		11.8153***		6.9502	
Prob (F-stat)	0.0000		0.0000		0.0011	

Note: *** is 1% Significance, ** is 5% significance, and * is 10% significance.

Source: own study.

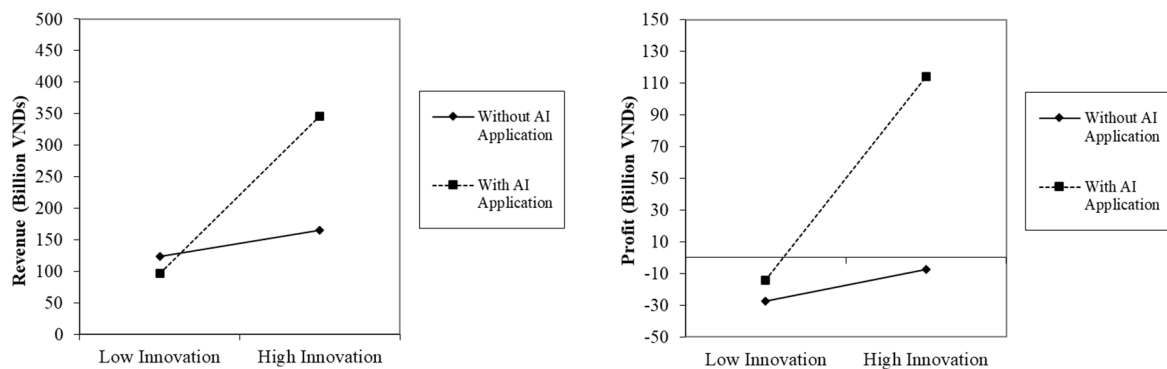


Figure 3. Moderation interaction AI*Innovation

Source: own elaboration.

Discussion

The findings from this study reveal that digital transformation, innovation, and AI significantly influence the financial performance of SMEs, consistent with the findings of prior studies. This study shows that SMEs actively engaging in digital transformation and innovation increase their revenue and profits. This result aligns with the findings of Ardito *et al.* (2024) and Abrokwah-Larbi and Awuku-Larbi (2024). Ardito *et al.* (2024) also identified a substantial positive correlation between digital transformation and SMEs' revenue growth, particularly when integrated with AI. They emphasise that AI's combination with technologies such as the Internet of Things and big data analytics significantly enhances strategic decision-making and operational efficiency, resulting in marked financial gains.

More importantly, this study advances the literature by showing that we should view AI not only as a direct predictor of performance but also as a moderating capability that strengthens the financial effects of digital transformation and innovation. This result is consistent with Khan and Gupta (2025), as well as Chen *et al.* (2022) and Wu and Monfort (2023), who stressed AI's role as a strategic resource enhancing organisational efficiency and decision quality. However, unlike much of the existing literature, which tends to examine AI, digital transformation, and innovation separately, our findings highlight their complementarity and show that performance gains are stronger when these capabilities are combined.

Moreover, the findings reinforce the RBV perspective. RBV argues that firms achieve superior performance when they possess valuable, rare, and difficult-to-imitate resources and capabilities that competitors cannot easily substitute (Wernerfelt, 1984; Barney, 1991). From this perspective, digital transformation, innovation, and especially AI act as strategic capabilities that help SMEs deploy re-

sources more effectively, enhance adaptability, and strengthen competitive advantage. This interpretation is consistent with prior studies showing that AI capabilities improve decision-making, operational efficiency, and firm competitiveness (Chen *et al.*, 2022), and that their value is stronger when combined with complementary digital resources such as IoT and big data analytics (Ardito *et al.*, 2024). It also aligns with evidence that AI-driven capabilities improve customer engagement, personalisation, and internal processes, thereby strengthening financial outcomes (Abrokwah-Larbi & Awuku-Larbi, 2024). Our findings extend this line of research by showing that AI not only contributes to performance directly but also amplifies the performance effects of digital transformation and innovation.

Finally, the results add important evidence from the context of SMEs in an emerging economy. Prior studies have noted that SMEs often face financial, technological, and institutional barriers that limit the effective use of advanced technologies (Melo *et al.*, 2023; Nguyen, 2024). Our findings refine this view by showing that when SMEs develop AI capability, the financial returns to digital transformation and innovation become significantly stronger. This suggests that the benefits of these strategic initiatives depend not only on adoption itself but also on the firm's ability to combine them with complementary capabilities such as AI.

CONCLUSIONS

This study empirically investigated the moderating role of AI in enhancing the relationship between digital transformation, innovation, and financial performance among small and medium-sized enterprises (SMEs). The findings indicate that digital transformation and innovation significantly improve SMEs' financial performance, notably revenue and profitability. Crucially, AI adoption substantially amplifies these positive effects, underscoring AI's critical strategic value in optimising digital and innovative initiatives.

Theoretically, this research enriches the technology-adoption literature by illustrating the synergistic interactions between AI, digital transformation, and innovation. While earlier studies typically examined these elements separately, our findings highlight the need to integrate AI into digital transformation and innovation strategies to maximise financial outcomes. By validating the RBV theory, the study emphasises the importance of AI as an intangible strategic resource that significantly contributes to competitive advantages and sustained financial success.

Practically, the findings offer meaningful insights for SME managers. SMEs should prioritise developing and integrating AI capabilities within broader digital and innovation initiatives. Specifically, investments in AI-driven automation, predictive analytics, and data-driven decision-making can significantly enhance operational efficiencies, customer interactions, and market responsiveness. Managers should adopt comprehensive technological strategies, recognising AI's potential to transform operational performance and maximise returns from digital investments and innovative activities.

For policymakers, the study highlights the necessity of creating supportive environments to facilitate SMEs' adoption of AI, digital transformation, and innovation. Policies could include financial incentives such as subsidies or tax breaks to encourage AI adoption. Moreover, implementing training programmes that improve digital literacy and AI competencies among SME leaders and employees should be prioritised. Establishing AI innovation hubs or collaborative ecosystems to offer SMEs access to essential AI expertise and resources would further enhance the adoption of these technologies. By implementing these policy measures, governments can significantly boost SME performance and contribute to broader economic growth and competitiveness.

Despite these meaningful contributions, we acknowledge some limitations. Firstly, the data collection relied on self-reporting by SME leaders, potentially introducing response bias or inaccuracies due to recall limitations or perceptions. This method may affect the objectivity of the findings. Moreover, the snowball sampling approach might constrain the results' representativeness and generalisability. Because participants were recruited through existing networks, the sample may not represent all SME groups in Vietnam or elsewhere.

Future research could address these limitations by employing more rigorous sampling methods, such as stratified random sampling or larger-scale surveys, to increase representativeness and mitigate potential biases associated with snowball sampling. Furthermore, future research could explore

other performance dimensions, such as market share, customer satisfaction, or environmental sustainability metrics, to understand comprehensively how digital transformation, innovation, and AI integration influence SME success beyond financial metrics. Extending research into comparative analyses across sectors or different geographical contexts could also yield valuable insights into variations in the effectiveness and applicability of AI-driven strategies.

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Authors

The authors' contribution shares are 40% to NKH (first author), 40% to NTAV (corresponding author), and 20% to NTMH. Conceptualisation NTAV; methodology NKH; data collection NKH, NTAV, NTMH; writing – original draft preparation NKH, NTAV; writing – review and editing NKH, NTAV, NTMH; funding acquisition NKH, NTAV.

Nguyen Khac Hieu

Nguyen Khac Hieu holds a PhD in Economics from the University of Economics in Ho Chi Minh City, Vietnam. Currently, he is a lecturer at the Faculty of Economics at HCMC University of Technology and University of Technology and Engineering (Vietnam). His research interests include quality management, Industry 4.0, economic development, digital transformation, and circular economy.

Correspondence to: Nguyen Khac Hieu, Faculty of Economics, HCMC University of Technology and Engineering, No. 1 Vo Van Ngan Street, Linh Chieu Ward, Thu Duc City, Ho Chi Minh City, Vietnam. e-mail: hieunk@hcmute.edu.vn

ORCID  <https://orcid.org/0000-0002-5138-2032>

Nguyen Thi Anh Van (corresponding author)

Nguyen Thi Anh Van holds a PhD in Economics and Management from Tomas Bata University in Zlin (Czech Republic). She is currently a lecturer at the Faculty of Economics, HCMC University of Technology and University of Technology and Engineering (Vietnam). Her research interests include total quality management, sustainable performance, Industry 4.0, and digital transformation.

Correspondence to: Nguyen Thi Anh Van, Faculty of Economics, HCMC University of Technology and Engineering, No. 1 Vo Van Ngan Street, Linh Chieu Ward, Thu Duc City, Ho Chi Minh City, Vietnam. e-mail: anhvan@hcmute.edu.vn

ORCID  <https://orcid.org/0000-0001-6950-6868>

Nguyen Thi My Hanh

Nguyen Thi My Hanh holds a PhD in Industrial Management at National Central University, Taoyuan, Taiwan. She is currently an assistant professor in Industrial Engineering and Management at Yuan Ze University, Taoyuan, Taiwan. Her research interests include supply chain management, smart manufacturing, pricing strategy, green supply chain, and channel coordination.

Correspondence to: Nguyen Thi My Hanh, Faculty of Industrial Engineering and Management, Yuan Ze University, No. 135, Yuandong Road, Zhongli District, Taoyuan City 320315, Taiwan. e-mail: ntmhanh@saturn.yzu.edu.tw

ORCID  <https://orcid.org/0000-0002-7608-8315>

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Use of Artificial Intelligence

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Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Is nepotism a good old-fashioned virtue? Examining its impact on family business succession and the role of familial pride: Evidence from Indonesia

Anita Maharani, Dewi Tamara

ABSTRACT

Objective: The objective of the article is to verify the role of familial pride in strengthening nepotism's influence on family business succession in Indonesia, as it relates to the communality value embedded in family business culture. Further, family businesses support the Indonesian economy, but according to several sources, their existence is threatened when the business passes to the next generation, and the second generation proves decisive.

Research Design & Methods: The research design was quantitative, and we collected data by distributing questionnaires via snowball sampling to second-generation members of family businesses in Indonesia. Because the population size was unknown, we adopted the ten-times rule. After ten months of data collection, we analysed the returned responses using partial least squares techniques.

Findings: Among the second generation of small and medium-sized family businesses in Indonesia, familial pride plays a significant role in family business succession. However, the expectation that familial pride amplifies nepotism's negative influence on succession finds no support because familial pride is inseparable from the dynamics between nepotism and family business succession.

Implications & Recommendations: The second generation in small and medium-sized family businesses sees family business succession as a complex process still shaped by nepotism and familial pride. Family business succession cannot be separated from familial pride, although nepotism is considered harmful. Familial pride will encourage family business succession and support business continuity and sustainability.

Contribution & Value Added: The study demonstrates the importance of familial pride and nepotism in delivering succession in family-owned businesses. The results merit examination at a larger scope, because Indonesia's cultural diversity and varied backgrounds can map the family business landscape, attract foreign business, and raise awareness.

Article type: research article

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INTRODUCTION

Family businesses are considered the backbone of the Indonesian and global economy. Family businesses cover most businesses in Indonesia (Purba & Tan, 2018; Utamaningsi, 2020) and range from micro-enterprises to conglomerates, thus contributing significantly to national GDP and employment and anchoring Indonesia's participation in the global economy (Mandiana & Suhartati, 2006).

The study of family businesses remains compelling, especially in countries where family businesses loom large amid economic dynamics. Families who establish businesses also demonstrate successful

entrepreneurial practice, and usually start from a small scale, becoming known as small and medium-sized enterprises. Ershova (2014) found a connection between the era of family business and the nation's economy. Existing research shows that family businesses contribute to the economy by creating jobs, introducing innovation, and stabilising the national economy (Paul, 2024), encouraging competitive advantage in the economy and ensuring business continuity from generation to generation (Czarnecka & Bednarz, 2023). Moreover, these businesses are crisis-resilient thanks to their stability, and they always strive to maintain business commitments (Gudzovata & Voronovska, 2023).

Existing family business studies often raise the importance of successor readiness. Previous studies assumed that effective succession planning can improve family member readiness, encourage strong relationships between family members, and maintain the established company culture (Rasyieda *et al.*, 2024). Meanwhile, our study focused on nepotism and familial pride, recognising that external pressures such as industry digitisation (Xie *et al.*, 2022; Baltazar *et al.*, 2023) and regulatory demands (*e.g.*, Indonesia's Omnibus Law) also shape succession outcomes. However, family business studies still stress improving family members' readiness, which then attracted the attention of researchers such as Li *et al.* (2023), and Sallay *et al.* (2024).

In Asia, family businesses economically strengthen several countries, for example, Indonesia, Malaysia, Singapore, and Thailand (Ding *et al.*, 2021). However, Sukamdani's study (2023) showed that Indonesia remains a compelling setting, because its succession dynamics are pronounced, especially given its diverse backgrounds, which can represent other Southeast Asian countries (Chen *et al.*, 2021). This background motivated us to conduct our research in Indonesia. Although the Indonesian economy is mostly fuelled from family business contributions (PWC, 2021), 70% of family businesses in Indonesia are unable to survive to the second generation (Dewi, 2022). Moreover, in Indonesia's collectivist culture (Gupta & Sukanto, 2020), factors like family loyalty and social ties heavily influence business decisions (Weimann *et al.*, 2021). From strong social ties, a tendency towards nepotism arises when leaders overestimate family members' qualifications (Burhan *et al.*, 2020), while familial pride drives the desire to maintain legacy since higher nepotism in family firms strengthens the relationship between organisational social capital and improved organisational performance (Schmid & Sender, 2021). Hence, family business succession in Indonesia remains an urgent matter.

This article aims to continue the study conducted in 2020 by Maharani *et al.* (2020) which tested the model in only one location, Surabaya, one of the largest cities in Indonesia and a city whose economy grows on family businesses ranging from small firms to large companies. Maharani *et al.* (2020) found that the role of non-family business members had no positive influence on succession in family businesses, and there was a negative influence of nepotism practices on succession in family businesses, as well as a positive and significant influence of familial pride on family business succession. Moreover, Maharani *et al.* (2020) note that Indonesia's unique succession dynamics make it an ideal setting to explore socioemotional factors (Sukamdani, 2023). Therefore, we retested the model and took data from various locations in Indonesia. By expanding the scope geographically, we sought to fully investigate the dynamics of family business succession in Indonesia's diverse business landscape.

Family business succession often involves nepotism, where leaders favour family members over external candidates, which leads to potential performance declines. Prioritising individuals from blood ties does not necessarily benefit the business. In other words, the business may not necessarily perform better if managed directly by family members. Scholars refer to this as a family business' lack of openness to outsiders who may have better qualifications. Familial pride can exacerbate this issue, as leaders may put family interests above selecting the most skilled successor. Consequently, the 'weakness of strong ties' phenomenon highlights the dangers of nepotism in decision-making within family businesses (Liu *et al.*, 2015).

The three-circle model of the family business system, revealed by Tagiuri and Davis (1996) anchors the understanding of family business management, where professionalism and blood ties intertwine. Moreover, the model emphasises the tension between family loyalty and professionalism. Although it was a fundamental study, Davis (2008) later stated that family businesses vary widely, and that the phenomenon remains dynamic and worth studying. Stanley *et al.* (2019) reinforce this

view by stating that the family's role remains very strong in two areas: ownership and business leadership. Hence, we cannot completely separate the important role of the family in business. It was one of the reasons for the study by Maharani *et al.* (2020), who found that the involvement of non-family members in the business can positively influence family business succession in a limited setting, namely among business owners in Surabaya, Indonesia.

Family business succession constitutes a critical challenge. Poor succession planning can lead to significant failures in family-owned businesses (FOBs). While nepotism may play a role in succession decisions, familial pride can also influence succession, as families often desire to maintain control and legacy (Collins, 2011). Nepotism arises from the belief that only close people are capable, and it is therefore considered to have a negative impact on the family business (Liu *et al.*, 2015), especially if nepotism appears because the family has a tendency towards arrogance (Stanley *et al.*, 2019). When a family business admits only certain individuals, it may overlook those with genuine skills, even though they may be well-suited for the business (Sugundan *et al.*, 2018). These findings led us to focus on nepotism, familial pride, and family business succession.

Most studies on family business succession focus on Western economies or developed Asian markets. Bachkaniwala *et al.* (2001) found that succession remains a problematic and neglected issue in South Asian family businesses, potentially affecting the future of Asian independent family businesses. However, Indonesia might present a unique case (Tirdasari & Dhewanto, 2020) due to its strong collectivist culture, high failure rate, which makes it an urgent setting to study succession barriers, and diverse business landscape, ranging from micro-enterprises to conglomerates, which offers broader insights than single-city studies. Although numerous studies examine family business succession, we found that few attempted to theoretically integrate the affective dimensions of family succession. Specifically, nepotism and pride each link to the behavioural and emotional components of socioemotional wealth theory.

Through this study, we sought to address a critical gap in family business succession research, one flagged by Gomez-Mejia *et al.* (2007), which identified the importance of examining socioemotional wealth in family businesses given culturally and non-economically rooted factors.

RQ1: Can nepotism still positively impact family business succession in Indonesia?

RQ2: Does familial pride have a role within the effect of nepotism on family business succession in Indonesia?

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Family Business Succession

We may define a family business as a business run by a family whose dominance in ownership and management is pronounced as expressed in a recent study by Kumar (2024). Family businesses care deeply about ensuring that the business founded by the first generation can continue over time. Although often considered an organisation facing extraordinary challenges in managing a business, family businesses are not without dynamics. As Donaldson (2024) states, family business is a complex yet adaptive organism because the relationships within the family directly influence business decision-making. Donaldson draws on Paul's view (2024) that a family business shows a unique bond between family members that influences who will manage and control the family business. There are many definitions of family business succession. However, in general, family business succession relates to the ownership and management of a business mostly handled by the family and lasts from generation to generation. We may look at family business succession also from Churchill and Hatten's perspective (1987). They state that the succession process is an anchor, where changes in management, strategy, and control are planned for and executed. Astrachan and Shanker (2003) and Ward (2011) support this view. Based on several previous studies and concepts, succession in family businesses is not simply a transfer of position from one person to another, but is closely tied to socioemotional processes conceptually linked to socioemotional wealth. The extended family's desire to maintain a family legacy, which has the potential to dominate the succession process, is closely linked to the issue of blood ties and the identity that will be maintained through family involvement.

Nepotism

Nepotism is quite common in family businesses and significantly influences the placement of those who are most suitable for the family business. Nepotism in family businesses more closely resembles favouritism, where only the most favoured family members are given the greatest opportunities for recruitment or promotion (Erdirençelebi & Çini, 2021). Even for strategic positions, family members may be appointed, as previous studies suggest, since involving family members in business relates to beliefs about socioemotional well-being (Jeong *et al.*, 2022). However, while nepotism may seem benign and common, studies have found that it can hinder organisational progress (Spahi *et al.*, 2022). Interestingly, from the socioemotional wealth perspective, nepotism is a natural mechanism families use to control and protect affective endowments. In turn, stewardship theory advises that trust is not favouritism: family members should act as stewards of the family legacy.

Familial Pride

Familial pride stems from the close relationship between family and business and a commitment to the future continuity and success of the family business (Robinson & Stubberud, 2012). Familial pride can hinder succession due to excessive dependence on family members, which ultimately affects long-term business performance (Heidrich *et al.*, 2016). Family influence on the company presumably encourages family members' commitment to maintaining the family business (Basly & Saunier, 2020). In the context of a family business, familial pride can foster positive impressions among next-generation members. However, negative impressions also arise if familial pride leads to arrogance and triggers injustice (Bernhard, 2022). One study found that culture and gender also influence familial pride (Bernhard, 2024). Interestingly, Brito (2022) found familial pride can also be considered the foundation for business continuity, bringing value not only to the family but also to the wider community indirectly involved in the business.

Familial Pride and Family Business Succession

The role of family dynamics in business succession remains interesting to study. Scholars argue that cohesive family culture and familiness are unique resources resulting from family involvement, and they are critical to successful transfer from generation to generation in family business (Bozer *et al.*, 2017), but family involvement needs attention: if the family is too deeply involved, adapting to new perspectives usually becomes tough; this might happen when later generations show resistance in accepting professionalisation in business practice (Davis & Harveston, 1998). For instance, while scholars often frame family harmony as a prerequisite for smooth succession (Rahmani *et al.*, 2023), excessive cohesion may lead to groupthink, which will hinder innovation and limit external involvement in the business (Carney, 2005). Successor's confidence and perceived incumbent support are widely recognised as the key predictors for long-term succession success (Gagné *et al.*, 2019). Over-relying on successors is risky, especially those appointed through familial ties rather than merit as research shows this leads to poor strategic decisions (Ahrens, 2013). These contradictions highlight a fundamental tension in family business succession: balancing emotional loyalty with organisational competence.

H1: There is a positive effect of familial pride on family business succession.

Nepotism and Family Business Succession

Evaluating business performance is important when involving family members to continue the business (Liu *et al.*, 2015). Families who prefer to employ family members may need to consider professional involvement (Ahrens, 2013). Professional involvement can affect the quality of decision-making (Barach *et al.*, 1988; Hamilton *et al.*, 2023). Fang *et al.* (2022) found that nepotism has a functional purpose: in collectivist societies, nepotism can increase organisational stability thanks to strong bonds of trust (Jaskiewicz & Dyer Jr., 2017) and Berrone *et al.* (2012). Furthermore, Zellweger *et al.* (2012) question the assumption that external employees inherently outperform family members, and the results of Kellermanns *et al.* (2012) show that family successors' superior commitment and company-specific knowledge actually protect family businesses from potential business problems.

H2: There is a positive effect of nepotism practices on family business succession.

Nepotism and Familial Pride

Tasdemir *et al.* (2017) state that nepotism is problematic favouritism. Schmid and Sender (2021) found nepotism may bring social capital benefits for family businesses as it facilitates tacit knowledge transfer through trusted familial networks (cf. Jaskiewicz *et al.*, 2013). Miller *et al.* (2020) found this positive side depends on context, later generations, and specific cultural settings (Vazquez, 2016). Davis's (2015) concept of 'nepotistic ideology' simultaneously creates in-group/outgroup dynamics that alienate non-family talent during cohesion.

H3: There is a positive effect of nepotism practices on familial pride.

Nepotism, Familial Pride, and Family Business Succession

Amore *et al.* (2021) found that family business successions bring cost efficiencies and additional financial value. If familial pride is coupled with emotional decision-making, business problems will arise (Liu *et al.*, 2015). Gilding's (2005) work highlights how non-economic factors such as legacy preservation and tax strategies often create a complex relationship between rational and emotional drivers during succession. This tension manifests in what Bozer *et al.* (2017) term the 'familiness paradox': while cohesive family culture and shared socialisation strengthen successor commitment, these same factors can also breed insularity and resistance to issues beyond the business. Recent meta-analyses suggest that this paradox may explain why family successions show such divergent outcomes across contexts (De Massis *et al.*, 2023).

H4: Familial pride acts as a moderator of the nepotism effect on family business succession.

H5: Familial pride mediates nepotism practices and family business succession.

RESEARCH METHODOLOGY

Population and Sample

Second-generation representatives of family businesses in Indonesia are not easy to find. It was difficult to obtain definite figures because most family businesses in Indonesia are still struggling to transition management from the first generation to the second generation, as noted in several studies of Indonesian family businesses (*e.g.*, Kumar & Prameswari, 2018). Given this constraint, we employed a targeted snowball sampling technique (Cantone & Tomaselli, 2022) moving from one second-generation member to the next one. We used snowball sampling because the family business constitutes a closed community whose members trust their own acquaintances. This came at a cost: the research required more time to gather the data. Overall, there were three key reasons: community accessibility, cultural appropriateness, and practical feasibility. We acknowledge the limitations of potential homogeneity; we verified business characteristics to ensure SME representation, and capped referrals at three per respondent to prevent network clustering.

When determining the research sample, we adopted the sample-size technique described in Barclay *et al.* (1995) and Hair *et al.* (2017). Namely, in multivariate research, sample size can refer to ten times the number of formative indicators used for the variables involved in the study. We understand that the limitation of this technique is oversimplification, but we expected to overcome this issue through common method variance. In this study, the total number of indicators was nine, so at least 90 respondents were involved. At first, the survey response rate was low, but by the end of October, we obtained 252 questionnaire responses. We distributed the survey form at a seminar for SMEs in Jakarta, Indonesia, and asked participants visiting our booth to fill in the survey. This sample suits model discovery and prediction, as it provides adequate statistical power.

To facilitate data collection, we limited surveyed family businesses to the small and medium-sized category, because communities supporting such businesses facilitated reaching respondents. We collected data for 10 months, from early January 2024 to the end of October 2024. This period

was longer than the initial plan, as we had scheduled only three months of data collection. The delay stemmed from stagnant field data collection.

We conducted the data analysis in three stages. The first stage involved cleaning the data of empty responses. In the second stage, we assessed the measurement model. In the third stage, we assessed the structural model. Throughout the analysis, we used SmartPLS 4.0 software.

Measures

The research approach was quantitative. We obtained data by distributing questionnaires online. We operationalised variables by adopting indicators developed in previous studies. To measure familial pride, we adopted items developed by Trapero *et al.* (2017). To measure nepotism, we adopted items developed by Abdalla *et al.* (1998) and Asunakutlu and Avci (2010). Finally, to measure family business succession, we adopted items from Coffman (2014) and Perret (2016). Table 1 presents the details.

Table 1. Variables' operationalisation

Variables	Indicators	Statements
Familial pride Trapero <i>et al.</i> (2017)	Involved with family business.	I feel like people would be proud to be involved with this family business.
	Full support.	I feel that people who are successful in the family business are those who have full support.
	Contribute to family business.	I feel that other people will be proud if they can contribute to this family business.
Nepotism Abdalla <i>et al.</i> (1998), Asunakutlu & Avci (2010)	Ties to the family that founded the business.	I feel like a person who has an important position in the business, because he has ties to the family that founded the business.
	Prioritising family members to be involved in the business.	I feel that in family businesses, there is a principle of prioritising family members to be involved in the business.
	Easier to get involved with a family business because it's part of the family.	I feel like people will find it easier to get involved with a family business, because it's part of the family.
Family business succession Coffman (2014), Perret (2016)	Prepare a successor to replace its predecessor.	I feel that a good family business is one that is able to prepare a successor to replace its predecessor.
	Well-thought-out plan for its successor.	I feel a good family business is one that has a well-thought-out plan for its successor.
	Gets the next generation involved from the start.	I feel a good family business is one that gets the next generation involved from the start.

Source: own study.

The questionnaire items used a Likert scale with value ratings from 1 to 5 (where 1 represents completely disagree and 5 – completely agree). This choice followed previous findings that the five-point Likert scale is ideal thanks to its minimal bias and high reliability (Babakus & Mangold, 1992). To ensure that the correct respondents took the survey, we applied a filter question: 'Are you actively involved in a family business as the second generation? (you may proceed if your answer is Yes).'

Common Method Variance

To ensure that all measurement items could represent the variables under study, we piloted the survey with 30 respondents. To ensure simplicity and consistency, we held the pilot test in the first week of January 2024. After data collection, we analysed the data using JAMOV and performed confirmatory factor analysis (CFA), from which we obtained factor loadings. From the factor loadings, we found that all factor loadings showed a strong relationship (Pride1 (0.793); Pride2 (0.46); Pride3 (0.811); Nepotism1 (0.666); Nepotism2 (0.793); Nepotism3 (0.645); FBS1 (0.687); FBS2 (0.693); FBS3 (0.559)), among these results, we retained FBS3 (0.559) in the measurement scale, following Hair *et al.* (2019). In addition to factor loadings, we also examined significance using P-values; results showed p-count < 0.001,

indicating that the relationship between each indicator and its factor was significant. The reference for decision-making came from (Benjamin & Berger, 2019). Then, the confidence intervals indicated the stability of the factor loadings, as one indication, for example, Pride1 (Lower = 0.605; Upper = 0.851) and so on, which had positive, narrow ranges, suggesting that larger samples would yield more stable results. Finally, the Z-score showed a calculated Z value > 1.96 (Doane & Seward, 2011) at a 95% confidence level, thus indicating strong significance.

Data Analysis

As Table 2 shows, among the 252 responses, most respondents were women and the largest group had been involved as the second generation for more than twenty years, thus the results represented this majority group.

Table 2. Respondent characteristics

Respondent characteristics	Frequency	Percentages
Gender		
Male	100	40.7
Female	152	59.3
How long have you been involved in this family business?		
< 5 years	39	15.5
6-10 years	52	20.6
11-15 years	24	9.5
16-20 years	26	10.3
>20 years	111	44
What business type?		
Culinary	142	56
Beauty	40	16
Fashion	70	28

Source: own study.

RESULTS AND DISCUSSION

Following the stages explained in the previous section, we began with data cleaning to ensure that the analysed responses were complete. Consequently, all data used were complete, and no revision of the final sample size was required. We then conducted the second stage of data analysis, with the following results.

Table 3. Construct reliability and validity

Variables	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Familial pride	0.716	0.726	0.842	0.642
Family business succession	0.677	0.676	0.823	0.608
Nepotism	0.737	0.743	0.850	0.655

Source: own study using SmartPLS.

Table 3 shows that almost all parameters required for construct reliability and validity were met. Although the Cronbach's alpha value for the family business succession variable was <0.7 (Chin, 1998), the composite reliability values of both rho_a and rho_c were acceptable, as suggested in Diamantopoulos *et al.* (2012). On AVE, all variables showed good convergent validity as suggested in Sarstedt *et al.* (2021). We next checked discriminant validity (Table 4).

The HTMT values fell below the 0.85 threshold suggested by Henseler *et al.* (2015). Thus, discriminant validity was strong and sufficient to proceed to the next stage.

Based on Table 5 and Chin (1998), the research model explains 21.8% of the variance in family business succession. Moreover, the variables considered to influence family business succession – namely

familial pride and nepotism – have limited predictive power (adjusted R-square = 21.1%). However, this research model can still help observe phenomena in the family business environment (Figure 1).

Table 4. Discriminant validity and heterotrait-monotrait ratio (HTMT)

Variables	Familial pride	Family business succession	Nepotism
Familial pride	–	–	–
Family business Succession	0.495	–	–
Nepotism	0.356	0.550	–

Source: own study using SmartPLS.

Table 5. Quality criteria: R-square

Variable	R-square	R-square adjusted
Family business succession	0.218	0.211

Source: own study using SmartPLS.

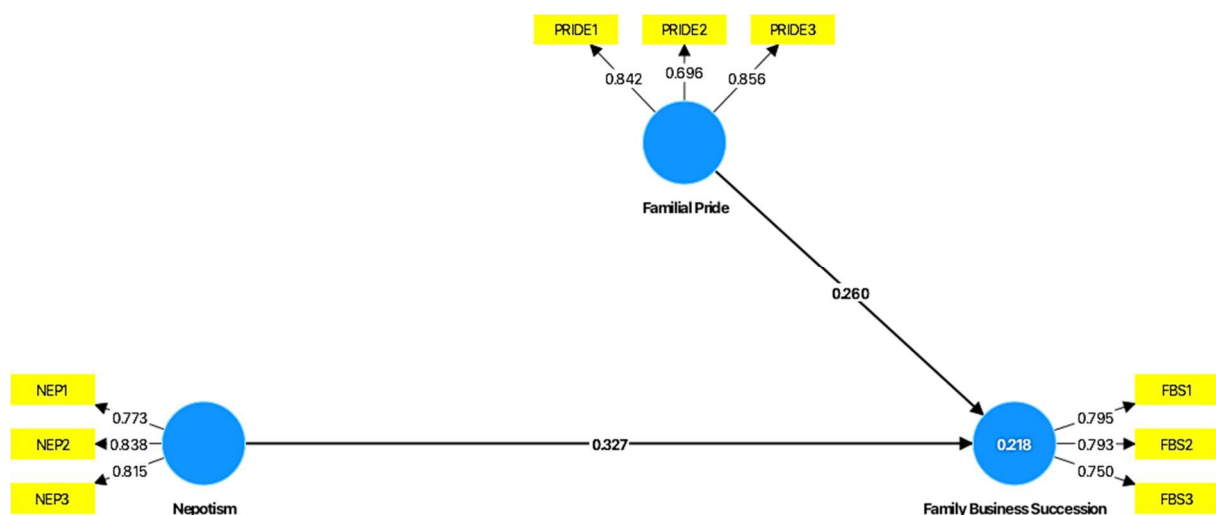


Figure 1. Measurement model assessment visualisation

Source: own elaboration using SmartPLS.

After we completed the measurement model assessment phase, we proceeded to the structural model assessment. Below, we present the results of this process (Table 6).

Table 6. Bootstrapping

Variable	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values	Decision
Familial pride -> Family business succession	0.257	0.263	0.066	3.904	0.000	Supported
Nepotism -> Familial pride	0.266	0.271	0.070	3.779	0.000	Supported
Nepotism -> Family business succession	0.320	0.326	0.073	4.399	0.000	Supported
Familial pride x nepotism -> Family business succession	0.040	0.038	0.072	0.565	0.286	Not supported
Nepotism -> familial pride -> family business succession	0.068	0.071	0.024	2.784	0.003	Supported

Note: Subsamples n = 5000, test type: one-tailed.

Source: own study using SmartPLS.

The results support four of the five proposed hypotheses. Nepotism has a direct and indirect positive impact on family business succession through familial pride. Familial pride positively influences

family business succession on its own. The interaction between nepotism and familial pride does not significantly affect family business succession (Figure 2).

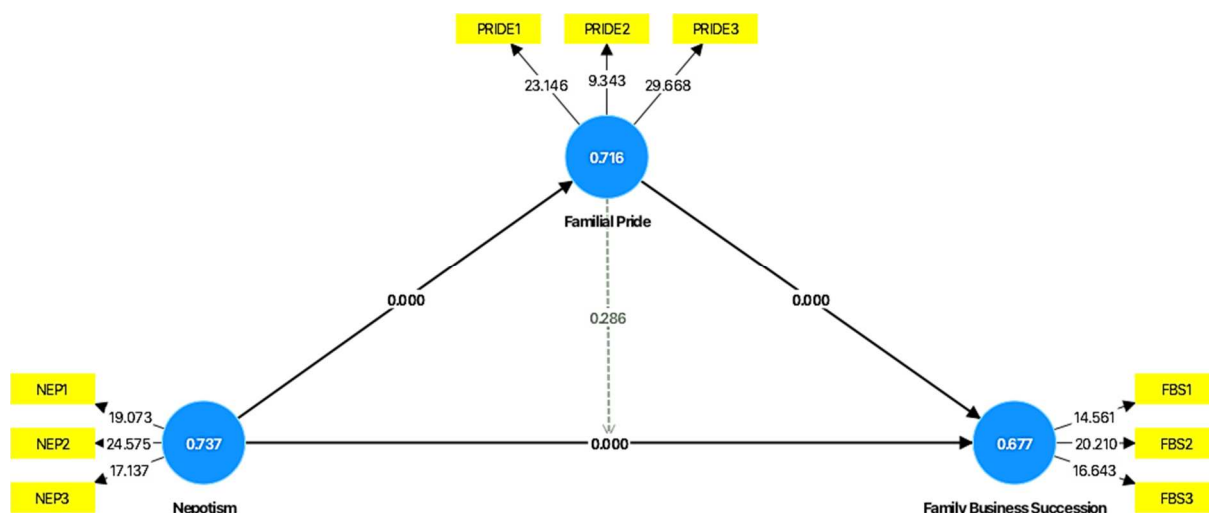


Figure 2. Structural model assessment visualisation

Source: own elaboration using SmartPLS.

The results demonstrate that familial pride positively influences family business succession (H1 supported). This suggests that when family members take pride in their business, they are more likely to maintain its continuity across generations. This finding aligns with Bozer *et al.* (2017), who argue that successful succession depends on preserving a cohesive, adaptable family culture. Similarly, Santiago's (2000) research on Philippine family businesses highlights how shared family values often prove more crucial than formal succession planning. In the Indonesian context, familial pride stems from traditional values that emphasise respect for ancestors and family ties (Lestari, 2018), fostering commitment to legacy preservation (Atmaja, 2018) and providing emotional resilience during transitions (Wulansari & Cahyani, 2024).

However, while familial pride and nepotism facilitate succession by reinforcing loyalty and continuity, they may also introduce risks such as resistance to change, managerial incompetence, or the exclusion of more qualified non-family professionals (Perez-Gonzalez *et al.*, 2006; Bennedsen *et al.*, 2007). Despite its role in sustaining familial commitment, nepotism can stifle innovation and lead to suboptimal decision-making if meritocracy is overlooked (Jones *et al.*, 2008). Future research should explore how family businesses balance these dynamics to ensure both legacy preservation and long-term competitiveness.

However, the benefits of familial pride must be balanced against its potential drawbacks. Excessive pride can lead to organisational rigidity, as successors may resist professionalisation to avoid compromising perceived family traditions (Heidrich *et al.*, 2016). For instance, Javanese family businesses often retain outdated operational methods out of reverence for founders' original practices (Lestari, 2018), potentially hindering growth. This phenomenon reflects Carney's (2005) 'groupthink paradox,' where family cohesion suppresses constructive dissent.

Our analysis confirms nepotism's positive role in Indonesian family business succession (H2 supported). This contrasts with Shah's (2022) argument that inexperienced family members threaten business continuity, highlighting how cultural context shapes nepotism's effects. In Indonesia's collectivist society, nepotism reflects familial duty and *gotong royong* (communal harmony), whereas Western individualistic cultures often perceive it as inefficient or unfair. While nepotism may enhance stability,

unregulated favouritism risks undermining performance. Succession requires next-generation members to explore opportunities to learn leadership before the succession (Sallay *et al.*, 2024), which presumably forms part of the mitigating mechanism. This approach aligns with Sentuti and Cesaroni's (2020) emphasis on the urgency for family businesses to involve younger generations.

Nevertheless, nepotism's risks warrant serious consideration. Beyond causing resentment (Bernhard, 2022), nepotism can perpetuate managerial incompetence; Dewi (2022) attributes 42% of Indonesian succession failures to unqualified heirs. Moreover, nepotism may stifle innovation by excluding external talent, particularly in industries that require rapid change. Even within collectivist cultures, overreliance on kinship ties can reduce competitiveness, as demonstrated by Malaysian Chinese family businesses (Tan & Fock, 2001).

The results support H3, confirming nepotism's positive relationship with familial pride. While pride enhances family business reputation (Bernhard, 2024), unchecked nepotism risks fostering resentment (Bernhard, 2022). Therefore, effective management must balance these dynamics (Schilpzand *et al.*, 2024), ensuring familial relationships improve rather than hinder team cohesion (Briggs, 2016).

We rejected H4 as familial pride does not moderate nepotism's effect on succession. This supports Bernhard's (2022) view that pride operates as an independent variable. Conversely, we accepted H5: familial pride mediates nepotism's impact on succession, thus reinforcing Bozer *et al.*'s (2017) 'familiness paradox.'

This mediation effect reveals familial pride's dual nature. Although it aligns nepotism with succession objectives (Briggs, 2016), familial pride may also obscure poor decision-making, such as retaining underperforming heirs. To counter this, businesses should complement pride-building activities (*e.g.*, legacy documentation) with independent performance audits (Schilpzand *et al.*, 2024), ensuring emotional attachments do not override competence.

Through this research, we improved on Maharani *et al.*'s (2020) results. That study previously found that non-family members' role in succession was not proven positive, and reported negative effects of nepotism practices on succession. Our study's results differed, albeit they validated the positive effect of familial pride on family business succession.

Our study needs further development, especially as it only involved respondents from limited backgrounds, as explained in respondent characteristics in Table 2. Adding the perspectives of other respondents from countries whose economic strength rests on family businesses would be very promising. The results of our study can trigger the exploration of phenomena related to the variables studied in family businesses in other situations like familial pride, which in this study supports the assumption that familial pride influences family business succession. Thus, a great future opportunity is exploring familial pride in concrete terms, whether rooted in business background, culture, or other factors. Hence, familial pride is part of the legacy that must be passed down from generation to generation in a family business, such as an identity recognised by the community that knows the family business.

CONCLUSIONS

Our study results answer the two research questions: they prove the role of nepotism in family business succession in Indonesia and the role of familial pride in the dynamics that stem from nepotism practised in family businesses. Furthermore, the results indicate that familial pride can play an important role in the succession of family businesses that practise nepotism.

Our study implies that familial pride is maintained by keeping the business sustainable. However, because nepotism was shown to have a positive influence on family businesses, it will be important to balance nepotism with strict selection of family members to ensure that successors involved in the family business are committed and competent. Implemented formally or informally, leader development through mentorship could maintain the credibility and performance of the business as built by the generation that pioneered it. To increase the role of nepotism in encouraging a sense of familial pride, family businesses need to ensure fairness and transparency to avoid potential conflicts among stakeholders.

Theoretically, our study highlights the dual role of nepotism as the driving factor for family business succession and an indirect driver mediated by familial pride, extending the familiness paradox by show-

ing that nepotism's dual role as the driver of succession and source of conflict depends on how familial pride is cultivated. Moreover, the study underscores the need for culturally grounded frameworks to assess family business succession in collectivist economies.

Future research should explore contextual variables that might shape nepotism and familial pride. Alternative methodologies – such as qualitative work with successors – might reveal issues left unexplored in this study. Contrasting countries would also exercise the research model and enhance generalisability.

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Authors

The authors contributed equally. Conceptualisation, literature, discussion, conclusion – ANT; methodology, calculations, discussion – DWI; review and editing – ANT, DWI

Anita Maharani (corresponding author)

Professor at the BINUS Business School Master Program. Her research interests include human resource management and entrepreneurship.

Correspondence to: Prof. Dr. Anita Maharani, Binus Business School Master Program Jl. Hang Lekir I no 6, RT 1 RW 3 Kebayoran Baru, Central Jakarta Indonesia, e-mail: anita.maharani@binus.edu

ORCID  <https://orcid.org/0000-0003-3942-9755>

Dewi Tamara

Associate Professor at the BINUS Business School Master Program. Her research interests include entrepreneurship, finance, and general business.

Correspondence to: Dr. Dewi Tamara, Binus Business School Master Program Jl. Hang Lekir I no 6, RT 1 RW 3 Kebayoran Baru, Central Jakarta Indonesia, e-mail: dtamara@binus.edu

ORCID  <https://orcid.org/0000-0002-8922-120X>

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This research has no potential conflict of interest, because it was funded independently and all respondents were volunteers.

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Development routes of resource and capability configurations in small and medium-sized enterprises

András Rideg, Gábor Márkus

ABSTRACT

Objective: The objective of the article is to identify and analyse the competitiveness of small and medium-sized enterprises (SMEs) in an international context by classifying 785 firms from eight countries into configurations based on performance across ten resource and capability pillars, linking configurations to competitiveness, and analytically inferring plausible, path-dependent development routes between them.

Research Design & Methods: We drew on the Global Competitiveness Project (GCP) dataset. We collected data between 2016 and 2020 in Bosnia and Herzegovina, Colombia, Costa Rica, the Czech Republic, France, Hungary, Mexico, and Spain through structured face-to-face interviews with SME owners or top executives. We classified firms into four configurations (Balanced, Core Competence, Harmonised, Bottleneck) based on skewness and relative variance across the ten pillars, quantified using GCP interview-based measures. We applied one-way Analysis of Variance (ANOVA) and binary logistic regression models to assess configuration differences in competitiveness and to support inferences about potential development routes.

Findings: The analysis revealed statistically significant differences in competitiveness across configurations: Harmonised firms displayed the highest competitiveness, whereas Balanced firms exhibited the lowest. The models suggest two main development logics. Balanced firms may reduce pillar dispersion and strengthen Technology, Decision-making, Marketing, and Networks to move towards a Harmonised configuration, or they may prioritise Technology (and, in some cases, Decision-making and Human Capital) in ways that generate a Bottleneck configuration. Core Competence firms may move towards Bottleneck by further reinforcing Technology, or towards Harmonised by broadening and aligning key pillars. However, some transitions appear economically unattractive, as the costs of incremental configuration change may outweigh competitiveness gains.

Implications & Recommendations: SME development strategies should strengthen configuration-specific pillars. Managers can use the identified configurations to diagnose their position and prioritise targeted improvements. Policymakers and practitioners should support SMEs in recognising their configuration and implementing focused interventions that improve the effectiveness of resource and capability deployment.

Contribution & Value Added: The study adds to resource-based view (RBV) and configuration-based research on SME competitiveness by linking an established competitiveness index to a four-type configuration scheme, including a Balanced configuration. It proposes a systematic, configuration-based framework for assessing how specific pillars shape competitiveness and for analytically inferring non-linear development routes between configurations, thereby refining GCP-related evidence and offering actionable guidance for SMEs.

Article type: research article

Keywords: resource-based view (RBV); SME competitiveness; configurations; business models; strategic development

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INTRODUCTION

The resource-based view (RBV) has emerged as the preeminent framework in the internal factor-based literature on competitive advantage, particularly for examining firm-level resources and capabilities in recent decades (Barney, 1991, 2001; Barney *et al.*, 2011, 2021; Peteraf, 1993; Prahalad & Hamel, 1990; Rugman & Verbeke, 2002; Wernerfelt, 1984). The RBV asserts that differences in firm performance and industry results stem from the resources and capabilities that firms can acquire, develop, and efficiently utilise. This approach emphasises core competencies, highlighting the importance of specific resources and capabilities that provide a competitive advantage. Some academics concentrate on specific variables of resources and capabilities, whereas others, such as those linked to the Global Competitiveness Project (GCP), promote the use of composite RBV indices. Composite methodologies provide a systematic framework for analysing configurations, as emphasised by Miller (1986, 1996). This approach is especially relevant for SMEs, because resources and capabilities are frequently not inherently distinctive and are often easily replicable or accessible (*e.g.*, Luo & Child, 2015).

Empirical investigations conducted by GCP researchers (*e.g.*, Alonso-Ubieta *et al.*, 2021; Bayon & Aguilera, 2021; Horváth & Lafuente, 2021; Lafuente *et al.*, 2020a, 2020b) into the practical implications of configurational theory underscore its significance in evaluating SMEs' competitive capacity. These results indicate that future research should concentrate on the configurational dimensions of competitiveness, analysing how the alignment and interaction of resources and capabilities affect business performance. Thorough investigations must examine the mechanisms by which organisations assimilate new and existing resources and ascertain the circumstances under which these configurations bolster competitiveness. Moreover, studies must examine how strategic resource allocation and the adjustment of configurations to external constraints influence competitive results across diverse business settings, market dynamics, and legislative interventions. This work seeks to address this call and enhance understanding of the configurations' dynamic characteristics.

Building on this research stream, the present article makes three contributions. Firstly, it extends prior GCP-based work by introducing a four-type configuration scheme – Balanced, Core Competence, Harmonised, and Bottleneck – derived from the skewness and relative variance of ten competitiveness pillars, and by explicitly identifying a Balanced configuration that combines markedly high- and low-performing pillars within the same firm. Secondly, it links these configurations systematically to an established competitiveness index, thereby providing a unified framework for assessing how specific pillars are associated with different configuration profiles and competitiveness levels. Thirdly, using cross-sectional data and a combination of ANOVA and binary logistic regression models, the study analytically inferred plausible development routes between configurations, which are interpreted as conceptual, path-dependent patterns rather than longitudinally observed trajectories.

Against this background, we pursued both descriptive and analytical objectives. On the descriptive side, we identified how SMEs' resources and capabilities aggregate into distinct configurations and how these configurations differ in terms of overall competitiveness and the underlying competitiveness pillars. On the analytical side, we explored whether and how the pillar structure of the configurations allowed us to infer potential development routes between them, and to what extent these routes can be interpreted as path-dependent patterns of configuration change.

Accordingly, we addressed the following research questions (RQ1-RQ3, Figure 1):

- RQ1:** How do resource- and capability-based configurations of SMEs differ in their overall competitiveness?
- RQ2:** How do the ten competitiveness pillars differ across the identified configurations?
- RQ3:** What plausible development routes between configurations can one analytically infer from their pillar profiles, and to what extent do these routes exhibit conceptual path-dependent patterns based on cross-sectional evidence?

By answering these research questions, the study aims to elucidate how SMEs manage strategic resources and capabilities through distinct configurations to improve their competitive positioning.

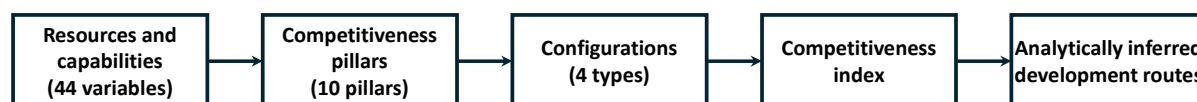


Figure 1. Conceptual framework of the study

Source: own elaboration.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

The Resource-based View, Configurations, and Path Dependency

Since the 1980s, firm-level resource and capability configurations have emerged as a central theme in the literature on competitive advantage. Early strategy research, including Porter's (1980) generic strategies and their subsequent developments (Dess & Davis, 1984), together with the contingency perspective of Hambrick (1983), provided the foundation for Miller's (1983, 1986) configuration theory, which has become one of the most widely cited approaches in the field. Miller and Whitney (1999) argue that, in line with internal factor-based theories of competitive advantage, a firm's resources and capabilities should be analysed in relation to each other within an integrated framework, as one cannot understand the system by examining its isolated components. Configuration research is particularly important because configurations are more difficult for competitors to imitate than individual resources or capabilities, thereby supporting the creation of defensible competitive positions in a Porterian sense (Porter, 1980). The literature suggests that integrating strategy and structure creates complementarities among configuration elements, which can provide a competitive advantage for the firm. This is especially crucial for SMEs, as a focused differentiation strategy is often the only feasible generic strategy.

Configuration generally denotes recurring arrangements of firm-level attributes (Meyer *et al.*, 1993, p. 1175). More narrowly, we may understand it as the alignment between a firm's external environment, its resources and capabilities, the entrepreneur's characteristics, and the managerial practices used, along with their suitability for specific tasks or objectives. This alignment constitutes a distinctive multidimensional feature of each enterprise (Miller, 1986; 1996).

The RBV and the discovery-oriented strategy approaches both focus on internal drivers of competitive advantage but emphasise different strategic levers. The resource- and capability-based paradigm (*e.g.*, Barney, 1991; Peteraf, 1993; Wernerfelt, 1984) stresses the quality and performance of resources and capabilities in executing tasks, while discovery-oriented perspectives (*e.g.*, McGrath, 2013) highlight the value of diversity in resources and capabilities. McGrath (2013) argues that diversity enables managers to recombine resources and capabilities in response to unforeseen threats or opportunities. In this study, we followed Barney's (1991) performance-oriented RBV logic for quantifying the performance of resources and capabilities, while acknowledging McGrath's insight that highly developed resources and capabilities may constrain strategic flexibility and limit managerial choice. If RBV logic is genuinely path dependent, this path dependency should also be observable at the level of configurations, implying that the 'path' is reflected in the development of resource and capability combinations rather than in isolated resources.

Dynamic Capabilities and Resource Orchestration

The literature on dynamic capabilities and resource orchestration further elaborates on the path-dependent nature of configurations. Sirmon and Hitt (2009) show that deviations from competitive norms in resource investment levels can be risky but may improve performance when aligned with appropriate strategies. The key dimensions of resource alignment include search, selection, configuration, and deployment (Helfat *et al.*, 2007). Thus, the dynamic capabilities of managers – the ability to create, integrate, configure, and reconfigure resources and capabilities – are central to achieving competitive advantage, adapting to changing market conditions, and enhancing the value of resources (Sirmon & Hitt, 2009).

Subsequent elaborations of this perspective by Sirmon *et al.* (2010, 2011) gave rise to resource orchestration theory, which combines resource management and asset orchestration models. Resource orchestration emphasises not only the stock and quality of resources and capabilities, but also

the processes by which managers structure, bundle, and leverage them over time. Therefore, this theoretical framework links RBV-based configuration ideas with discovery-driven strategy logic by focusing on how resource–capability combinations are actively shaped and re-shaped.

There is also a close theoretical connection between configuration theory, business model perspectives, and resource orchestration. The RBV-based configuration theory seeks to identify effective, synergistic combinations of resources and capabilities that generate internal consistency. Resource orchestration introduces a dynamic, processual view by integrating resource acquisition, development, and deployment with managerial decision-making. Business model theories further extend this perspective by incorporating external stakeholders and environmental conditions to explain how firms achieve both internal and external coherence in value creation (Klang *et al.*, 2014; Teece, 2010). These theoretical strands jointly suggest that configurations of resources and capabilities are both a source of competitive advantage and subject to path-dependent evolution over time, especially in SMEs whose resource bases are constrained (Luo & Child, 2015).

Empirical Evidence on SME Configurations and Competitiveness

Empirical research on resource and capability configurations faces challenges due to the lack of a unified conceptual framework and inconsistencies in measurement (Miller *et al.*, 2013), as well as practical difficulties in operationalising models built around key competencies (Bhamra *et al.*, 2010). Nevertheless, configurational approaches offer a valuable lens for understanding value creation in both strategic management and new venture contexts (Kraus *et al.*, 2011). In the early stages of the firm lifecycle, legal formation and market entry reflect management's assumptions about how market opportunities align with value propositions, internal resources and capabilities, and transformation processes; these assumptions jointly define an initial configuration of resources and capabilities, or (more generally) the firm's first business model (Teece, 2010). As firms evolve, it becomes increasingly challenging to maintain and upgrade key capabilities. Organisations must adapt to changing environments by modifying and selectively retaining patterns of strategic action (Pentland *et al.*, 2012), while continuously developing organisational routines that embed resources and capabilities in everyday operations (Klang *et al.*, 2014). Maintaining tight integration across levels of organisational hierarchy is also crucial for achieving both efficiency and effectiveness (Salvato & Rerup, 2011).

The empirical literature emphasises the need for continuous maintenance and upgrading of key capabilities and the adaptive reconfiguration of resources and capabilities in response to environmental change. Studies highlight a contextual balance between conformity (similarity) and diversity (differentiation), suggesting that stable environments favour conformity, whereas uncertain and heterogeneous environments require greater diversity. Analysing 113 Austrian tourism SMEs, Kallmuenzer *et al.* (2019) identified optimal configurations combining entrepreneurial orientation, financial resources, and professional networks, with their effectiveness depending on environmental uncertainty. Lorentz *et al.* (2016) used cluster analysis on 190 Finnish manufacturing SMEs to distinguish reactive partial innovators, suppliers/subcontractors, and manufacturing–technical service providers, finding that flexibility and service capabilities are particularly important during macroeconomic shocks. Raymond *et al.* (2010) identified entrepreneurial, technical, and administrative configurations for 292 manufacturing SMEs in Canada, showing that entrepreneurial configurations relying on strategic competences such as product development and market building outperform other groups.

Qualitative work also underscores the role of configurational diversity. Pfeifer *et al.* (2017) found that configurational diversity enhances competitiveness among Croatian micro firms in creative industries, particularly in advertising, architecture, and design. Hagen *et al.* (2017), examining 550 SMEs in Italy, Finland, and Greece, identified four strategic postures and show that innovation- and technology-oriented configurations are more adaptive to global challenges. Forsman (2011), studying 708 Finnish micro and small firms, reported substantial internal diversity in configurations, even when manufacturing and service sectors differ only modestly on average. From a demand-side perspective, Sohl *et al.* (2020) showed that business model diversification improves profitability in heterogeneous demand contexts, highlighting the benefits of diversity under unstable conditions. Kim and Min (2015) pro-

posed a 'discriminative alignment thesis' for incorporating complementary (conforming) and competing (divergent) elements into existing business models, arguing that complementary elements can be integrated directly, whereas competing elements may require separate organisational units.

GCP-based Evidence on Resource and Capability Configurations

The empirical analysis in this article relies on the international dataset of the GCP. Over the past decade, GCP researchers have published a growing number of studies on resource and capability configurations and their relationship with firm-level competitiveness and efficiency (*e.g.*, Alonso-Ubieta *et al.*, 2021; Bayon & Aguilera, 2021; Horváth & Lafuente, 2021; Lafuente *et al.*, 2020a, 2020b). Analysing 625 Hungarian SMEs, Lafuente *et al.* (2020a) showed that firms possessing one or two outstanding resources or capabilities benefit most from further strengthening these areas, whereas firms lacking strong resources or capabilities should prioritise alleviating bottlenecks. Alonso-Ubieta *et al.* (2021) used non-parametric data envelopment analysis (DEA) on 231 Costa Rican SMEs and found that efficiency and balanced resource allocation, together with innovation, are central to competitiveness. Using DEA on 115 Spanish SMEs, Horváth and Lafuente (2021) demonstrated that configurations of resources and capabilities are closely associated with efficiency: on average, firms could improve their competitiveness by 53.53% through optimising key capabilities. Human capital and strategic planning are particularly important for manufacturing and construction, whereas innovation is crucial for knowledge-intensive business services.

Applying cluster analysis to 62 Mexican SMEs, Bayon and Aguilera (2021) highlighted that managers' perceptions of the strategic relevance of resources and capabilities strongly influence firm competitiveness. Lafuente *et al.* (2020b) stressed the importance of competitive configurations in enhancing efficiency in a DEA analysis of 103 KIBS firms in Hungary, Spain, Colombia and Costa Rica, showing that optimising strengths and addressing weaknesses could increase efficiency by 47.43%. Together, these GCP studies emphasise the need to consider differences arising from industry, demand, and regional characteristics, and called for more comprehensive empirical work on resource and capability configurations at the business model level.

Earlier GCP studies focused mainly on high-performing key capabilities, low-performing bottlenecks and harmonised configurations of resources and capabilities in between. The present study advances this literature by identifying and analysing a novel 'Balanced' configuration, defined as a configuration that combines a similar number of markedly high- and low-performing resources and capabilities relative to the firm's overall resource and capability profile, in addition to the Core Competence, Harmonised, and Bottleneck configurations.

Research Gap and Hypotheses

The above literature review highlights three main points. Firstly, RBV, configuration theory, resource orchestration, and business model perspectives jointly suggest that firm-level configurations of resources and capabilities constitute key determinants of competitiveness and are likely to evolve in path-dependent ways. Secondly, empirical SME studies, including GCP-based research, show that differences in resource and capability configurations are associated with differences in competitiveness and efficiency. Thirdly, despite this progress, there is still limited evidence on how different configuration types relate systematically to an established competitiveness index, and how one can infer potential development routes between configurations from the structure of competitiveness pillars, especially when introducing a Balanced configuration alongside Core Competence, Harmonised, and Bottleneck types.

Against this background, we formulated three hypotheses that correspond directly to the research questions.

There is substantial evidence that the structure of resources and capabilities is linked to competitiveness. Configuration theory suggests that the integration of resources and capabilities into coherent systems can generate competitive advantage because such systems are difficult to imitate (Miller, 1986, 1996; Miller & Whitney, 1999). Dynamic capabilities and resource orchestration perspectives further argue that the way in which resources and capabilities are configured and reconfigured over time is central to performance (Helfat *et al.*, 2007; Sirmon & Hitt, 2009; Sirmon *et al.*, 2010, 2011). Empirical results

from GCP-based and related studies (*e.g.*, Alonso-Ubieta *et al.*, 2021; Horváth & Lafuente, 2021; Lafuente *et al.*, 2020a, 2020b) confirm that more effective utilisation and alignment of resources and capabilities are associated with higher competitiveness. This led us to the first pair of hypotheses:

H1a: There is a connection between configuration and the level of competitiveness.

H1b: There is a significant difference in the level of competitiveness between the configurations.

If configurations are related to competitiveness, it is reasonable to expect that they also differ in the underlying pillars that define the competitiveness index. Prior research indicates that some pillars, such as technology, innovation, human capital, networks, or strategic orientation, can be particularly important drivers of competitiveness and efficiency in SMEs (*e.g.*, Forsman, 2011; Hagen *et al.*, 2017; Kallmuenzer *et al.*, 2019; Raymond *et al.*, 2010). The GCP studies also point to specific pillars whose improvement yields disproportionate gains (Lafuente *et al.*, 2020a, 2020b). Accordingly, we expect that at least some of the ten pillars will differ significantly across configuration types:

H2: There are significant differences in the competitiveness pillars between the configurations.

Finally, McGrath's (2013) observation that resources and capabilities may constrain strategic flexibility, together with RBV-based arguments about path dependency, raises the question of whether configurations can be changed freely or whether there are particular 'routes' between configurations that are more plausible than others. The literature on dynamic capabilities and resource orchestration implies that configuration change is not random but conditioned by existing structures of resources and capabilities and by managerial choices (Helfat *et al.*, 2007; Sirmon *et al.*, 2010, 2011). Building on these ideas, we examined whether the estimated models would allow us to infer plausible, path-dependent development routes between the identified configurations based on their pillar profiles. This led to our third hypothesis:

H3: There are development 'routes' between configurations.

RESEARCH METHODOLOGY

Data Collection and Sample

The empirical analysis relies on a unique primary dataset from a research project on the competitiveness of SMEs funded by the European Union (EFOP-3.6.2-16-2017-00017). We collected the data between 2016 and 2020 in eight countries: Bosnia and Herzegovina (127 firms), Colombia (53), Costa Rica (156), the Czech Republic (94), France (80), Hungary (186), Mexico (40), and Spain (49). The explicit objective of the data collection was to analyse firm-level competitiveness in an international SME context by assessing the performance of resources and capabilities. The GCP designed the international data collection protocol (Global Competitiveness Project, n.d.). Detailed information on the sampling and survey procedures is available in Lafuente *et al.* (2020a, 2020b). A team at the Faculty of Business and Economics, University of Pécs, Hungary, compiled and managed the final dataset used in this study.

Data collection proceeded in two stages. Firstly, we contacted firms by telephone to obtain permission to participate. Secondly, we conducted a face-to-face interview with the business owner (if part of the top management team) in firms with fewer than 20 employees, and with a top executive in firms with 20 or more employees, regardless of ownership status. The survey took the form of a structured, self-administered questionnaire in which managers responded mainly to closed-ended questions. The questionnaire has been extensively used in Hungary since 2013 for research purposes, and its translated versions have been refined to minimise ambiguous or misleading items.

We carefully filtered the raw data. We retained only observations with complete information for all variables used in the analysis, and excluded firms with fewer than five employees. The resulting final sample comprised 785 SMEs. The average firm employed 42 people and had 16 years of market experience. Regarding sectoral composition, 27.9% of the firms operated in agriculture and industry, 16.7% in retailing, and 55.4% in professional services. To assess non-response bias, we compared early and late respondents in terms of firm size (employees), firm age and revenues across sectors; we found no significant differences.

Variables and Measurement

We derived two main groups of variables from the questionnaire. The first group captured the performance and strategic relevance of various resources and capabilities. The second group included key firm characteristics: country, sector (NACE classification), firm size (number of employees), and firm age.

Following Irwin *et al.* (1998) and Douglas and Ryman (2003), we asked respondents to evaluate the strategic importance of different resources and capabilities on a Likert-type scale from '0' to '4'. A value of '0' indicates that the focal resource or capability has no strategic relevance, whereas values from '1' to '4' capture increasing levels of strategic importance. The scale reflects the notion that the value of resources and capabilities is contingent on managerial perceptions (Priem & Butler, 2001). The subdivision of positive scale points (from '1' to '4') allows for sufficient differentiation in the assessment of the variables (Lederer *et al.*, 2013). In total, we collected 44 resource- and capability-related variables for each SME. We provide the complete list of variables in Appendix 1.

Construction of the Competitiveness Index

We measured firm-level competitiveness using a composite competitiveness index consistent with earlier GCP-related work (Lafuente *et al.*, 2020a; Szerb *et al.*, 2014; Szerb & Hornyák, 2016). The index had a two-layer structure: four main fields (market orientation, manufacturing, demand, and strategic decision-making) and ten second-layer pillars. Figure 2 presents the structure of the index.

We computed the competitiveness index in six steps:

1. Identification of variables and calculation of raw values.
2. Normalisation of all variable values to the [0, 1] range.
3. Calculation of pillar scores by averaging the relevant normalised variables.
4. Normalisation of pillar scores to the [0, 1] range.
5. Adjustment of normalised pillar scores to a common average across pillars by raising them to the same power of k .
6. Calculation of the final competitiveness score by summing the adjusted pillar values.

This procedure yields a firm-level competitiveness score and ten pillar scores for each SME, enabling both overall and pillar-specific analyses.



Figure 2. Structure of the SME competitiveness index

Source: Szerb and Hornyák (2016, p. 313).

Configuration Construction

The core objective of the study was to classify SMEs into resource- and capability-based configurations and examine how these configurations relate to competitiveness (RQ1-RQ3; H1a-H3). We based the configuration analysis on the ten competitiveness pillars. We aimed to form four config-

uration groups of approximately equal size using the distributional properties of the pillar scores. The classification proceeded in two stages.

1. In the first stage, we calculated the skewness of the ten pillar scores for each firm. We assigned SMEs with the highest skewness values to configuration group 1 ('Core Competence'), while those with the lowest skewness values were assigned to configuration group 4 ('Bottleneck').
2. In the second stage, we split firms with intermediate skewness values into two equal groups based on their relative variance (the within-firm variance of the ten pillar scores divided by the firm's overall competitiveness score). We classified SMEs with low relative variance as configuration group 2 ('Harmonised'), while those with high relative variance as configuration group 3 ('Balanced').

We chose the cut-off points to yield four groups of approximately equal size and to operationalise the intended distributional contrasts: the upper and lower quartiles of firm-level skewness define Core Competence and Bottleneck, while firms in the interquartile range were split by the median of the relative-variance measure into Harmonised and Balanced configurations. This procedure followed the logic of constructing theoretically interpretable configurations while avoiding a purely level-driven grouping.

Table 1 summarises the criteria and resulting group sizes. Table 2 presents descriptive statistics for the four configuration groups.

Table 1. Criteria for building configuration groups of SMEs

Configuration group	Skewness	Variance (relative)	N
1. Core Competence	> 0.523	–	196
2. Harmonised	-0.423 – 0.523	< 0.032	197
3. Balanced	-0.423 – 0.523	> 0.032	196
4. Bottleneck	< -0.423	–	196

Source: own study.

Table 2. Descriptive statistics of competitiveness scores by configuration of SMEs

Configuration group	N	Min.	Max.	Mean	St. dev.	Median	Mode
Balanced	196	1.690	6.783	4.405	1.119	4.392	1.690
Core Competence	196	1.677	7.841	4.777	1.226	4.680	1.677
Bottleneck	196	1.879	8.589	5.669	1.415	5.667	1.879
Harmonised	197	3.104	8.302	5.999	1.128	6.162	3.104

Source: own study.

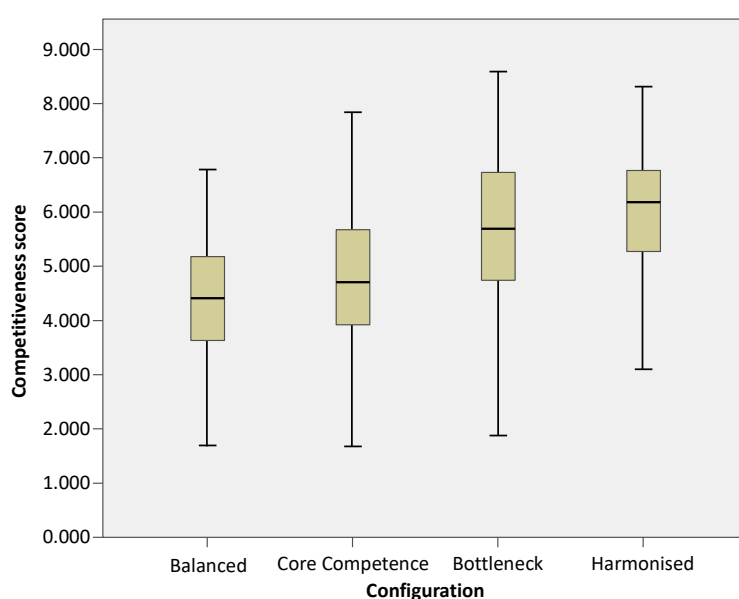


Figure 3. Distribution of competitiveness scores by configuration of SMEs

Source: own elaboration.

Importantly, the classification procedure was designed to be independent of the absolute level of competitiveness. Equal skewness values could occur at different levels of pillar scores, and the variance measure was normalised by the competitiveness score to reduce the influence of overall competitiveness on the configuration assignment. The empirical question, addressed in the next section, was whether the resulting configurations nonetheless exhibited systematic differences in competitiveness and pillar values (H1a, H1b, H2), and whether they would allow us to infer analytically plausible development routes (H3).

Analytical Approach

The empirical analysis proceeds in three steps, aligned with the research questions and hypotheses.

Firstly, to test whether configurations were associated with different levels of competitiveness (RQ1; H1a, H1b), we examined the relationship between configuration and competitiveness using chi-square tests and one-way ANOVA. Figure 3 and Figure 4, together with Appendix 2, report the descriptive and inferential results, including post-hoc comparisons between configurations.

Secondly, to examine whether the ten competitiveness pillars differentiate configuration membership (RQ2; H2), we estimated a set of binary logistic regression models in which the dependent variable was a binary indicator contrasting a more competitive configuration (Bottleneck or Harmonised) with a less competitive reference configuration (Balanced or Core Competence). We report odds ratios ($\text{Exp}(B)$) and p-values. An odds ratio greater than 1 indicated that higher values of the corresponding pillar were associated with higher odds of belonging to the more competitive configuration relative to the reference category. As a robustness check, we re-estimated the binary logistic regression models with country and industry (NACE) controls. The estimated pillar associations and the implied configuration contrasts were substantively unchanged; accordingly, the inferred development routes were not affected.

Thirdly, to infer plausible development routes between configurations (RQ3; H3), we interpreted the estimated logistic regression models by comparing more and less competitive configurations. The models were estimated with reference categories corresponding to the less competitive configurations (Balanced and Core Competence), and the odds ratios ($\text{Exp}(B)$) indicated how changes in pillar values affect the likelihood of belonging to a more competitive configuration (Bottleneck or Harmonised). By combining these results with the ANOVA-based competitiveness differences, we derived analytically plausible, path-dependent development routes between configurations, as visualised in Figure 5. Accordingly, route 'directionality' was interpreted as model-consistent plausibility, not as observed temporal transition.

RESULTS AND DISCUSSION

Configurations and Competitiveness

The first step of the analysis examined whether the four configuration types differed in their overall competitiveness levels (RQ1; H1a, H1b). Although the configurations were constructed to be independent of competitiveness scores, it was still possible that they would be systematically associated with different competitiveness levels.

Appendix 2 reports the chi-square tests on the association between configuration and categorical competitiveness levels. The Pearson chi-square test was highly significant ($\chi^2 = 153.836$, $df = 6$, $p < 0.001$), and the ordinal association measures (Somers' d, Kendall's tau and Gamma) also indicated a positive and statistically significant relationship between configuration and competitiveness. This suggests that configurations were not randomly distributed across competitiveness levels, providing initial support for H1a.

We then used one-way ANOVA to compare mean competitiveness scores across the four configurations. Table 2 and Figure 3 present the descriptive statistics, while Figure 4, Table 3¹ and Appendix 2 summarise the ANOVA results and post-hoc tests. Mean competitiveness increased monotonically from Balanced (4.405) and Core Competence (4.777) to Bottleneck (5.669) and Harmo-

¹ Levene test is significant at any level, equal variance cannot be assumed, Tamhane post-hoc was used. Other corresponding tests are presented in Appendix 2.

nised (5.999). Figure 4 highlights that the Balanced configuration exhibited the lowest competitiveness, whereas the Harmonised configuration achieved the highest.

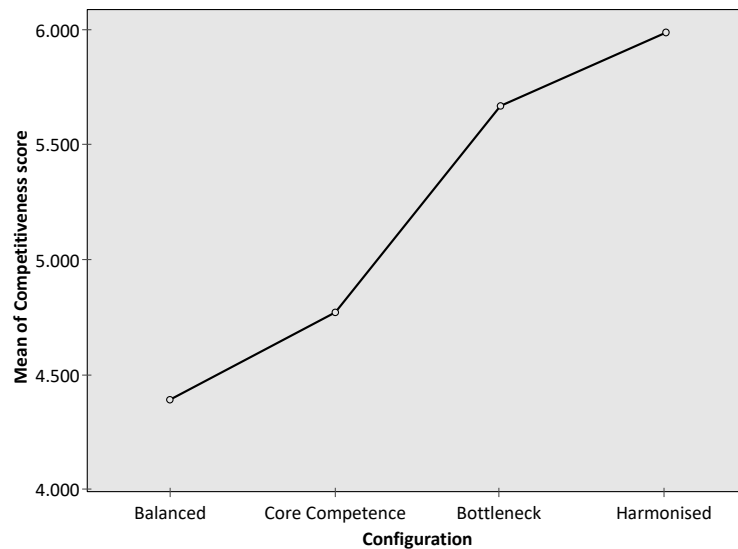


Figure 4. Mean of competitiveness scores by configuration of SMEs

Source: own elaboration.

Table 3. Post-hoc comparisons of competitiveness scores between configurations of SMEs

Post-Hoc	(I) Configuration	(J) Configuration	Mean Difference (I-J)	Std. Error	Sig.
Tamhane	Balanced	Core Competence	-0.372**	0.119	0.011
		Bottleneck	-1.264*	0.129	0.000
		Harmonised	-1.594*	0.113	0.000
	Core Competence	Balanced	0.372**	0.119	0.011
		Bottleneck	-0.892*	0.134	0.000
		Harmonised	-1.222*	0.119	0.000
	Bottleneck	Balanced	1.264*	0.129	0.000
		Core Competence	0.892*	0.134	0.000
		Harmonised	-0.330***	0.129	0.064
	Harmonised	Balanced	1.594*	0.113	0.000
		Core Competence	1.222*	0.119	0.000
		Bottleneck	0.330***	0.129	0.064

Notes: *, **, *** indicate significance at the 1%, 5% and 10% significance levels, respectively.

Source: own study.

Post-hoc comparisons using Tamhane's, Dunnett's T3, Games–Howell, and Dunnett C tests confirmed that the mean differences between most configuration pairs were statistically significant. The difference between Balanced and Core Competence was significant at the 5% level, and the difference between Bottleneck and Harmonised was marginally significant at around the 6-7% level; all other pairwise differences were significant at conventional levels. These results show that configurations were associated with distinct competitiveness levels, despite being constructed without reference to competitiveness scores, thereby supporting H1b.

At the same time, the reverse relationship did not hold deterministically: competitiveness was not fully determined by configuration. As Figure 3 indicates, firms with a Balanced configuration could still be found in the upper competitiveness range, just as some Harmonised firms did not reach the highest scores. However, the probability of attaining high competitiveness was much lower for Balanced firms (11.2%) than for Harmonised firms (56.3%). Thus, configurations capture systematic but not deterministic differences in competitiveness, consistent with the notion that configurations indicate, but do not fully determine, performance outcomes.

Pillar-level Differences Between Configurations

Having established that configurations differ in their average competitiveness levels, in the next step, we investigated whether and how the underlying competitiveness pillars differ across configurations (RQ2; H2). To this end, we estimated a series of binary logistic regression models, using pillar scores as predictors and configuration membership as the dependent variable.

The main results are summarised in Table 4² (with additional detail in Appendix 3), which reports odds ratios (Exp(B)) from the binary logistic regression models estimated for each pairwise comparison of competitiveness configurations (see Appendix 3 for full model outputs). For transparency and ease of reading, we documented the reference category and reporting conventions in the Table notes.

Table 4. Binary logistic regression results: Competitiveness pillars distinguishing configurations of SMEs

Competitive pillars	Bottleneck		Harmonised		Bottleneck		Harmonised		Significant models (5%)	Significant models (1%)
	to Balanced				to Core Competence					
	Model 1 Exp(B)	Model 1 p	Model 2 Exp(B)	Model 2 p	Model 4 Exp(B)	Model 4 p	Model 5 Exp(B)	Model 5 p		
Competitive Strategy	–	–	8.130*	0.003	–	–	15.315*	0.000	2	2
Decision-making	4.767*	0.006	4.132**	0.035	–	–	-	-	2	1
Human Capital	5.074**	0.016	4.292***	0.053	–	–	-	-	1	–
Internationalisation	–	–	–	–	–	–	4.044***	0.055	–	–
Marketing	3.503***	0.071	5.464**	0.032	–	–	–	–	1	–
Networks	-	-	4.049**	0.034	4.303*	0.009	5.340*	0.009	3	2
Product	3.545**	0.037	3.774***	0.054	–	–	–	–	1	-
Technology	10.485*	0.007	10.638**	0.015	53.514*	0.000	23.371*	0.001	4	3
Chi-square test	105.151	–	155.394	–	71.092	–	112.408	–	–	–
Nagelkerke R ²	0.314	–	0.435	–	0.221	–	0.332	–	–	–
H&L test	0.195	–	0.373	–	0.521	–	0.577	–	–	–
Correctly predicted (%)	70.2	–	74.6	–	67.6	–	70.7	–	–	–
ROC AUC	0.777	–	0.837	–	0.738	–	0.792	–	–	–
Observations	392	–	393	–	392	–	393	–	–	–

Note: Odds ratios (Exp(B)) and p-values are reported; the configuration shown in italics is the reference category. An odds ratio greater than 1 indicates that higher values of the pillar increase the odds of belonging to the non-reference configuration relative to the reference configuration.

Odds ratios are reported for one-unit increases in pillar scores; given that pillar scores are bounded and constructed on a normalised scale, seemingly large odds ratios should be interpreted as reflecting the scale of the underlying metric rather than as literal marginal effects over an unconstrained range.

*, **, *** indicate significance at the 1%, 5% and 10% significance levels, respectively.

ROC AUC = receiver operating characteristic area under the curve.

Source: own study.

Across the models, the goodness-of-fit statistics, predictive accuracy and explanatory power indicated that configurations were meaningfully differentiated by the pillars. The Nagelkerke R² values range from 0.221 to 0.435 for the core models, and correctly classified cases range from 67.6 to 74.6%. The Hosmer–Lemeshow tests suggest acceptable model fit, and the ROC AUC values indicate acceptable-to-good discriminating power (AUC = 0.738–0.837 in the core models and 0.570–0.593 in the auxiliary models). A consistent pattern of results emerged.

Firstly, in the core comparisons in Table 4 (with Balanced or Core Competence as the reference), the effects are directionally consistent: higher pillar scores are associated with a greater likelihood of belonging to the more competitive configuration, with odds ratios above 1 throughout these contrasts. This supports the substantive interpretation that stronger pillar profiles systematically co-vary with competitiveness across the main baseline comparisons. A notable exception was the

² Pairwise comparison generates altogether six models. Because of the poor statistics, we present Model 3 and Model 6 only in Appendix 3. Partial results of ‘enter’ and ‘backward’ modelling are available upon request.

Bottleneck–Harmonised contrast, where the association reverses (odds ratios below 1 for the relevant pillars). This is theoretically meaningful rather than definitional: it suggests that, in this specific pairing, higher pillar scores align with lower odds of membership in the more competitive configuration, consistent with configuration-contingent trade-offs between bottleneck-relief and harmonisation logics. This finding reinforces the classification logic and supports H2.

Secondly, seven out of the ten pillars had a statistically significant effect at the 5% level in at least one of the models, and four out of ten were significant at the 1% level. Technology stood out as the most influential pillar. Its odds ratios ($\text{Exp}(B)$) were the largest across the four core models, and it was significant in all four core comparisons at the 5% or 1% level. Competitive Strategy had a smaller but still noteworthy effect. Networks and Decision-making exerted moderate yet robust effects across several models. Human Capital, Marketing, Product and, to a lesser extent, Internationalisation also played significant roles in specific configuration comparisons.

Thirdly, the models failed to identify stable and statistically meaningful relationships in some configuration pairs. In particular, we were unable to derive a satisfactory model distinguishing between the lower-competitive Balanced and Core Competence configurations on the one hand, and between the higher-competitive Bottleneck and Harmonised configurations on the other, based on pillars alone. This suggests that not all configuration transitions are equally well supported by the pillar structure, which has implications for the analysis of development routes.

Taken together, these results show that configurations are associated with distinct profiles across the ten competitiveness pillars and that specific pillars – above all Technology, but also Competitive Strategy, Networks, and Decision-making – are especially important in differentiating more and less competitive configurations. This evidence supports H2.

Analytically Inferred Development Routes Between Configurations

The final step of the analysis addressed RQ3 and H3 by examining whether the logistic regression results, combined with the competitiveness differences, would allow us to infer plausible development routes between configurations. These routes represent conceptual, path-dependent patterns that align with the cross-sectional results, rather than empirically observed changes over time.

The increase in pillar scores had two main effects: (1) higher pillar values raised the overall competitiveness index, and (2) they increased the probability of belonging to a more competitive configuration. The second effect could occur in two ways. Firstly, firms could reduce dispersion across pillars, moving towards a more harmonised distribution (lower relative variance). Secondly, firms may strengthen specific pillars to such an extent that those pillars become dominant, generating a Bottleneck configuration.

SMEs with a Balanced configuration were characterised by a symmetric distribution of pillar scores with relatively high variance: they exhibited a mix of markedly low and high-performing pillars within the same firm. The models comparing Balanced with Bottleneck and Harmonised configurations indicated two primary development routes:

- Route Balance1 (towards Harmonised): Firms can aim to reduce disparities between pillar scores by adopting a revised competitive strategy that emphasises Technology, Decision-making, Marketing, and Networks. Strengthening these pillars while narrowing inter-pillar gaps leads to a Harmonised configuration, characterised by a symmetric distribution with low relative variance. In this route, firms primarily seek to align and level up pillars rather than to create a single dominant pillar.
- Route Balance2 (towards Bottleneck): Alternatively, firms may focus on Technology and/or Decision-making, followed by Human Capital and/or Product, in a way that makes these pillars particularly strong and salient. In this case, the distribution becomes right-skewed, with one or a few pillars acting as a bottleneck for further development. This leads to a Bottleneck configuration, in which further competitiveness gains require addressing remaining weaker pillars.

Small and medium-sized enterprises with a Core Competence configuration displayed a left-skewed distribution, with a small set of relatively strong pillars and several weaker ones. The models comparing Core Competence with Bottleneck and Harmonised configurations suggested two analogous development routes:

- Route Core Competence 1 (towards Bottleneck): Firms may concentrate on Technology (and potentially on Networks) and intensify investment until Technology becomes the dominant pillar that constrains further progress. This leads to a Bottleneck configuration where technological capabilities are strong, but other pillars lag and limit additional competitiveness gains.
- Route Core Competence 2 (towards Harmonised): Alternatively, firms may adopt a revised competitive strategy that continues to emphasise Technology while simultaneously strengthening Networks and, potentially, Internationalisation. By raising the weaker pillars and reducing variance across pillars, firms can move towards a Harmonised configuration, where pillar scores are more evenly aligned at a higher level.

Incompatible Configuration Transitions and Cost Considerations

Importantly, the empirical results also suggest that not all configuration transitions are equally plausible or cost-effective. The lack of robust logistic models between Balanced and Core Competence, and between Bottleneck and Harmonised, indicates that some configuration changes may not be supported by clear pillar-based patterns.

From a practical perspective, this implies that certain configuration changes are unlikely to be pursued in an incremental and economically justified manner. For example, an SME with a Balanced configuration but relatively high competitiveness may not benefit from small adjustments aimed solely at reaching a Core Competence configuration with similar competitiveness. Given the modest expected competitiveness gains, the costs of such reconfiguration may outweigh the benefits. A similar logic applies to firms attempting to move from Bottleneck to Harmonised when their competitiveness levels are already close.

These observations are consistent with the idea that configuration changes are path dependent and constrained by the existing combination of pillars and the associated adjustment costs. Therefore, the empirically observed patterns support H3: there appear to be development ‘routes’ between configurations that are more plausible than others, and these routes are shaped by the structure and relative strength of specific pillars.

Figure 5 synthesises these routes by integrating the competitiveness differences (Figure 4) with the pillar-level effects from the logistic regressions (Table 4). The thickness of the arrows represents the explanatory strength of each model, and the most influential pillars, especially Technology, Decision-making, Networks, and Competitive Strategy, are highlighted.

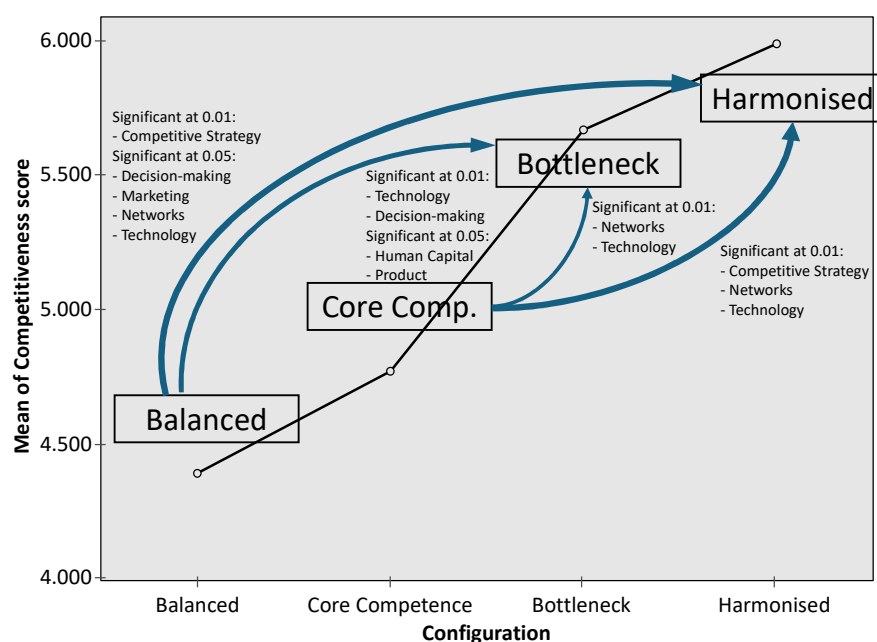


Figure 5. Analytically inferred development routes between configurations of SMEs

Source: own elaboration.

Overall, the results show that configuration is not a managerial choice variable in the narrow sense: firms do not select a configuration directly. Nonetheless, it is shaped by the way SMEs build and deploy their resources and capabilities. Configurations indicate the prevailing pattern of pillar strengths and weaknesses at a given point in time. By targeting specific pillars, SMEs can, in principle, nudge their configuration towards more competitive patterns, although not all routes are equally accessible or economically viable. This interpretation is consistent with RBV and dynamic capability arguments about path dependency and with the empirical evidence obtained from our cross-sectional analysis.

CONCLUSIONS

We analysed the competitiveness of small and medium-sized enterprises (SMEs) using a cross-country dataset of 785 firms from eight countries collected within the Global Competitiveness Project. Building on an RBV- and configuration-based perspective, we examined organisational resources and capabilities through ten competitiveness pillars derived from forty-four underlying variables, and classified SMEs into four configuration types (Balanced, Core Competence, Harmonised, and Bottleneck) based on the skewness and relative variance of their pillar scores. We then linked these configurations to an established competitiveness index and used ANOVA and binary logistic regression models to explore how specific pillars shape competitiveness differences and to analytically infer plausible development routes between configurations.

The empirical results reveal substantial differences in competitiveness across the four configuration types. Harmonised firms, characterised by relatively high and aligned pillar scores (low relative variance), displayed the highest average competitiveness, whereas Balanced firms, which combine markedly high and low pillar values (high relative variance), occupied the lowest position. Core Competence firms performed moderately better than Balanced firms, while Bottleneck firms were somewhat less competitive than Harmonised firms but still clearly outperformed the two less competitive configurations. At the same time, competitiveness was not mechanically determined by configuration: firms in all configurations could attain relatively high or low index values, although with different probabilities. This pattern supports H1a and H1b by confirming a robust association between configurations and competitiveness levels, while also indicating that configurations delimit but do not fully fix competitive outcomes.

At the pillar level, the findings support H2 by showing that configurations differ systematically in several key competitiveness pillars. Technology emerged as the most influential discriminator between configurations, followed by Competitive Strategy, Networks, and Decision-making, with Human Capital, Marketing, Product and, to a lesser extent, Internationalisation also playing a role. Higher scores in these pillars simultaneously raise the competitiveness index and increase the odds of belonging to more competitive configurations. Importantly, we did not find evidence that reducing pillar scores, for example, in the name of greater ‘balance,’ would improve competitiveness, which reinforces the internal consistency of the configuration scheme.

On this basis, we interpret H3 in terms of plausible, analytically inferred development routes between configurations. The estimated models suggest that less competitive firms can move towards more competitive structures through two main types of changes in their pillar profiles: (1) reducing internal dispersion by upgrading weaker pillars while preserving existing strengths, and (2) further reinforcing one or a few key pillars to the point where they become critical bottlenecks for further development. However, not all configurations appear to be mutually attainable in a cost-effective manner. In particular, incremental shifts from Balanced to Core Competence or from Bottleneck to Harmonised configurations seem less plausible; in such cases, the marginal gains in competitiveness may not justify the required reconfiguration costs. Therefore, we interpret the development routes as patterned but non-deterministic: they highlight more likely directions of change, conditioned by existing capability structures and managerial choices.

From a theoretical perspective, the study refines RBV- and configuration-based views of SME competitiveness in three ways. Firstly, it conceptualises configurations as path-dependent bundles of resources and capabilities, whose internal structure, captured by the distribution of pillar scores, both

enables and constrains future strategic options. Secondly, it differentiates explicitly between Harmonised and Balanced profiles among firms with broadly similar overall competitiveness ranges: while Harmonised configurations combine high pillar levels with low dispersion, Balanced configurations embody mixed internal strengths and weaknesses, which is associated with lower average competitiveness. Thirdly, by analytically inferring development routes between configurations based on pillar patterns and model results, the study offers a structured way to think about non-linear, path-dependent configuration change in SMEs, without assuming that such routes are unique or inevitable.

Methodologically, the article contributes by applying and extending a skewness–variance-based approach to configuration analysis. Using skewness to distinguish Core Competence and Bottleneck configurations, and relative variance to separate Harmonised and Balanced profiles among firms with intermediate skewness, allowed us to go beyond level-based typologies and incorporate distributional properties of capability portfolios into the classification. Integrating this four-type scheme with a composite competitiveness index offers a replicable framework for assessing how pillar structures translate into different configuration profiles and competitiveness outcomes. The use of binary logistic regressions, with configurations as dependent variables and pillars as predictors, provides a transparent way to identify which pillars are most strongly associated with more competitive configurations and to construct model-based inferences about potential development routes.

The empirical results also carry configuration-specific managerial implications. For Balanced firms, which combine strong and weak pillars, the priority is to reduce internal dispersion. Managers of such firms should focus on upgrading the weakest pillars while deliberately strengthening Technology, Decision-making, Marketing, and Networks to move towards a Harmonised configuration, where high and internally aligned pillar values support higher competitiveness. Alternatively, Balanced firms may intentionally specialise by concentrating on Technology (and in some cases Decision-making, Human Capital or Product), accepting a Bottleneck configuration in which one or a few pillars become dominant but also critical constraints for further growth.

For Core Competence firms, which exhibit one or two particularly strong pillars alongside weaker supporting domains, managers face a strategic choice between deepening and broadening. One route is to further reinforce Technology (and possibly Networks), moving towards a Bottleneck configuration where a narrow capability base underpins relatively high competitiveness but also increases dependence and potential vulnerability. The other route is to progressively broaden and align capabilities by continuing to emphasise Technology while strengthening Networks and, potentially, Internationalisation, thereby reducing pillar dispersion and approximating a Harmonised configuration. The choice between these routes reflects managerial preferences regarding specialisation versus diversification of capabilities and the firm's exposure to environmental uncertainty.

As the most competitive configuration, Harmonised firms should focus on maintaining and selectively upgrading their balanced capability structure. For these firms, the key challenge is not to create balance but to avoid erosion or excessive concentration of capabilities. Managers should monitor whether investments in specific pillars (*e.g.*, Technology or Networks) begin to generate new bottlenecks or imbalances, and ensure that improvements are accompanied by appropriate enhancements in complementary domains such as Decision-making, Human Capital, and Competitive Strategy. In this sense, the main managerial task is dynamic capability maintenance rather than radical reconfiguration.

For Bottleneck firms, whose high competitiveness rests on one or a few outstanding pillars, managerial priorities revolve around managing dependence and mitigating risk. One option is to further exploit the existing bottleneck by deepening investments in the dominant pillar (typically Technology and/or Networks), while progressively strengthening selected supporting pillars to reduce vulnerability. Another option, albeit more demanding, is to gradually broaden the capability base and move closer to a Harmonised configuration by upgrading weaker pillars without undermining the key advantage. In both cases, managers should be aware that attempts to transform Bottleneck into Core Competence or Balanced profiles through small adjustments are unlikely to be efficient, given the structure of the configurations and the modest competitiveness gains such shifts would bring.

The study has several limitations that suggest avenues for future research. Firstly, the analysis relied on cross-sectional data from eight countries and a fixed set of ten competitiveness pillars,

which constrained the generalisability of the findings and limited our ability to observe actual configuration transitions over time. Secondly, the measurement of resources and capabilities was based on managerial perceptions, which may have been affected by subjective biases despite the use of a standardised and extensively tested questionnaire. Thirdly, while the logistic models capture important associations between pillars and configurations, their explanatory and predictive power is necessarily partial, and contextual factors such as sector, country and institutional environment may further shape configuration–performance relationships.

These limitations open up several promising directions for future work. Longitudinal and mixed-method designs could track configuration trajectories over time and empirically test the development routes and path-dependent patterns hypothesised in this study. Sector-specific and country-comparative applications of the framework could examine how industry dynamics and institutional conditions influence the prevalence and performance of different configurations. Finally, further methodological refinements, for example, multi-level modelling or alternative clustering and classification techniques, could deepen our understanding of how resource and capability pillars interact in shaping SME competitiveness.

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Appendix 1:**List of resource and capability pillars and variables for SMEs' competitiveness**

Pillar	Code	Variable description
Human Capital	H2	The problems with employees
	H3	The share of employees participating in training programmes
	H4	The sophistication of compensation systems
	H5	The uniqueness of human capital
Product	P1	Product innovation
	P2	Activities/effort concerning the introduction of new or amended product
	P3	The share of new product in sales
	P4	The uniqueness of firm's product and continuous innovation
Domestic Market	DM1	The geographic scope of selling
	DM2	The level of firm's competition in the market
	DM3	The expected growth of the target market in five years
	DM4	The intensity of competition
	DM5	Quick response to customers' demand
Networks	N1	The number of economic cooperation and innovation agreements
	N2	The time of networking as compared to the establishment of the firm
	N3	The reliance on outside help in business development
	N4	Uniqueness of networking relationship
Technology	T1	The level of firm's technology
	T2	The age of available technology used by the firm and technological innovation
	T3	Environmental investment and quality assurance
	T4	The level of application of ICT tools
	T5	Uniqueness of applied technology, possession of license or know-how, product management and quality assurance
Decision-making	D1	The application of the different sources of information
	D2	The application of financial analyses in the business
	D3	Information sharing
	D4	Consultation in decision-making
	D5	Administrative routines/operations, knowledge sharing of the business organisation
Competitive Strategy	S1	The direction of strategy (defensive, proactive)
	S2	Growth strategy based on the number of business units
	S3	The leader's entrepreneurial traits
	S4	The uniqueness of firm's proactive strategy
Marketing	M1	The uniqueness of products
	M2	The pricing of the main product
	M3	Sophistication of distribution channels
	M4	Applied marketing and communication tools
	M5	Marketing innovation
	M6	The uniqueness of marketing methods
Internationalisation	I1	The significance of foreign buyers
	I2	The share of export in sales
	I3	Language capabilities at business level
	I4	The uniqueness of location
Online Presence	O1-2	Web 1.0 (speed, complexity and appearance of online presence)
	O3	Web 2.0 (Mail, Apple, GPlus, Facebook, Twitter, Instagram)
	O4	Online marketing applications

Source: Lafuente *et al.*, 2020a.

Appendix 2: Statistical tests of the relationship between configuration and competitiveness

Connection between configuration and competitiveness I.

Chi-Square Tests	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	153.836 ^a	6	0.000
Likelihood Ratio	163.132	6	0.000
Linear-by-Linear Association	6.166	1	0.013
N of Valid Cases	785	–	–

Notes: a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 65.17.

Source: own elaboration.

Directional Measures	Value	Asymp. Std. Error ^a	Approx. T ^b	Approx. Sig.
Ordinal by Ordinal Symmetric	0.077	0.031	2.504	0.012
Somers' d Configuration Dependent	0.081	0.032	2.504	0.012
Competitiveness Dependent	0.072	0.029	2.504	0.012

Notes: a. Not assuming the null hypothesis; b. Using the asymptotic standard error assuming the null hypothesis.

Source: own elaboration.

Symmetric Measures	Value	Asymp. Std. Error ^a	Approx. T ^b	Approx. Sig.
Ordinal by Ordinal Kendall's tau-b	0.077	0.031	2.504	0.012
Kendall's tau-c	0.081	0.032	2.504	0.012
Gamma	0.105	0.042	2.504	0.012
N of Valid Cases	785	–	–	–

Notes: a. Not assuming the null hypothesis; b. Using the asymptotic standard error assuming the null hypothesis.

Source: own elaboration.

Connection between configuration and competitiveness II.

Configuration group	N	Mean	Std. Deviation	Std. Error	Minimum	Maximum
Balanced	196	4.405	1.119	0.080	1.690	6.783
Core Competence	196	4.777	1.226	0.088	1.677	7.841
Bottleneck	196	5.669	1.415	0.101	1.879	8.589
Harmonised	197	5.999	1.128	0.080	3.104	8.302
Total	785	5.214	1.386	0.049	1.677	8.589
Random Effects	–	–	–	–	–	–

Source: own elaboration.

Post-Hoc	(I) Configuration	(J) Configuration	Mean Difference (I-J)	Std. Error	Sig.
Tamhane	Balanced	Core Competence	-0.372*	0.119	0.011
		Bottleneck	-1.264*	0.129	0.000
		Harmonised	-1.594*	0.113	0.000
	Core Competence	Balanced	0.372*	0.119	0.011
		Bottleneck	-0.892*	0.134	0.000
		Harmonised	-1.222*	0.119	0.000
	Bottleneck	Balanced	1.264*	0.129	0.000
		Core Competence	0.892*	0.134	0.000
		Harmonised	-0.330	0.129	0.064
	Harmonised	Balanced	1.594*	0.113	0.000
		Core Competence	1.222*	0.119	0.000
		Bottleneck	0.330	0.129	0.064
Dunnett T3	Balanced	Core Competence	-0.372*	0.119	0.011
		Bottleneck	-1.264*	0.129	0.000
		Harmonised	-1.594*	0.113	0.000
	Core Competence	Balanced	0.372*	0.119	0.011
		Bottleneck	-0.892*	0.134	0.000
		Harmonised	-1.222*	0.119	0.000
	Bottleneck	Balanced	1.264*	0.129	0.000
		Core Competence	0.892*	0.134	0.000
		Harmonised	-0.330	0.129	0.064
	Harmonised	Balanced	1.594*	0.113	0.000
		Core Competence	1.222*	0.119	0.000
		Bottleneck	0.330	0.129	0.064
Games-Howell	Balanced	Core Competence	-0.372*	0.119	0.010
		Bottleneck	-1.264*	0.129	0.000
		Harmonised	-1.594*	0.113	0.000
	Core Competence	Balanced	0.372*	0.119	0.010
		Bottleneck	-0.892*	0.134	0.000
		Harmonised	-1.222*	0.119	0.000
	Bottleneck	Balanced	1.264*	0.129	0.000
		Core Competence	0.892*	0.134	0.000
		Harmonised	-0.330	0.129	0.053
	Harmonised	Balanced	1.594*	0.113	0.000
		Core Competence	1.222*	0.119	0.000
		Bottleneck	0.330	0.129	0.053
Dunnett C	Balanced	Core Competence	-0.372*	0.119	—
		Bottleneck	-1.264*	0.129	—
		Harmonised	-1.594*	0.113	—
	Core Competence	Balanced	0.372*	0.119	—
		Bottleneck	-0.892*	0.134	—
		Harmonised	-1.222*	0.119	—
	Bottleneck	Balanced	1.264*	0.129	—
		Core Competence	0.892*	0.134	—
		Harmonised	-0.330	0.129	—
	Harmonised	Balanced	1.594*	0.113	—
		Core Competence	1.222*	0.119	—
		Bottleneck	0.330	0.129	—

Source: own elaboration.

Appendix 3:

Detailed results of the binomial logistic regression

Competitive pillars	<i>Balanced to</i>				<i>Core Competence to</i>				<i>Bottleneck to</i>			
	Bottleneck		Harmonised		Core Competence		Bottleneck		Harmonised		Harmonised	
	Model 1 Exp(B)	Model 1 p	Model 2 Exp(B)	Model 2 p	Model 3 Exp(B)	Model 3 p	Model 4 Exp(B)	Model 4 p	Model 5 Exp(B)	Model 5 p	Model 6 Exp(B)	
Competitive Strategy	–	–	8.130*	0.003	–	–	–	–	15.315*	0.000	4.566**	0.011
Decision-making	4.767*	0.006	4.132**	0.035	–	–	–	–	–	–	–	–
Human Capital	5.074**	0.016	4.292***	0.053	–	–	–	–	–	–	–	–
Internationalisation	–	–	–	–	–	–	–	–	4.044***	0.055	–	–
Marketing	3.503***	0.071	5.464**	0.032	–	–	–	–	–	–	2.915***	0.087
Networks	–	–	4.049**	0.034	–	–	4.303*	0.009	5.340*	0.009	–	–
Product	3.545**	0.037	3.774***	0.054	2.667**	0.036	–	–	–	–	–	–
Technology	10.485*	0.007	10.638**	0.015	–	–	53.514*	0.000	23.371*	0.001	0.266***	0.066
Chi-square test	105.151	–	155.394	–	4.442	–	71.092	–	112.408	–	12.847	–
Nagelkerke R2	0.314	–	0.435	–	0.015	–	0.221	–	0.332	–	0.043	–
H&L test	0.195	–	0.373	–	0.010	–	0.521	–	0.577	–	0.469	–
Correctly predicted (%)	70.2	–	74.6	–	54.1	–	67.6	–	70.7	–	55.7	–
ROC AUC	0.777	–	0.837	–	0.570	–	0.738	–	0.792	–	0.593	–
Observations	392	–	393	–	392	–	392	–	393	–	393	–

Note. Odds ratios (Exp(B)) and p-values are reported; the configuration shown in italics is the reference category. An odds ratio greater than 1 indicates that higher values of the pillar increase the odds of belonging to the non-reference configuration relative to the reference configuration.

Odds ratios are reported for one-unit increases in pillar scores; given that pillar scores are bounded and constructed on a normalised scale, seemingly large odds ratios should be interpreted as reflecting the scale of the underlying metric rather than as literal marginal effects over an unconstrained range.

*, **, *** indicate significance at the 1%, 5% and 10% significance levels, respectively.

ROC AUC = receiver operating characteristic area under the curve.

Source: own elaboration.

Authors

The contribution shares of the authors are equal and amount to 50% for each author.

András Rideg – conceptualisation, literature writing, Gábor Márkus – methodology, calculations, discussion.

András Rideg (corresponding author)

Associate Professor and Researcher at the Department of Management Science, Faculty of Business and Economics, University of Pécs. His research interests include RBV-based SME competitiveness and SME strategy.

Correspondence to: Dr. habil. András Rideg, Faculty of Business and Economics, University of Pécs, Rákóczi út 80, Pécs, Hungary. Postcode: 7622, e-mail: ridega@tkk.pte.hu

ORCID  <https://orcid.org/0000-0001-7332-7803>

Gábor Márkus

Assistant Professor and Researcher at the Department of Finance and Accounting, Faculty of Business and Economics, University of Pécs. His research interests include SME competitiveness, financial performance and international accounting standards.

Correspondence to: Dr. Gábor Márkus, Faculty of Business and Economics, University of Pécs, Rákóczi út 80, Pécs, Hungary. Postcode: 7622, e-mail: markus.gabor@tkk.pte.hu

ORCID  <https://orcid.org/0000-0001-8132-1129>

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Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Enhancing entrepreneurial self-efficacy development through teaching quality, learning methods, and university support systems

James Tuffour, Albert Acheampong, Frank Agyemang Karikari, Edward Marfo-Yiadom

ABSTRACT

Objective: The objective of the article is to identify how universities influence students' entrepreneurial self-efficacy (ESE) through teaching quality, learning methods, and external engagement activities, with a focus on the mediating role of university support systems.

Research Design & Methods: The study employed a quantitative research design, using structural equation modelling to analyse data from 1 246 students across 11 public and technical universities in Ghana.

Findings: The results show that teaching quality and learning methods directly enhance ESE, while external engagement activities exert their influence indirectly through university support systems. The strongest contributor to ESE is university support systems, followed by teaching quality, learning methods, and external engagement. The study highlights the importance of an integrated teaching approach reinforced by institutional support and external engagement for fostering ESE.

Implications & Recommendations: Universities should strengthen their support systems and adopt teaching methods that combine experiential learning with external engagement activities to enhance students' ESE. Policymakers and educators should prioritise institutional frameworks that facilitate these interactions.

Contribution & Value Added: The article contributes to self-efficacy and social cognitive career theories by empirically validating the mediating role of university support systems. It also enriches the literature on entrepreneurship education by providing evidence from an emerging economy context (Ghana), where such studies are limited.

Article type: research article

Keywords: entrepreneurship education; entrepreneurial self-efficacy; external engagement activities; learning methods; teaching quality; university support systems

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INTRODUCTION

Sub-Saharan Africa (SSA) continues to grapple with persistently high youth unemployment, a pressing socio-economic concern exacerbated by a youthful demographic profile, with nearly half the population below 20 years of age (African Development Bank, 2025). Despite this demographic dividend, many African economies struggle to absorb young people into productive employment, with youth unemployment worsening in the post-COVID-19 period (International Labour Organization, 2024). Ghana exemplifies this challenge, recording youth unemployment of about 12% alongside underemployment rates exceeding 50%, prompting calls for urgent policy interventions (World Bank, 2020). In this context, scholars increasingly view entrepreneurship as a sustainable pathway for job creation, particularly within economies dominated by informal small-scale enterprises (Okoro *et al.*, 2022; Tuffour *et al.*, 2024; 2025).

To address youth unemployment, African governments have implemented various entrepreneurship promotion initiatives. In Ghana, these include the National Youth Employment Agency, the National Entrepreneurship and Innovation Programme, and the Nation Builders Corps (Jumpah *et al.*, 2020). Similar interventions have emerged in other African countries, including Tunisia, Egypt, and Morocco, particularly following the Arab Spring (Prince *et al.*, 2018). While these policy efforts underscore the strategic importance of entrepreneurship, their effectiveness depends largely on the capacity of educational institutions to equip learners with the skills, confidence, and support required to pursue entrepreneurial careers.

Indeed, universities are uniquely positioned to nurture entrepreneurial mindsets by combining knowledge acquisition with skills development, creativity, and resilience building (Nyukorong, 2022). However, limiting entrepreneurship education (EntEdu) to classroom-based content delivery has proven insufficient in addressing Africa's unemployment challenges (Okoro *et al.*, 2022). For EntEdu to meaningfully influence students' entrepreneurial behaviour and entrepreneurial self-efficacy (ESE), universities must adopt a more holistic approach that integrates teaching quality, experiential learning methods, institutional support systems, and engagement with external stakeholders. Scholars have identified practical business seminars, mentorship programmes, innovation hubs, and business incubators as critical mechanisms through which theoretical knowledge can transform into market-ready solutions (Agyapong, 2020; Oliver & Oliver, 2022).

Despite growing investments by some Ghanaian universities in entrepreneurship hubs and support structures, evidence suggests that many students still lack the confidence to initiate entrepreneurial ventures due to limited institutional support and inadequate exposure to real-world business challenges (Shahzad *et al.*, 2021). This prompts a core question within entrepreneurship education research: how effective are university-led entrepreneurial initiatives in strengthening students' entrepreneurial self-efficacy? Resolving this issue is essential for assessing universities' contributions to sustainable employment creation and progress towards Sustainable Development Goal 8, particularly Target 6, which focuses on youth employment, education, and skills development (United Nations, 2015).

Prior research in EntEdu predominantly examined the direct influence of teaching quality, learning methods, and curriculum design on students' entrepreneurial intentions and self-efficacy (Iwu *et al.*, 2021; Mensah-Williams & Derera, 2024). Although these studies offer important insights, they often position university support systems as background conditions rather than as active mechanisms shaping entrepreneurial outcomes. Consequently, the mediating role of university support systems in linking teaching quality and learning methods to students' ESE remains underexplored, particularly in SSA. This gap limits a comprehensive understanding of how university-based entrepreneurial ecosystems function as integrated systems rather than as isolated components.

To address this research gap, we explored how teaching quality (TQ), learning methods (LM), university support (US) systems, and external engagement (EE) activities jointly influence students' ESE. Drawing on data from 1 246 students across 11 public and technical universities in Ghana, we moved beyond content-focused evaluations of EntEdu by assessing the robustness of institutional interventions and support structures. In doing so, we respond to recent calls for more nuanced analyses of EntEdu that capture the quality of instruction, experiential learning, and ecosystem-level support (Duong *et al.*, 2024).

Theoretically, this research draws upon Bandura's self-efficacy framework and the social cognitive career perspective, both of which highlight how contextual supports, experiential learning, and interpersonal dynamics collectively influence the formation of career-oriented cognitions and actions. This investigation contributes distinctively by focusing on the intermediary function of institutional support structures within universities, specifically how such systems channel the effects of teaching quality and learning methods on ESE. By empirically testing this mediation within an African context, the study extends EntEdu literature beyond predominantly Western and direct-effect models.

By focusing on Ghana, the study provides contextually grounded insights relevant to other emerging economies facing similar youth unemployment challenges. We expected the findings to inform university administrators, policymakers, and other stakeholders on how to strengthen entrepreneurial ecosystems within higher education institutions to produce job creators rather than job seekers.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Theoretical Review

Self-efficacy Theory

Bandura's (1977) self-efficacy theory describes the development of self-efficacy by individuals through four major factors: mastery experiences, vicarious experiences, social persuasion, and physiological state. Theoretically, self-efficacy is domain-specific (Lent & Brown, 2019). In the context of entrepreneurship training, ESE refers to students' confidence in their abilities to undertake entrepreneurial tasks such as opportunity search, strategic preparation, resource mobilisation, and risk management (Al-Qadasi *et al.*, 2023). High self-efficacy makes one more likely to participate in entrepreneurial activities, work more diligently, or persevere in spite of challenges (Newman *et al.*, 2019).

In EntEdu, self-efficacy sources manifest through mastery experiences (business planning, pitch presentations), vicarious experiences (guest entrepreneurs, case studies), and social persuasion (instructor feedback, peer encouragement) (Akhtar *et al.*, 2022; Newman *et al.*, 2019). The theory's triadic reciprocal determinism explains how TQ and US, as environmental factors, interact with LM to foster ESE development, while universities manage psychological states during entrepreneurial learning (Aboobaker & Zakkariya, 2023).

Social Cognitive Career Theory

Drawing on Bandura's foundational work on self-efficacy, Lent *et al.* (1994, 2000) developed the social cognitive career theory (SCCT) to explain the cognitive and motivational mechanisms underlying the development of vocational interests, career choice processes, and performance-related outcomes. The theory emphasises the interaction between personal beliefs, learning experiences, and environmental conditions in shaping career trajectories. Notably, SCCT is particularly relevant to EntEdu because it explains how educational contexts influence ESE, beliefs about prospective outcomes, and career-directed actions (Brown & Lent, 2023).

Social cognitive career theory includes three interconnected models: interest development, choice-making, and performance (Lent *et al.*, 2000). The interest development model describes how experiential inputs help build self-efficacy cognitions and performance expectations, which serve as precursors to vocational interest formation (Wang *et al.*, 2022). In university settings, teaching quality and learning methods play a key role in providing mastery experiences, social persuasion, and observational learning that bolster students' ESE and interests (Duong *et al.*, 2024). Therefore, well-designed entrepreneurship curricula, experiential learning activities, and problem-based pedagogies are crucial mechanisms through which universities promote entrepreneurial aspirations.

The choice-making framework emphasises the function of external enabling factors and obstacles in transforming interests into defined career objectives and purposeful actions (Brown & Lent, 2023). Within EntEdu settings, institutional support infrastructure represents critical contextual enablers that promote entrepreneurial decision-making (Boahen *et al.*, 2023; Tuffour *et al.*, 2025). The infrastructure manifests through venture incubation facilities, structured mentoring schemes, dedicated innovation spaces, and resource mobilisation channels. External engagement with industry partners and role models further reinforces these choices by providing feedback, validation, and exposure to real-world entrepreneurial challenges (Akinlolu *et al.*, 2023).

Finally, the performance model explains how self-efficacy and outcome expectations guide sustained effort and achievement in career-related activities (Lee *et al.*, 2021). Applied to entrepreneurship, this model underscores how supportive university environments enhance students' capacity to transform entrepreneurial intentions into effective entrepreneurial behaviour. Accordingly, SCCT provides a robust theoretical lens for examining how teaching quality and learning methods influence ESE, both directly and indirectly through university support systems, an emphasis central to this study.

Entrepreneurial Efficacy Development: Teaching Quality and Learning Methods

Empirical evidence shows that TQ is one of the factors that play a significant role in ESE development, with research establishing its positive relationship with students' self-efficacy beliefs (Luo *et al.*, 2022; Wu *et al.*, 2022). However, researchers have not agreed on a common definition for TQ. Some authors point to interactive teaching practices and learning environments (Yang *et al.*, 2021), while others underscore state-of-the-art course content design, using formative assessments (Zhong, 2023). Authors like Iwu *et al.* (2021) often view improved entrepreneurship instruction as requiring critical thinking techniques, allowing students to apply theoretical entrepreneurship concepts in practice. Moreover, Donaldson and Villagrasa (2024) view TQ as a well-designed entrepreneurship course that combines theoretical foundations with interactive learning using business simulations or cases. This article proposes that the role of TQ must be explored by studying students' behaviour in initiating or continuing entrepreneurial activities that become real businesses.

Entrepreneurship LM has shifted from instructor-focused to learner-centred pedagogy, emphasising experiential learning through business simulations, startup incubators, and competitions (Boahen *et al.*, 2023; Donaldson & Villagrasa, 2024; Vivekananth *et al.*, 2023). Experiential approaches significantly improve ESE compared to traditional case-study methods (Abd Rahim *et al.*, 2022; Anwar & Abdullah, 2021), building resilience and creativity while enabling students to experiment with real-world business ideas (Wang *et al.*, 2023). These pedagogical techniques allow risk experimentation with acceptable consequences, while industry-practitioner linkages facilitate innovative ideas and enhance self-efficacy (Akinlolu *et al.*, 2023; Iwu *et al.*, 2021). Mentorship programmes further strengthen industry networks, enabling students to develop requisite entrepreneurial skills.

Notably, the general assertion that instructional quality influences ESE constitutes enough justification for testing the relationship between teaching quality and ESE. Again, sufficient empirical evidence exists to support the assertion that a variety of teaching delivery settings improve ESE. Based on these empirical data, we hypothesised:

H1: Teaching quality positively influences ESE among university students.

H2: Learning methods directly affect ESE in higher education settings.

Universities' External Stakeholder Engagements and Entrepreneurial Self-efficacy

Several studies demonstrate that EE enhances ESE by offering students practical exposure, professional affirmation, and interaction with entrepreneurial role models (Andayani *et al.*, 2020; Atta-Owusu & Fitjar, 2022). Institutions maintaining robust partnerships with industry, alumni, and public agencies can better create experiential opportunities that let students translate theoretical learning into real-world application, thereby reinforcing ESE (Agyapong, 2020; Hassan, 2024). However, empirical findings on the direct impact of EE on ESE are not entirely consistent. While some studies report strong positive effects (Andayani *et al.*, 2020), others find weaker or context-dependent relationships, particularly where external engagements are short-term, informal, or poorly integrated into academic programmes (Atta-Owusu & Fitjar, 2022). These contradictions suggest that EE does not uniformly translate into enhanced self-efficacy unless it is structured, supported, and reinforced by institutional mechanisms.

Notably, scholars argue that the efficacy of EE rests on the extent to which universities provide complementary support structures, such as coordination units, mentoring frameworks, and follow-up mechanisms, that enable students to reflect on and internalise their external experiences (Al-Qadasi *et al.*, 2023). Without such support, external engagements may raise awareness of entrepreneurial challenges without enhancing students' confidence to pursue entrepreneurial action. This perspective provides a plausible explanation for why some studies observe direct effects of EE on ESE, while others do not. Nonetheless, given the substantial body of evidence highlighting the potential benefits of external engagement on ESE, we hypothesised:

H3: External engagement activities enhance students' ESE.

Universities' Support Systems and Entrepreneurial Self-efficacy

There has been a growing interest in understanding the role of university support systems in entrepreneurial development. Besides linking students to external partners, universities often create internal opportunities for students to boost their entrepreneurial capabilities. These internal support systems include, among other things, business incubators and entrepreneurship centres, financial support schemes, and effective entrepreneurship curricula (Agyapong, 2020; Dharmanegara *et al.*, 2022). Moreover, support systems like ideation, business plan training, and market research equip students with skills to navigate entrepreneurial challenges (Al-Fattal, 2021). In a study of nearly 14 000 Chinese graduates, Lu *et al.* (2021) found that strong university support systems positively affect students' ESE.

Beyond the provision of physical resources, researchers report that universities' social and psychological support structures influence ESE (Padi *et al.*, 2022; Su *et al.*, 2021). For example, where students can engage with faculty and peers through these intangible support systems, critical entrepreneurial cultures (such as innovation and risk-taking) emerge (Padi *et al.* 2022). Yesmin *et al.*'s (2024) examination of university support frameworks concluded that university community engagements enhance students' entrepreneurial abilities. Wang and Huang (2019) confirmed the relationship between entrepreneurial success and acting upon university support structures, which are theorised to affect entrepreneurial intention through various psychological channels. Dharmanegara *et al.* (2022) confirmed that such support structures exert a significant influence on fostering ESE in an educational setting.

Based on this compelling empirical evidence across diverse educational contexts and methodologies, we argue that universities with robust support structures create a psychological safety net for entrepreneurs to thrive. Thus, both physical and intangible support systems are critical for sharpening students' ESE. Therefore, we hypothesised:

H4: University support positively influences ESE.

Relationship Between Teaching Quality, Learning Methods, and External Engagement

Empirical evidence shows a strong link between the quality of teaching and support structures within universities. For instance, Farooqi *et al.*'s (2023) examination of 686 students found that teaching quality in universities influences the allocation of institutional resources and support systems. This finding aligns with the quantitative analysis by Toledo *et al.* (2022), which indicates that structured teaching support programmes provided greater overall institutional assistance to 114 university teachers.

Similarly, Farooqi *et al.*'s (2023) study of university faculty members revealed that good teaching skills correspond to higher levels of administrative support. Furthermore, Li and Austria (2023) demonstrate that universities with a well-structured teaching quality management programme provides better faculty support. Zhong (2023) and Farooqi *et al.* (2023) corroborated these findings. They showed that the management of teaching quality directly affects university support systems through funding and infrastructure development. This evidence informed our hypothesis:

H5: Teaching quality positively influences university support.

Research indicates a strong relationship between university learning systems and support structures. For example, Gaspar Pacheco *et al.* (2024) show that innovative learning methods supported by universities increase faculty participation and institutional support. A mixed-methods study of business students found that integrated learning approaches reinforce university support mechanisms (Pugh *et al.*, 2021). Furthermore, Descals-Tomás *et al.* (2021) affirm that learning methods backed by faculty support enhance university support, suggesting that problem-based learning methodologies are engines for strengthening university-support systems. These findings laid the foundation for the next hypothesis:

H6: Learning methods positively influence university support.

Meanwhile, studies show the pivotal role of external engagement in universities' support systems. Descals-Tomás *et al.* (2021) demonstrate that external engagements like family support enhance institutional support. Yang *et al.* (2021) found that faculty support and external engagement activities improve university support structures. According to Atta-Owusu and Fitjar (2022), external

engagement enhances university support through the creation of avenues for funding and knowledge exchange.

Moreover, Atta-Owusu and Fitjar (2023) suggest that external engagement in the form of university partnerships directly enhances institutional support systems; their study of European universities found that structured external engagement programmes were critical for strengthening institutional support. Again, empirical evidence from Law *et al.* (2021) indicates that stronger external engagement frameworks enhance the sustainability of institutional support. Based on this evidence, we hypothesised:

H7: External engagement positively influences university support.

Relationship Between Teaching Quality, Learning Methods, External Engagement, and University Support Systems

The function of university support systems in entrepreneurial training has received increasing attention. Scholarship revealed that educational institutions' support frameworks have a significant impact on entrepreneurial success (Padi *et al.*, 2022). Lu *et al.* (2021) validated that strong university support systems positively impact students' ESE and orientation, specifically through structured institution frameworks. Vivekananth *et al.* (2023) corroborated this and claimed that institutional support frameworks play a critical role in fostering self-efficacy through both instructional design and the delivery of support services. Supplementary evidence from Su *et al.* (2021) affirms that university support systems indirectly influence entrepreneurial behaviour, thereby improving students' ESE.

Su *et al.* (2021) confirmed a positive relationship between entrepreneurial success and university support. These scholars found that entrepreneurial intentions are influenced by institutional support structures through a variety of cultural and psychological channels. Moreover, Aboobaker *et al.* (2023) confirmed that both institutional and family support structures significantly contribute to ESE. Wu *et al.* (2022) supplement these findings by indicating that supporting structures and professional training have significant effects on ESE development.

Past studies have confirmed direct relationships among ESE, external involvement, learning approaches, and teaching quality. Meanwhile, the intermediary role of university support in these relationships remains relatively underexplored. In an attempt to bridge the literature gap, we aimed to understand how university support structures mediate such relationships. Drawing on the theoretical framework and empirical insights reviewed, we hypothesised:

H8a: University support mediates the relationship between teaching quality and ESE.

H8b: University support mediates the relationship between learning methods and ESE.

H8c: University support mediates the relationship between external engagement and ESE.

Conceptual Framework

Figure 1 presents our research framework examining the relationships between TQ, LM, EE, US, and ESE in higher education. The framework shows direct paths (H1-H3) from TQ, LM, and EE to ESE. It also depicts how TQ, LM, and EE influence US (H5-H7), and how US affects ESE (H4). The model further illustrates the intermediary role of the US between the independent variables (TQ, LM, EE) and ESE through hypotheses H8a, H8b, and H8c, providing a structure for understanding ESE development among Ghanaian university students.

RESEARCH METHODOLOGY

Research Context

Ghana's entrepreneurial landscape provides a unique context for studying ESE development, given high youth and graduate unemployment (World Bank, 2020). Government policies like the National Entrepreneurship and Innovation Programme aim to foster entrepreneurial mindsets and transition from a job-seeking to a job-creating economy (Jumpah *et al.*, 2020). Universities play a critical role, with entrepreneurship courses becoming mandatory across programmes (Mensah-Williams & Derera, 2024).

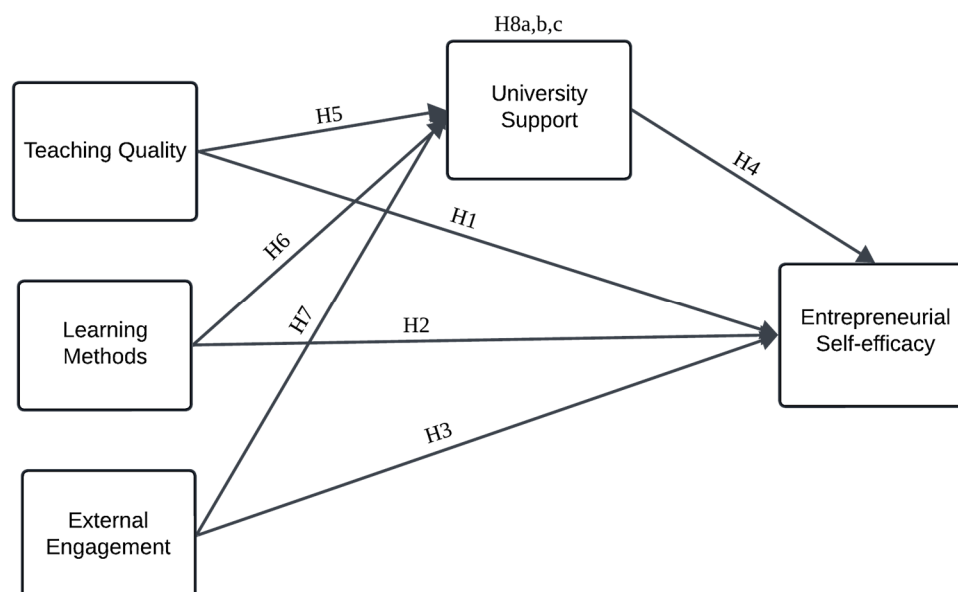


Figure 1. Conceptual framework

Source: own elaboration.

Sampling and Measurement Instruments

Methodologically, the study followed a quantitative design, with data sourced from students attending 11 public and technical tertiary institutions in Ghana over three months (June-August 2024) (Table 1A). To maintain a fair representation of the research respondents, we organised the population into three geographical clusters (Southern Belt, Middle Belt, and Northern Belt). We gathered data using a stratified random sampling technique. Within each geographical cluster, we established sampling quotas and identified potential participants randomly.

Table 1A. Participating public and technical universities by geographical region

No.	Name of Institution	Cluster	Sample
1	University of Ghana	Southern	83
2	University of Cape Coast	Southern	233
3	University of Education, Winneba	Southern	69
4	Cape Coast Technical University	Southern	133
5	Kwame Nkrumah University of Science and Technology	Middle	210
6	University of Energy and Natural Resources	Middle	97
7	Sunyani Technical University	Middle	110
8	University of Development Studies	Northern	73
9	Dombo University of Business and Integrated Development Studies	Northern	121
10	Tamale Technical University	Northern	97
11	Dr Hilla Limann Technical University	Northern	20
Total:			1 246

Source: own study of data from fieldwork in 2024.

The diverse sample encompasses both undergraduate and postgraduate students at various academic levels. The informants were students who had completed formal entrepreneurship courses and had gained practical experience through external engagement and other university activities such as internships, industry collaborations, and mentorship programmes. This sampling technique ensured that respondents could meaningfully evaluate both theoretical instruction and practical application aspects of EntEdu at their institutions. This diversity in institutional representation is in line with similar studies in developing economies (Wang *et al.*, 2023) and gives a holistic picture of EntEdu in Ghana's higher education system. From the initial distribution of 1 500 questionnaires, we

analysed 1 246 valid responses, representing an 83.1% response rate, which exceeds the threshold recommended by Hair *et al.* (2017) for structural equation modelling studies. We surveyed all constructs using standardised scales (Table 1B) with a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree), with mean scores ranging from 4.618 to 4.840.

Table 1B. Measurement instruments

Constructs	Adapted Scale	References
ESE	A nine-item scale covered entrepreneurial confidence for tasks such as developing entrepreneurial ideas, resource utilisation, and identifying opportunities.	McGee <i>et al.</i> , 2009; Akhtar <i>et al.</i> , 2022
TQ	A four-item scale covered course material, tests, and instructor competence.	Brown & Hanlon, 2016; Gedeon, 2017
LM	A three-item scale covered the relevance of study cases and instructor feedback.	Gaspar Pacheco <i>et al.</i> , 2024
EE	A three-item scale covered internships, network development, and entrepreneurial competitions.	Viswanath <i>et al.</i> , 2024
US	A six-item scale measured entrepreneurial support services related to entrepreneurial competitions, personal guidance, and networking sessions.	Ruskovaara <i>et al.</i> , 2015

Source: own study.

Data Analysis

After cleaning and coding the data in Microsoft Excel, we analysed both the measurement and structural models using SmartPLS version 4.1.0.9. We employed partial least squares structural equation modelling (PLS-SEM) due to its suitability for complex model estimation and its robustness to violations of data normality assumptions (Sarstedt *et al.*, 2022). Moreover, we mitigated potential common method bias (CMB) through procedural and statistical control measures recommended by Podsakoff *et al.* (2003). Following a partial correlation remedy for statistics, we reduced the variance to 40.54%; hence, CMB was not a problem. As shown in Table 2, variable correlations remained significant even in a post-common method variance (CMV) adjustment, with adjusted correlations below and zero-order correlations above the diagonal, confirming strong relationships between the variables.

Table 2. Correlations adjusted for CMV

Variables	1	2	3	4
1. TQ	—	0.878***	0.818***	0.724***
2. LM	0.802***	—	0.878***	0.731***
3. EE	0.705***	0.802***	—	0.694***
4. ESE	0.537***	0.549***	0.490***	—

Note: Sample comprises 1 246 respondents. Lower diagonal values represent correlations adjusted for common method variance; upper diagonal values indicate unadjusted bivariate correlations. Significance thresholds: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Source: own study.

Ethical Consideration

We obtained ethical clearance for this study from the Research Ethics Board of Anglia Ruskin University (Reference: ETH2324-9913). Each participant provided informed consent following clear communication of their rights, including voluntary involvement and unrestricted withdrawal. We protected participant anonymity through response coding and present all findings in aggregate form to preserve confidentiality.

RESULTS AND DISCUSSION

Measurement Model Assessment

We validated the measurement model through a systematic assessment protocol. We ascertained construct reliability using Cronbach's alpha (CA) alongside composite reliability (CR) coefficients.

We demonstrated convergent validity through average variance extracted (AVE) calculations and verified discriminant validity by applying the Fornell-Larcker criterion (Hair *et al.*, 2019). Each construct exhibited robust reliability metrics: CA (0.893-0.967) and CR (0.894-0.967) exceeding the recommended thresholds of 0.7 and 0.6, respectively. Factor loadings ranged from 0.854 to 0.925, exceeding the 0.7 benchmark, while AVE values (0.761-0.829) surpassed the 0.5 threshold, confirming convergent validity (Hair *et al.*, 2019) (Table 3).

Table 3. Factor loadings, CA, CR and AVE for variables

Constructs	Factor loadings	CA	CR	AVE
EE	0.895-0.923	0.897	0.899	0.829
ESE	0.859-0.906	0.967	0.967	0.789
LM	0.897-0.914	0.893	0.894	0.824
TQ	0.882-0.925	0.927	0.927	0.820
US	0.854-0.899	0.937	0.938	0.761

Source: own study.

Discriminant Validity

As outlined above, we evaluated discriminant validity using the Fornell-Larcker criterion (Table 4). Results showed that the square root of the AVE for each construct was greater than its correlations with all other constructs, indicating satisfactory discriminant validity.

Table 4. Discriminant validity

Fornell-Larcker criterion	ESE	EE	LM	TQ	US
ESE	0.888	–	–	–	–
EE	0.694	0.910	–	–	–
LM	0.723	0.868	0.908	–	–
TQ	0.723	0.819	0.872	0.906	–
US	0.754	0.648	0.657	0.646	0.872

Source: own study.

Structural Model Results

Guided by Hair *et al.*'s (2017) protocol, we evaluated the structural model via R^2 (explanatory power), Q^2 (predictive accuracy), f^2 (effect magnitude), and path coefficient analysis. The analysis employed bootstrapping resampling (5 000 subsamples) with default parallel processing options to assess path coefficients' significance. This approach tested the effect of TQ, LM, and EE on ESE, both directly and indirectly via US as a mediator. This process provided in-depth information on entrepreneurial capability development in a university context.

Predictive Accuracy and Predictive Relevance

We determined the model's explained variance and predictive relevance through R^2 and Q^2 metrics (Table 5). R^2 values indicated high predictive accuracy for ESE (0.675) and moderate accuracy for US (0.469). Q^2 values exceeding zero for both ESE (0.563) and US (0.465) confirmed strong predictive relevance. RMSE and MAE values were within acceptable ranges, validating model accuracy.

Table 5. Predictive accuracy and predictive relevance

Variable	R^2	R^2 adj.	Q^2 predict	RMSE	MAE
ESE	0.675	0.674	0.563	0.662	0.465
US	0.469	0.468	0.465	0.733	0.539

Source: own study.

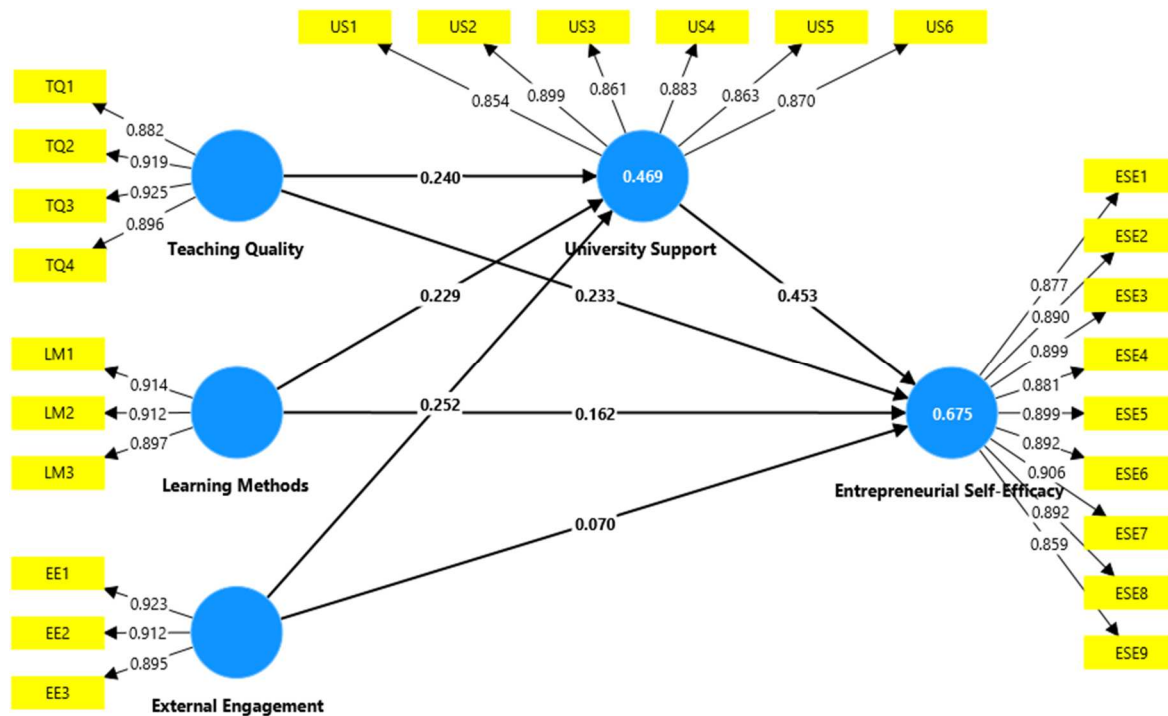


Figure 2. Indicator loadings

Source: own elaboration.

The Effect Size

We performed an f^2 analysis to determine the relative influence of the model's predictors on ESE. Following the guidelines of Benitez *et al.* (2020), we considered f^2 values of 0.02-0.149 as small, 0.150-0.349 as medium, and ≥ 0.350 as large effects. The results indicate varying degrees of practical significance, with university support showing the strongest impact ($f^2=0.335$), reflecting a medium-to-large effect on ESE. Meanwhile, both TQ ($f^2=0.036$) and LM ($f^2=0.013$) exhibited minimal effects (Figure 2). On the other hand, while EE displayed a negligible effect size ($f^2=0.003$), US, as a dependent variable, demonstrated small effect sizes for all three predictors (Table 6).

Hypotheses Testing

The path analysis results from our structural equation modelling revealed significant support for six of the seven hypothesised relationships. The analysis provided empirical support for H₁ and H₂, with TQ ($\beta=0.233$, $p<0.001$) and LM ($\beta=0.162$, $p<0.001$) both significantly enhancing ESE. Notably, H₃ was not substantiated, as EE's direct influence on ESE lacked statistical significance ($\beta=0.070$, $t=1.824$, $p=0.068$). Remarkably, US manifested the strongest direct effect on ESE ($\beta=0.453$, $t=12.772$, $p<0.001$), providing robust validation for H₄. The findings also confirmed that TQ ($\beta=0.240$, $t=4.652$, $p<0.001$), LM ($\beta=0.229$, $t=4.027$, $p<0.001$), and EE ($\beta=0.252$, $t=5.372$, $p<0.001$) each significantly predict US, thereby corroborating H₅, H₆, and H₇ (Table 6).

Table 6. Hypotheses results

Hypotheses	Estimate	f^2	STD.DEV	T-statistics	P-values	Decision
TQ -> ESE (H1)	0.233	0.036	0.046	5.048	0.000	Supported
LM -> ESE (H2)	0.162	0.013	0.043	3.782	0.000	Supported
EE -> ESE (H3)	0.070	0.003	0.038	1.824	0.068	Unsupported
US -> ESE (H4)	0.453	0.335	0.035	12.772	0.000	Supported
TQ -> US (H5)	0.240	0.024	0.051	4.652	0.000	Supported
LM -> US (H6)	0.229	0.017	0.057	4.027	0.000	Supported
EE -> US (H7)	0.252	0.028	0.047	5.372	0.000	Supported

Source: own study.

Mediation Analysis

As discussed earlier, we used a bootstrapping of 5 000 resamples on our dataset of 1 246 respondents to examine the mediating effects. The mediation analysis revealed significant indirect effects for all three hypothesised mediating relationships. The analysis showed that the US significantly mediates the relationship between TQ and ESE ($\beta = 0.108$, $STDEV = 0.025$, $p < 0.001$), with bias-corrected confidence intervals (CI – 0.063, 0.161) not containing zero. Similarly, significant mediating effects were found for the US in the relationship between LM and ESE ($\beta = 0.104$, $STDEV = 0.027$, $p < 0.001$, and CI – 0.053, 0.159), as well as between EE and ESE ($\beta = 0.114$, $STDEV = 0.023$, $p < 0.001$, and CI – 0.074, 0.163). These results provided strong support for hypotheses H8a, H8b, and H8c, confirming the mediating role of university support in our conceptual framework (Table 7).

Table 7. Results of mediation analysis

Hypotheses	Estimate	STDEV	Bias-corrected 97.5% CI			Percentile 97.5% CI		
			Lower	Upper	p-value	p-value	p-value	p-value
TQ -> US -> ESE (H8a)	0.108	0.025	0.063	0.161	0.000	0.061	0.160	0.000
LM -> US -> ESE (H8b)	0.104	0.027	0.053	0.159	0.000	0.053	0.158	0.000
EE-> US -> ESE (H8c)	0.114	0.023	0.074	0.163	0.000	0.072	0.161	0.000

Source: own study.

Performance Analysis

The analysis of performance scores presents the comparative importance and effectiveness of disparate factors influencing ESE among university students (Table 8). US had the greatest impact of 0.453, and a performance rating of 62.155, suggesting its significant role in developing university students' ESE. Teaching quality emerged with the second-largest impact, with an overall effect of 0.341 and a performance rating of 60.330. LM had a moderate impact (overall effect 0.266) but a high performance of 62.875. External engagement ranked fourth with an impact of 0.184 and a high performance of 62.751. Overall, the outcome revealed the hierarchical value of institution-backed frameworks and instruction methodologies in developing ESE among university students. This suggests that university-backed frameworks particularly drive students' ESE.

Table 8. Important performance analysis

Variable	Total effects	Performance	Rankings
US	0.453	62.155	1
TQ	0.341	60.330	2
LM	0.266	62.875	3
EE	0.184	62.751	4

Source: own study.

Discussion

Our findings support H1 and H5, confirming significant positive relationships between TQ and both ESE and US. These results corroborate Luo *et al.* (2022), demonstrating that quality EntEdu directly influences ESE development. Beyond confirming prior empirical evidence, the findings align with institutional theory, which posits that organisational practices, such as teaching quality, serve as regulative and normative mechanisms that shape individual behaviour within institutions. Regarding LM, our findings revealed significant positive relationships with both ESE (H2) and US (H6). These results correspond with studies by Abd Rahim *et al.* (2022) and Anwar and Abdullah (2021). While prior studies largely emphasise the pedagogical superiority of experiential learning, our findings extend this literature by showing that the effectiveness of such methods is institutionally contingent. The results of the indirect effect examination further indicate that US transmits a significant portion of LM's influence to ESE, suggesting that institutional support enhances the effectiveness of diverse learning approaches.

A key insight of this study is that EE exerts no significant direct impact on ESE (H3); instead, its influence operates strongly through US as a mediating factor (H8c). This finding contrasts with studies such as Andayani *et al.* (2020), which report direct positive effects of EE on ESE. An institutional lens may explain the divergence. In contexts where universities possess strong formalised support structures, students may immediately internalise external engagement activities, producing direct efficacy gains. However, in emerging economies like Ghana, EE often remains loosely coupled with institutional systems, limiting its standalone impact on self-efficacy.

From the perspective of institutional theory, EE represents an exogenous institutional influence that requires internal organisational alignment to become effective. Without structured mentoring, reflection mechanisms, and institutional follow-up, EE may lack the cognitive reinforcement necessary to shape self-efficacy. Thus, our findings suggest that EE contributes to ESE only when universities provide the institutional scaffolding required to legitimise, interpret, and integrate these experiences into students' entrepreneurial identity formation.

Moreover, the direct influence of US on ESE (H4) is strongly positive, which aligns with the findings of Lu *et al.* (2021) from a large-scale study of 13 954 graduates. The strength of the relationship implies that institutional support mechanisms significantly contribute to the development of students' entrepreneurial capabilities, thus supporting Yesmin *et al.*'s (2024) assertion that a well-structured support environment is critical for ESE development.

The study indicated significant relationships between TQ and US (H5), corroborating Farooqi *et al.* (2023), who found among 686 students that TQ influences institutional resource allocation. Likewise, our findings demonstrate that LM affects US (H6), corroborating the findings of Descals-Tomás *et al.* (2021) that LM strengthens institutional support mechanisms. The substantial effect of EE on US (H7) further supports the findings of Atta-Owusu and Fitjar (2023; 2022). These studies show that external partnerships positively impact supportive institutional frameworks. This relationship highlights the importance of maintaining meaningful connections between industry and academia to enhance support frameworks.

A further key finding of this study is the strong mediating role of US, showing significant positive relationships with ESE (H4) and mediating all three independent variables (H8a, b, c). Vivekananth *et al.* (2023) support the strong mediation, emphasising the importance of institutional support structures in the enhancement of entrepreneurship. This implies that US systems are prerequisites for converting educational inputs into entrepreneurial capacities. Our performance analysis shows a clear influence hierarchy, with US being the strongest contributor to ESE development, followed by TQ, LM, and EE. The high-performance scores across the board suggest that a holistic approach towards EntEdu, integrating all these elements through strong institutional support systems, is the most effective way of nurturing students' ESE.

CONCLUSIONS

Drawing on data from 1 246 students across 11 Ghanaian universities, this study demonstrates that TQ and LM directly enhance ESE, while EE influences ESE through US mediation. The hierarchy of influences (US > TQ > LM > EE) reveals US systems' critical catalytic role in transforming educational inputs into entrepreneurial competence. Universities should strengthen support structures through entrepreneurship centres, mentorship programmes, faculty development, and experiential learning. Policymakers should prioritise US systems and academic-industry partnerships to help Ghana transition from a job-seeking to a job-creating economy.

The Study's Implications and Recommendations

This research extends the self-efficacy theory by empirically validating US systems' mediating role in ESE development. While previous studies examined direct TQ-ESE and LM-ESE relationships, our findings reveal institutional support mechanisms as critical intermediaries, and theorises the complex pathways through which entrepreneurial competence develops in emerging economies.

Given US systems' strongest effect on ESE, universities should prioritise a comprehensive support infrastructure including entrepreneurship hubs, business incubators, innovation labs, and seed

funding schemes. Since EE influences ESE only through US mediation, institutions must deliberately integrate internship programmes, industry partnerships, and networking events within formalised support structures to maximise entrepreneurial development.

The significant TQ-ESE and LM-ESE relationships indicate that universities should invest in faculty development programmes emphasising experiential learning methods, case study development, and real-world problem integration. Curriculum designers should incorporate business simulations, student-run enterprises, and industry-based projects, supported by mentorship programmes linking students with experienced entrepreneurs.

For policymaking, to address youth unemployment, we recommend the establishment of structured entrepreneurship support offices to provide seed funding, technical assistance, market linkages, and monitoring systems. Universities should form strategic collaborations with industry associations and government agencies to create internship and mentoring pathways that transform theoretical knowledge into market-ready entrepreneurial capabilities.

The Study's Limitations and Future Research Agenda

This study has some limitations that influence the results' interpretation. Firstly, the sampling encompassing only students with EntEdu exposure potentially inflated ESE scores and strengthened observed relationships, limiting generalisability. Secondly, the cross-sectional design prevented causal inference; we could not determine whether university interventions caused ESE development or whether students with higher pre-existing ESE engaged more with programmes. Thirdly, the Ghana-only context may have limited transferability, particularly the strong US mediating role and non-significant EE→ESE direct effect, which may reflect Ghana's specific institutional environment. Future research should: (a) compare ESE between students with and without formal entrepreneurship training, (b) conduct longitudinal studies tracking graduates' entrepreneurial activities to establish causality and long-term effectiveness, and (c) perform cross-country comparisons within SSA to examine how institutional and cultural contexts influence these relationships.

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Authors

The contribution share of authors is as follows: James Tuffour (25%): conceptualisation, data curation, project administration, resources, supervision, writing – original draft, writing – review & editing; Albert Acheampong (25%): conceptualisation, investigation, methodology, writing – original draft, writing – review & editing; Frank Agyemang Karikari (25%): data curation, software, formal analysis, methodology, writing – original draft, writing – review & editing; and Edward Marfo-Yiadom (25%): supervision, resources, project administration, methodology, writing – original draft, writing – review & editing.

James Tuffour

Associate Professor at Burman University with over 20 years of industry and academic experience across Ghana, UK, and Canada. His research interests include sustainability accounting, small business development, corporate governance, and business history.

Correspondence to: Professor James Tuffour, School of Business, Burman University, 6730 University Drive, Lacombe, Alberta T4L 2E5, Canada, e-mail: jamestuffour@burmanu.ca

ORCID  <https://orcid.org/0000-0002-8447-7062>

Albert Acheampong (corresponding author)

Chartered Accountant currently pursuing a PhD at Anglia Ruskin University in England. His research interests include entrepreneurship, small enterprise development, and sustainable development in the extractive industry.

Correspondence to: Albert Acheampong, School of Economics, Finance and Law, Faculty of Business and Law, Anglia Ruskin University, East Road, Cambridge CB1 1PT, United Kingdom. e-mail: aa3715@pgr.aru.ac.uk

ORCID  <https://orcid.org/0009-0003-5438-3414>

Frank Agyemang Karikari

Student of Master of Applied Economics at the Northwestern Polytechnical University, China. He holds a Bachelor of Commerce in Accounting from the University of Cape Coast, Ghana. His research interests include entrepreneurship, sustainability, and energy economics.

Correspondence to: Frank Agyemang Karikari, School of Public Policy and Administration, Northwestern Polytechnical University, Xi'an, P.R. China 710072, e-mail: fkarikari@mail.nwpu.edu.cn

ORCID  <https://orcid.org/0009-0001-9638-1084>

Edward Marfo-Yiadom

Associate Professor in the Department of Accounting, University of Cape Coast, and a fellow of the Institute of Chartered Accountants (Ghana). His research interests include small business finance, working capital management, tax planning, corporate governance, and strategic management.

Correspondence to: Professor Edward Marfo-Yiadom, Department of Accounting, School of Business, University of Cape Coast, Cape Coast, Ghana, e-mail: emarfo-yiadom@ucc.edu.gh

ORCID  <https://orcid.org/0009-0001-4001-1842>

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Towards sustainable tourism: Exploring the role of entrepreneurship through an integrative review

Sanchita Bansal, Priya Nangia, Nisha Chanaliya, Dariusz Cichoń, Marek Dudek

ABSTRACT

Objective: The objective of the article is to evaluate the extant literature on tourism entrepreneurship, innovation, and sustainability, and argues for developing a more unified framework to explain these important and interconnected areas.

Research Design & Methods: The study adopted an integrative review methodology to systematically synthesise and critically evaluate the conceptual and empirical literature. We employed a structured review process involving literature selection, appraisal, and thematic integration to enable theory development and advance novel scholarly perspectives.

Findings: The study used thematic and inductive analysis and provided an aggregated insight into the six thematic areas pertinent to the tourism entrepreneurship and sustainable development nexus by aggregating them into three overarching dimensions: tourism entrepreneurship, sustainable value creation, and inclusive development. The nexus comprised sustainability perspectives, economic and social impact, entrepreneurial orientation, innovation and entrepreneurial ecosystems, entrepreneurial opportunities, and sustainable tourism development.

Implications & Recommendations: The study constitutes a powerful message for a long-term global strategy to reshape tourism from a hyper-consumptive industry into a sustainable one focused on knowledge and science tourism, nature and biodiversity preservation, and global exploration.

Contribution & Value Added: The study adds future research and policy development conceptual framework by illustrating the strategic underpinning of entrepreneurial orientation and innovation in relation to the institutions and sustainable tourism development.

Article type: literature review
Keywords: tourism entrepreneurship; tourism industry; innovation; integrative literature review; sustainable development
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INTRODUCTION

Over the years, tourism has evolved and diversified to become one of the world's fastest-growing economic sectors, comprising an increasing number of new destinations (Saura *et al.*, 2024a). Tourism has risen to the rank of a vital driver of socio-economic improvement as a result of these processes. This evolution needs entrepreneurs and new business start-ups to serve rising markets, contributing to value creation while also being sustainable (Lordkipanidze *et al.*, 2005). Sustainability has become a global issue, including environmentalism, social equity, and economic development, as many industries began to change processes and products to achieve sustainable goals, including tourism. The sector transforms dynamically because of shifting consumer preferences and the advent of new technology. The structural

transformation and transition to more experience-based products in tourism, in particular, necessitate entrepreneurial action to execute sustainable innovations (Sundbo *et al.*, 2007).

The UN Tourism (formerly United Nations World Tourism Organization) defines sustainable tourism as being linked to the environmental, economic, and socio-cultural issues underlying tourism development (UNWTO, 2016). The UN Tourism's goals include enhancing the living standards of the host people in the short and long term, meeting the needs of tourists, and protecting the natural environment (Işık *et al.*, 2022). There are two schools of thought on sustainable tourism, as there are in most study theories and fields. According to researchers on the opposing side of sustainable tourism, sustainability is not always applicable in tourism because there are too many competing interests and trade-off judgements that prioritise certain interests over others (Ratten, 2020). The number of tourists, meaning the number of people who can be successfully accommodated, remains a critical concern for the detrimental consequences of excess tourism on the destination's sustainability (Nguyen *et al.*, 2020). While admitting the problems, many researchers contend that sustainable tourism is attainable in all destinations, for both mass and small-scale tourism, because sustainability is a long-term goal regardless of scale. To attain this goal, destinations must reconsider tourism's goals and shift away from selfish, individualistic, and hedonistic goals and instead allow tourism to serve as a facilitator of education, cross-cultural engagement, ecological appreciation, and spiritual development (Bichler *et al.*, 2020).

With these two schools of thought in mind, as well as the recent COVID-19 outbreak, new obstacles have arisen in the pursuit of sustainable tourism growth (Streimikiene *et al.*, 2021). With this in view, we may suppose that tourism planning and development should be done consciously, sustainably, and in terms of new and cutting-edge concerns, challenges, policies, and strategies. Scholarship in this vital area is evolving at a rapid pace. To that end, most research into sustainability in the sector is contemporaneous or forward-looking (Job *et al.*, 2017), albeit recent works consider the development and history of sustainable tourism by analysing the role of entrepreneurs in this process (Jones *et al.*, 2016).

Prior studies attempted to summarise the available literature on the topic. For instance, in a more or less descriptive, bibliometric manner, Andrade-Valbuena *et al.* (2022) provide an overview of economic well-being with environmental, social, and cultural sustainability in the field of hospitality and tourist research. Belias *et al.* (2022) conducted another systematic study, examining the effect of social tourism entrepreneurship on the sustainability of the tourist industry. However, analysing just 20 publications on the topic appears insufficient to make any substantial advancements in the field. While Ratten (2020) discusses tourist entrepreneurship research, she does not address sustainability, whereas Santos *et al.* (2021) discuss sustainability and innovation, but do not address entrepreneurship. Given these startling results and the lack of a holistic strategy, it is clear that additional study is needed in this area, which follows the increasing interest in sustainable industries as a whole. Indeed, there are several significant gaps in our understanding, such as the unique motivations, challenges, preferences, and benefits that various parties would encounter, such as governments, public and private sector enterprises, or individuals.

To address these research gaps and integrate the fragmented findings of the previous literature, we aimed to evaluate the relevance of global tourist entrepreneurship, concentrating on the roles of innovation and sustainability in this sector, and how entrepreneurial possibilities in tourism and entrepreneurial orientation contribute to sustainable tourism growth. This article's novelty lies in our conceptualisation of entrepreneurship as a transformative mechanism for achieving sustainable tourism by integrating economic, environmental, and social dimensions into a unified framework, thereby moving beyond the fragmented and sector-specific approaches prevalent in existing literature. By highlighting novel hypotheses and challenges for the development of sustainable tourism enterprises, the current article hopes to give direction for future research. Based on study results, we may write that a new, worldwide strategy for sustainable tourism is necessary to create a robust future path. The current article advances the theoretical understanding of sustainable tourism by synthesising entrepreneurial orientation and innovation ecosystem perspectives within sustainability transition frameworks. The article views entrepreneurship as a major force behind innovation-led sustainability in tourist systems, building on recent extensions of entrepreneurial orientation and sustainable entrepreneurship (Kraus *et al.*, 2018). Addition-

ally, the study findings contribute to how entrepreneurial ecosystems facilitate the co-creation of economic and social value through institutional support and resource integration, drawing on sustainability transitions and ecosystem-based approaches (Geels, 2019). The synthesis in this article contributes to theory by linking micro-level entrepreneurial processes with macro-level sustainability outcomes, particularly in emerging domains such as rural and inclusive tourism development.

The article achieves its objective by finding answers to two key questions: how entrepreneurial opportunities in the tourism sector shape entrepreneurial orientation and contribute to sustainable tourism development, and how innovation and socio-economic engagement transform tourism entrepreneurship into broader sustainability outcomes at both firm and destination levels. We examined the literature on tourist entrepreneurship, including a focus on sustainable practices, and an examination of the factors that have contributed to the expansion of this field. We project the literature in several ways, including a thematic map, and an inductive analysis using aggregate dimensions. The thematic map highlights six key areas, including 'sustainability perspectives,' 'economic and social impact,' 'entrepreneurial orientation,' 'innovation and entrepreneurial ecosystem,' 'entrepreneurial opportunities in tourism,' and 'sustainable tourism development.' We studied the literature to integrate these themes into aggregate dimensions, namely 'tourism entrepreneurship,' 'sustainable value creation,' and 'inclusive development.' Through thematic and inductive analysis, we have also presented a conceptual framework demonstrating how entrepreneurial opportunities in the tourism industry lead to an entrepreneurial orientation and, when combined with disruptive innovation and the industry's socio-economic impact, can contribute to the industry's long-term sustainability.

MATERIAL AND METHODS

To produce new theoretical frameworks and viewpoints, we based our research approach on a comprehensive review strategy of integrative review (Bansal *et al.*, 2022; Klarin & Suseno, 2021). Unlike a standard systematic literature review (SLR) that primarily aggregates existing data, an integrative review approach exponentially expands the corpus of research by offering a conceptual framework and identifying future research prospects based on our theme and inductive analysis (Lim *et al.*, 2024). Although our results are based on bibliometric data (such as the number of publications and citations over time) to visualise the intellectual structure of the field, we based them primarily on an integrative review, providing the more thorough theoretical interpretation required for identifying future research opportunities.

Data Collection

For this study, our primary database was the Web of Science (WoS) Core Collection. Even though Scopus has a wider coverage of the social sciences citation index, we prioritised WoS because of its stringent indexing criteria and highly impactful metadata necessary to ensure the quality of sampled literatures in a transdisciplinary field in sustainable tourism entrepreneurship (Martín-Martín *et al.*, 2018). Using a PRISMA diagram, we have illustrated the entire data-collection process (Figure 1). We conducted the search in January 2026. We divided the entire process into four steps: identification, screening, eligibility, and inclusion. Using search terms such as tourism and entrepreneur* and 'sustainabl*', we identified 838 articles during the identification phase. Following the initial screening, we eliminated 57 records based on article type (we selected only article and review articles), leaving us with 781 articles. We then refined the database again to include only English-language articles, resulting in the removal of eight articles. To ensure thematic precision, we refined the subject category to focus on pertinent areas: management, business, economics, environmental studies, and sociology, which led to the exclusion of 425 articles. We assessed the remaining 348 articles for relevance based on their titles, abstracts, keywords, and the unavailability of full-text, leaving us with 311 articles for the final analysis.

Data Analysis

For the purpose of data analysis, we used a hybrid analytical approach to find out the intellectual structure of the field. We manually reviewed each of the 311 publications to provide a deeper understanding of the intellectual structure of the field of tourism entrepreneurship and sustainability, from which we

draw conclusions and recommendations for future study and policy. In line with grounded theory, we distilled and coded our concepts by grouping them into themes based on their prevalence and growth over the last two decades in the literature (Nangia *et al.*, 2023). To reduce subjectivity in thematic mapping, based on co-occurrence frequencies, we evaluated the themes according to their 'centrality' (the strength of links to other clusters) and 'density' (the internal strength of a cluster's tie). We were then able to classify themes into four sections: 'motor' (good development and core), 'fundamental' (core, but basic design), 'niche' (specialised), and 'emerging/declining.' We identified six notable themes, namely, sustainability perspectives, economic and social impact, innovation and entrepreneurial ecosystem, entrepreneurial orientation, entrepreneurial opportunities and tourism, and sustainable tourism development. The integration of thematic analysis allows for a comprehensive identification of both established and emerging research directions in the field. Thematic analysis not only improves the reliability of the intellectual structure identified but also ensures a balanced and holistic interpretation of the evolving literature. We further studied these themes to integrate them into three aggregate dimensions: innovation and entrepreneurial ecosystem, entrepreneurial orientation, and economic and social impact. The key result was the proposed conceptual framework for understanding how entrepreneurial opportunities in tourism and entrepreneurial orientation lead to sustainable tourism growth. The derived themes and subthemes contribute to a broader and more nuanced understanding of the research topic. Consequently, the article offers a solid foundation for future empirical and theoretical advancements in sustainable tourism and entrepreneurship research (Figure 1).

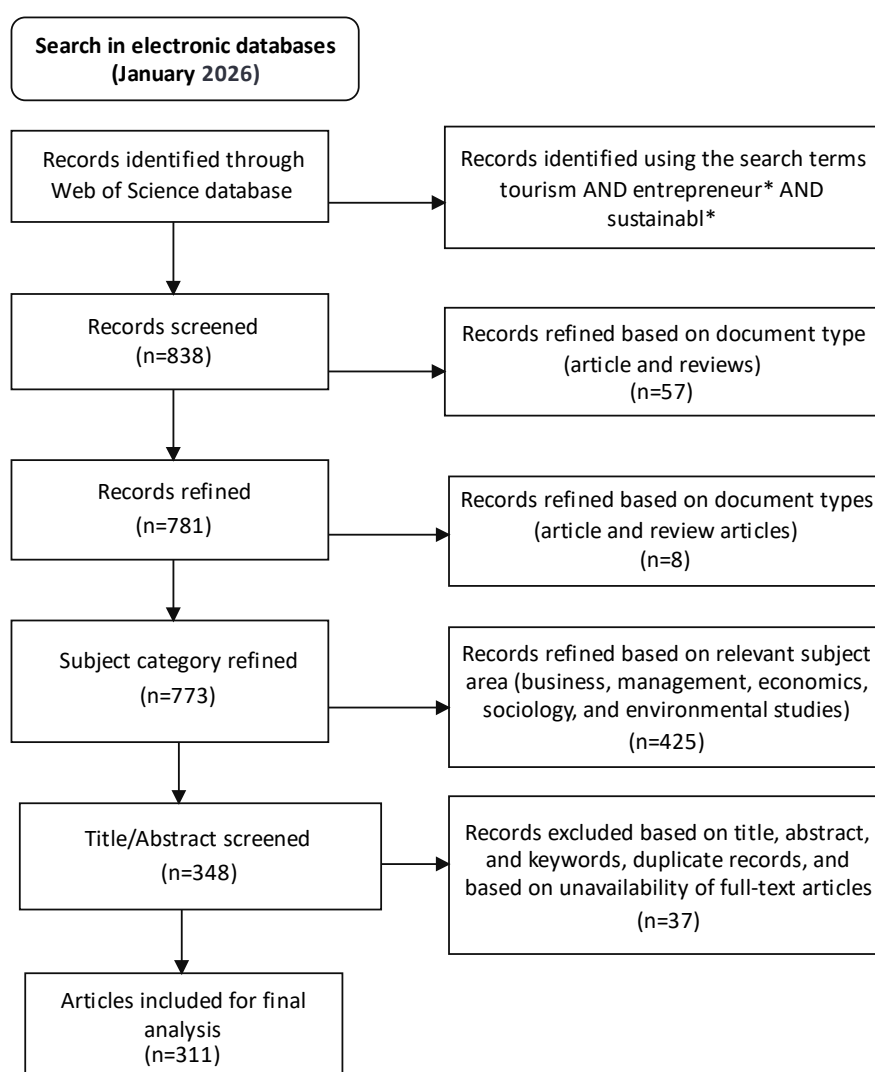


Figure 1. PRISMA diagram

Source: own elaboration.

Publication Growth and Citations

Figure 2 shows the trend in the number of published articles with respective study-related citations annually from 2004 until 2026. Darker orange bars represent total citations, while the blue line shows the number of articles published each year. At the top of the early years (2004-2014), we see a relatively low publication activity, but some articles were cited more than others and some received occasional citation spikes. A general increase in the number of publications began in 2015, followed by a peak in 2021, indicating an emerging academic interest in the area of sustainable tourism entrepreneurship. Over this period, there was also a notable increase in total citations, especially for the years 2019 and 2020, indicating that research published in these years received significant attention from scholars. Nonetheless, citations drop from 2022 to 2026. Much of this reflects the smaller citation window for new publications than any collapse in research quality or relevance. The expanding body of literature in the subject of sustainable tourism entrepreneurship underlines the potential for study in tourist entrepreneurship with a greater proportion of women (Figueroa-Domecq *et al.*, 2020), lifestyle tourism entrepreneurs (Bredvold & Skålén, 2016), tourism businesses (Jørgensen *et al.*, 2021), etc.

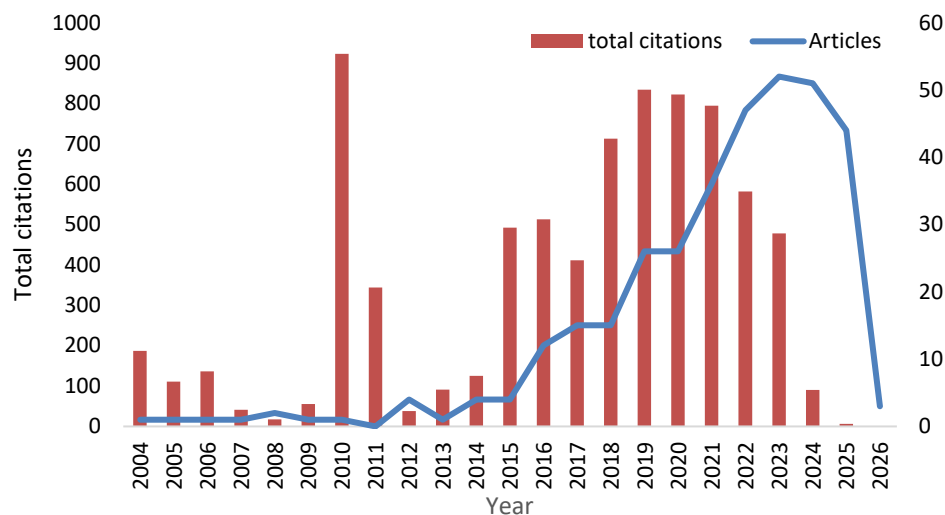


Figure 2. Growth over the years

Source: own elaboration.

LITERATURE REVIEW AND THEORY DEVELOPMENT

Recent tourism literature increasingly highlights entrepreneurial potential as a fundamental strategy for fostering rural economic development and sustainable tourism results. Empirical research from rural tourism contexts demonstrates that tourism entrepreneurship fosters job creation, income generation, and economic diversification by allowing communities to leverage local cultural and natural resources (Utami *et al.*, 2023). These entrepreneurial ventures bolster rural economies by diminishing reliance on conventional livelihoods and promoting locally integrated business activity. Moreover, entrepreneurship centred on tourism has demonstrated the capacity to provide extensive socio-economic effects in rural locales. Tourism entrepreneurship fosters inclusive rural development by augmenting employment prospects and invigorating local economic engagement. Such prospects are especially pertinent in areas experiencing structural economic limitations, where tourism offers alternative revenue sources and bolsters community resilience (Ramaano, 2023). These results underscore the significance of entrepreneurial prospects in tourism as a strategy focused on development rather than merely a market-driven endeavour.

A recent body of work examines the role of tourism entrepreneurship in enhancing women's economic engagement and social inclusion. Research indicates that tourism provides accessible entrepreneurial opportunities for women owing to less capital demands and adaptable business

frameworks (Koliouska *et al.*, 2023). The involvement of women in tourist entrepreneurship correlates with increased household income stability and elevated social standing, hence strengthening the social impact aspect of entrepreneurial opportunities in tourism (Vujko *et al.*, 2024). Opportunities for entrepreneurship in tourism are intricately associated with the cultivation of entrepreneurial orientation among local stakeholders. Entrepreneurial orientation, characterised by innovativeness, proactiveness, and risk-taking, empowers tourism entrepreneurs to identify market opportunities and adjust to changing tourist demand (Batista *et al.*, 2022). Empirical evidence demonstrates that locations with vibrant tourism entrepreneurship show elevated innovation and competitiveness, as entrepreneurs consistently enhance products and services to distinguish their offerings (Burton *et al.*, 2025). The innovation and entrepreneurial environment prove crucial for enhancing entrepreneurial orientation in tourism destinations. Recent research highlights the significance of institutional support, legislative frameworks, and collaborative networks in promoting entrepreneurial activity (Batista *et al.*, 2022). Access to training, financial resources, and knowledge-sharing platforms augments entrepreneurs' ability to innovate and adopt sustainable business methods, hence strengthening the correlation between entrepreneurial orientation and long-term destination performance (Bonfanti *et al.*, 2024). The economic and social effects of tourism entrepreneurship further strengthen entrepreneurial attitude. Favourable economic results, including elevated income and job generation, bolster community support for tourist development and encourage ongoing entrepreneurial participation (Alvarez-Sousa, 2018). Recent literature increasingly associates entrepreneurial orientation with sustainable tourism development.

The above studies offer robust evidence for a structured relationship wherein entrepreneurial opportunities in tourism promote entrepreneurial orientation resulting in sustainable tourism development. This cohesive viewpoint strongly corresponds with current tourism research that highlights sustainability driven by entrepreneurship in rural and community-oriented locations. Despite the growing recent evidence linking entrepreneurial opportunities, entrepreneurial orientation, and sustainable tourism development, the literature remains limited in empirically examining their integrated relationships within a single framework that would simultaneously capture innovation ecosystems and socio-economic impacts in rural tourism contexts – a gap that the present study directly addresses.

DISCUSSION

Thematic Findings

As shown in Figure 3, we manually analysed the evaluated literature to generate a strategic/thematic map of the field. We divided the map into four sections, labelled 'motor,' 'fundamental/basic,' 'niche,' and 'emerging/declining.' Centrality represents how well one topic relates to other themes, while density illustrates how many connections exist between individual themes (Aparicio *et al.*, 2019; Murgado-Armenteros *et al.*, 2015). Six main concepts stood out, we chose them chosen for their significance and growth rate.

The key themes that refer to bandwagon elements vital to the field remain insufficiently explored. The underlying ideas may have been explored extensively in the past, or they may have great promise as future driving ideas. Fundamental concepts better characterise the heart of the study field: the 'sustainability perspective' and the 'economic and social impact' are the two major topics of our strategic diagram. One of the most significant themes to emerge from the literature was the 'sustainability perspective,' which includes terms like 'nature tourism,' 'lifestyle entrepreneurs,' 'resources,' 'risk management,' and 'eco-tourism.' These themes are important because, until now, authors have highlighted both the positive and negative effects that tourism may have on sustainability. Overcrowding, disruption of local economies, and harm to the natural environment are just a few examples of how tourism may negatively affect a location (Maldonado-Erazo *et al.*, 2022). The many positive effects on a destination include new jobs development, protection of historic buildings and sites, cultural artifacts interpretation, and restoration of natural habitats for native species (Terkenli & Georgoula, 2022). According to García-Gallo *et al.*'s research (2021) on intangible assets along with economic and financial differences between tourism startups by region and by sector of activity

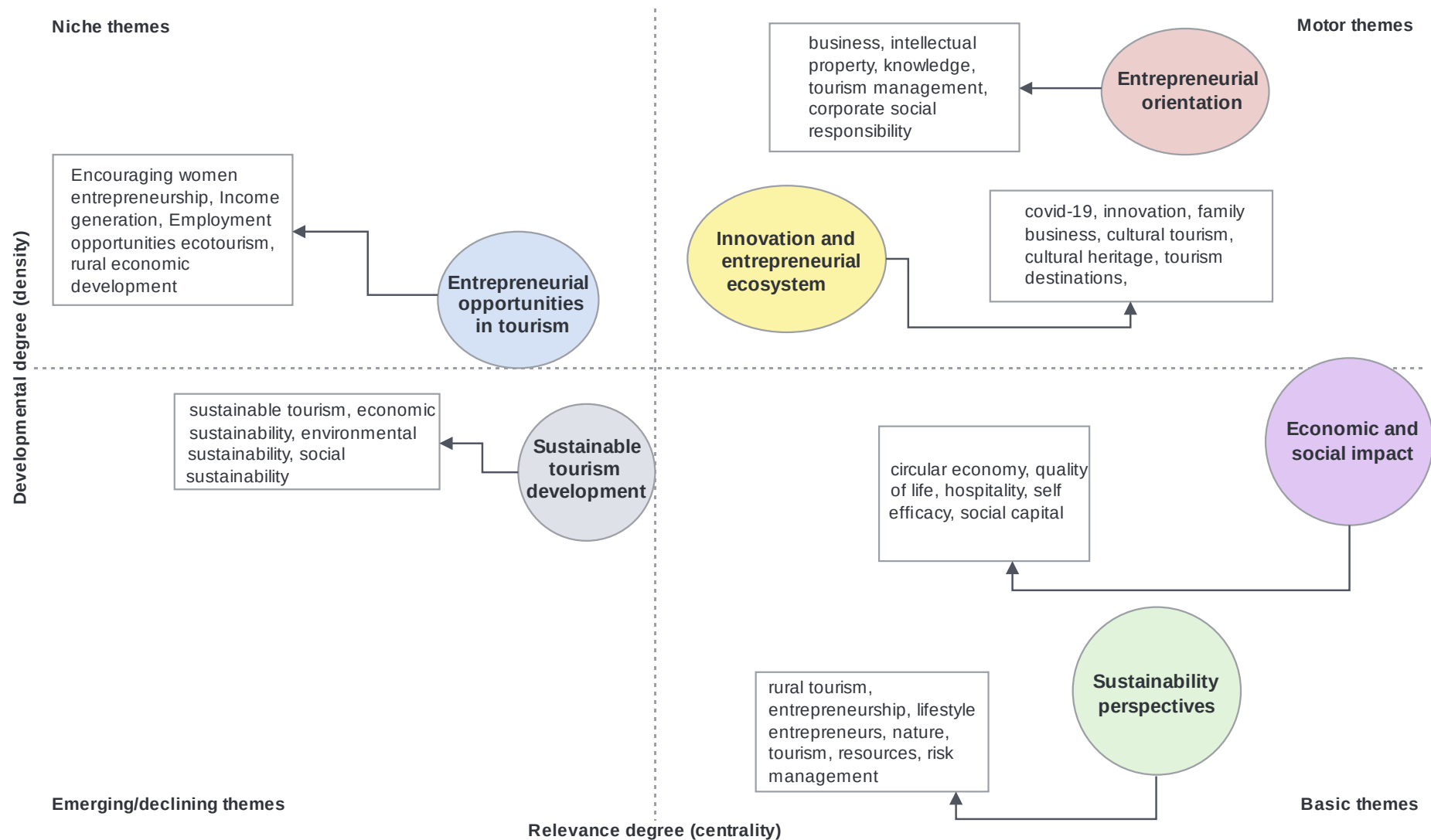


Figure 3. Thematic map

Source: own elaboration.

to determine their sustainability both in a situation of economic crisis and growth, investment in intangibles along with economic and financial sustainability constitute key variables in any of the crises situations such as the COVID pandemic. Contrarily, Pérez-Calderón *et al.* (2020) examined users' perspectives on the long-term viability of places like national parks in their immediate vicinity, finding verified strong correlations between users' perceptions of economic development and quality of life but not social development. Scholars also observed that in contrast to large conglomerates, small businesses are actively engaged in accepting responsibility for being sustainable (Font *et al.*, 2016). Furthermore, recent articles highlight the role of adaptive management and stakeholder coordination in balancing conservation and commercialisation (Alegre & Berbegal-Mirabent, 2016; Glowka & Zehrer, 2019; Ryan, 2002), particularly in fragile destinations. Sustainability is no longer treated as an external constraint but as a strategic resource, enabling differentiation, legitimacy, and long-term competitiveness for tourism entrepreneurs. The growing intersection of sustainability with innovation suggests a shift towards proactive sustainability strategies rather than compliance-driven approaches.

'Economic and social impacts' are another overarching theme; related terms include 'circular economy,' 'quality of life,' 'hospitality,' 'self-efficacy,' and 'social capital.' The integration of circular economy principles introduces new measurement dimensions, linking waste reduction, resource efficiency, and social well-being. Thus, this theme bridges entrepreneurship research with development studies by highlighting how tourism ventures shape not only growth but also social cohesion and institutional trust (Guerra & Gonçalves, 2024; Saura *et al.*, 2024b). Furthermore, the estimation of how a community could alter in response to an uptick or dip in tourism activity makes this subject even more vital. Depending on how it is organised and promoted, tourism can significantly contribute to a region's social, cultural, and economic well-being. The economic health of an area or even a country is directly impacted by tourism (Ferreira *et al.*, 2021). Cohen (1984) argues that tourism has generally acknowledged favourable impact on foreign exchange, income, employment, distribution of benefits, pricing, ownership and control, regional development, and government revenues (Isik *et al.*, 2018; Piuchan *et al.*, 2018). Foreign direct investment, enhanced infrastructure, and economies of scale all contribute to lower manufacturing costs as a result of tourism (Arain *et al.*, 2020). Long after researchers began scrutinising economic effects of tourism, they analysed the broader social and cultural ripples that make the byproduct of locals' direct and indirect interactions with visitors. According to studies, the behaviours, customs, social lives, beliefs, and values of non-nationals in a particular community impact the connection between locals and visitors (Almeida García *et al.*, 2015).

Motor Themes

The themes in the motor quadrant are the most fundamental to the organisation of the knowledge base, and their development has progressed further than any other. Two main themes, 'entrepreneurial orientation' and 'innovation and entrepreneurial ecosystem,' drive this research base's strategic map. The number of studies on a topic is reflected by the size of the sphere used to depict it. The most developed topic is 'entrepreneurial orientation,' which includes the phrases business, intellectual property, knowledge, tourist management, corporate social responsibility, and so forth. Many business possibilities arise as a result of the wide range of services, facilities, and attractions that form the tourism industry. The tourism sector is widely recognised as a major economic driver and employer in a wide range of global locations. Entrepreneurial orientation (EO) and its characteristics have been studied in the context of the travel sector. Fadda (2018) conducted a test to determine if EO dimensions are significant determinants of firm performance and which EO dimension exerts the strongest effect, and found that innovativeness, proactiveness, and autonomy were significantly associated with tourism firm performance, while risk-taking and competitiveness were not. Employee autonomy is the most essential feature to explain the performance of tourist enterprises, followed by inventiveness and proactivity. This theme represents the strategic posture and behaviour of tourism entrepreneurs. It includes risk-taking, innovation, and proactiveness traits often associated with successful entrepreneurial ventures. It is central because it underpins many tourism strategies, especially in dynamic and competitive destinations. The inclusion of intellectual property and corporate responsibility shows that

today, entrepreneurship in tourism requires ethical, responsible, and knowledge-based decision-making (García-Gallo *et al.*, 2020; Sarabia-Molina *et al.*, 2022). Furthermore, EO interacts with contextual factors such as destination maturity and regulatory frameworks, challenging the assumption of universally positive effects. Furthermore, the incorporation of ethical orientation and responsible leadership signals an evolution of EO theory towards more socially embedded forms of entrepreneurship, particularly relevant in tourism contexts where social legitimacy is critical (Ruiz-Ortega *et al.*, 2021).

There are several terms associated with the second motor theme, 'innovation and entrepreneurial ecosystem,' including such sub-themes as 'COVID-19,' 'innovation,' 'family business,' 'tourist destinations,' 'green innovation,' and 'eco-innovation.' Previous studies examined how far the tourist industry has come in terms of sustainability and new ideas. Like many others, the tourist business saw the effects of the current pandemic outbreak, which has slowed the progress towards more environmentally friendly innovations. According to Crespi-Vallbona and Mascarilla-Miró (2021), tourism is one of the activities most desperately in need of innovation to keep its growth. It is also important to learn how established tourist spots and their management discover novel approaches to everyday problems to sustain the industry's upward trajectory. Recent inventions, such as green and eco-innovations, have been shown to directly contribute to lowering the travel industry's carbon emissions. While green innovation has a beneficial effect on the hotel industry's sustainability performance through antecedents such as environmental legislation, green innovation strategy, and green organisational culture (Asadi *et al.*, 2020), business model innovation (BMI) directly contributes to sustainability in the tourism and hospitality sphere, as visitors seek tourism activities with creative and sustainable themes (Presenza *et al.*, 2019). Furthermore, BMI reflects the systemic support structure that enables tourism innovation, including family-run enterprises and cultural tourism, which are important components of tourism resilience, especially during disruptions like the COVID-19 pandemic.

Niche Theme

One major theme emerged in the upper left quadrant, sometimes known as the niche themes, namely 'entrepreneurial opportunities in tourism.' This theme included the phrases encouraging women entrepreneurs, income generation, employment opportunities, and rural economic development. The themes in this area are considered to be on the periphery or in a specific niche since they have strong internal ties but few external ones. As one of the world's fastest-growing industries, tourism is propelled not just by people's basic necessities and their insatiable wanderlust but also by the commercial opportunities that arise from satisfying people's ever-evolving desires and curiosity (Nikraftar & Hosseini, 2016). Opportunity creation in tourism is increasingly linked to social innovation, particularly in peripheral and rural regions where tourism serves as a development catalyst. However, the weak integration of this theme with ecosystem and innovation research suggests a missed opportunity to theorise how inclusive entrepreneurship can be structurally supported (Dote-Pardo *et al.*, 2025). Researchers are coming to the conclusion that opportunity identification is the defining characteristic and foundational feature of entrepreneurs as they dig more into the field of empirical entrepreneurship studies (Bichler *et al.*, 2020; Çiçek *et al.*, 2019). Employment possibilities for both rural and urban residents, as well as new sources of revenue, are generated as a consequence of the growth of tourism-related enterprises, which in turn contributes to economic expansion.

Emerging/declining Theme

This research premise yields just one issue, which is 'sustainable tourism development.' The themes in this area are either just starting to emerge or decline, due to weak internal relationships and few exterior connections. Based on our research, we expect this theme to evolve into either a basic or motor theme. Because of its rising economic, social, and cultural significance at both the national and international levels, the tourism industry presents promising opportunities for long-term, equitable progress (León-Gómez *et al.*, 2021). There is a substantial body of research that illustrates the many impacts of tourism (Farzanegan *et al.*, 2021; Niñerola *et al.*, 2019; Rasoolimanesh *et al.*, 2020), since the economic relevance and expansion of the tourist industry is a topic of great worth today. Similarly, sustainability is important

in the tourist industry because it is viewed as a means to meet the demands of all parties involved, regardless of industry (Liu *et al.*, 2018). Therefore, the tourist industry is always worried about its future and its potential to expand (Asmelash & Kumar, 2019; Cucculelli & Goffi, 2016; Manzoor *et al.*, 2019).

Strategic Insights for Tourism Entrepreneurship

We examined each publication separately to identify keywords or first-order concepts employed in that research as shown in Figure 4. Next, we combined these keywords to form six distinct themes (second-order themes): ‘entrepreneurial opportunities in tourism,’ ‘innovation and entrepreneurial ecosystem,’ ‘sustainable tourism development,’ ‘sustainability perspective,’ ‘entrepreneurial orientation,’ and ‘economic and social impact.’ Furthermore, combining these themes yielded the following aggregate dimensions: tourism entrepreneurship, sustainable value creation, and inclusive development. Aggregate dimensions reflect a synthesis of the study’s topics and concepts (Thomas & Tee, 2022).

Tourism Entrepreneurship

Tourism entrepreneurship refers to the process by which individuals or groups recognise, exploit, and innovate around opportunities within the tourism sector to create value (Zeng *et al.*, 2024). This dimension encompasses both the identification of unmet needs in tourism and the creation of products, services, or systems that respond to evolving demands of tourists and host communities alike. Tourism entrepreneurship includes themes entrepreneurial opportunities in tourism and innovation and entrepreneurial ecosystem, covering the creation of new business models such as rural homestays, women-led ecotourism ventures, and community-based tourism. Tourism entrepreneurship emphasises opportunity recognition, resource mobilisation, and market development in underutilised regions (Dias *et al.*, 2025). Furthermore, in innovation, tourism entrepreneurship involves the role of digital tools, cultural heritage valorisation, and post-pandemic resilience strategies in nurturing an ecosystem that supports entrepreneurial ventures (Mahato *et al.*, 2021). Moreover, tourism entrepreneurship emphasises how creativity, institutional support, and networks contribute to a thriving tourism-based entrepreneurial culture (Mzembe *et al.*, 2019). Thus, tourism entrepreneurship constitutes a powerful mechanism to diversify local economies, reduce dependence on traditional sectors, and stimulate creative industries (Moyle *et al.*, 2020). Moreover, it encompasses strategic thinking, adaptability, and the ability to respond to market trends or external disruptions such as global pandemics or climate change.

Sustainable Value Creation

Sustainable value creation encapsulates the imperative for tourism to go beyond short-term profits and instead contribute to the long-term well-being of environmental, economic, and socio-cultural systems. This dimension reflects the integration of sustainable development principles into tourism strategies and operations. It encapsulates how tourism can drive economic growth while preserving ecological and cultural integrity (Henche *et al.*, 2020). Sustainable value creation integrates sustainable tourism development and a sustainable perspective. It focuses on economic, environmental, and social sustainability that emphasises practices like eco-certification, conservation tourism, green infrastructure, and responsible resource use. Moreover, sustainable value creation broadens the lens by including risk management, rural resource allocation, and holistic approaches to the long-term viability of tourism destinations. This dimension promotes the idea that tourism should not deplete the very resources it depends on (Escoto *et al.*, 2019). Instead, sustainable value creation should regenerate ecosystems, empower communities, and create enduring value for both tourists and host populations (Sarabia-Molina *et al.*, 2022). It encourages tourism stakeholders – entrepreneurs, governments, NGOs, and tourists – to adopt sustainable practices that ensure the tourism system remains resilient, regenerative, and inclusive (Salem *et al.*, 2023). Furthermore, sustainable value creation transforms tourism from a consumptive industry to a constructive force for sustainable development. Hence, together, these themes contribute to regenerative tourism, which not only minimises harm but actively works to revive ecosystems, enhance cultural heritage, and build resilient local economies.

Inclusive Development

Inclusive development captures the social equity and participatory aspects of entrepreneurship within the tourism sector. It reflects how tourism-led entrepreneurship can lead to broad-based economic growth while addressing social disparities and promoting human well-being (Escoto *et al.*, 2019). This dimension brings together the entrepreneurial orientation, such as knowledge development, innovation capacity, and responsible risk-taking and the economic and social impacts that improve life quality, foster community development, and promote justice. Furthermore, inclusive development acknowledges that tourism should not benefit only a few but must create opportunities for underrepresented and marginalised groups, including women, indigenous communities, rural residents, and informal workers (Dragin *et al.*, 2024). It ties economic growth to social outcomes, ensuring tourism is a tool to improve life quality, foster community development, and promote justice (Maziliauske, 2024). By integrating these two themes, inclusive development as a dimension addresses the disparities in opportunity, income, and access in the tourism economy. It envisions tourism not just as a business sector but as a catalyst for human development, fostering equity, dignity, and agency among all stakeholders.

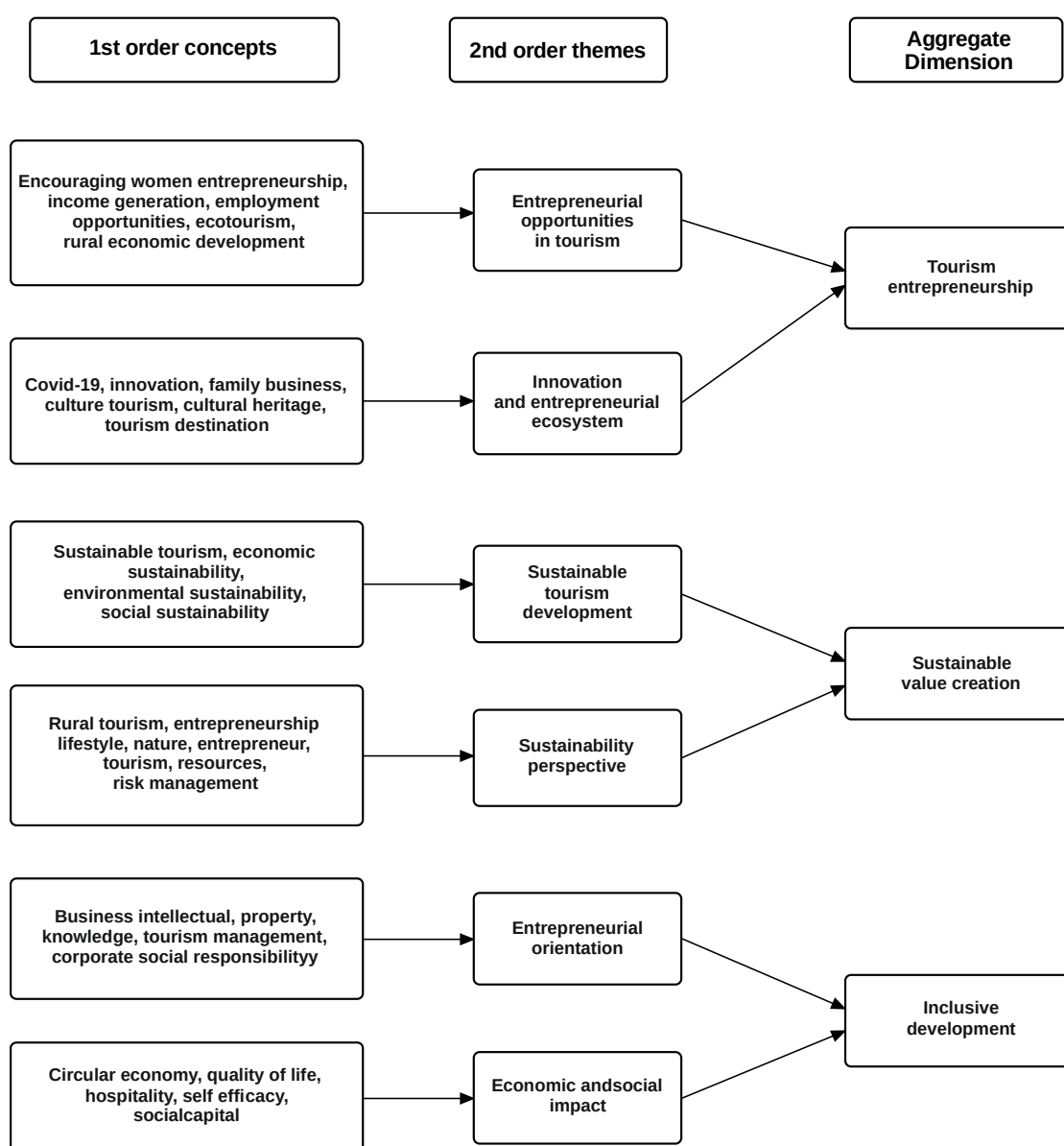


Figure 4. Strategic insights for tourism entrepreneurship

Source: own elaboration.

Conceptual Framework

In Figure 5, the conceptual framework synthesises the study findings and demonstrates how we addressed the research questions by illustrating the interrelationships among entrepreneurial opportunities, entrepreneurial orientation, innovation, socio-economic engagement, and sustainable tourism development. The people who start businesses are the ones that fuel the entrepreneurial spirit in any country, which is why entrepreneurship is often considered a national asset. Entrepreneurship is a dynamic process that may develop wealth and also produce value for people's benefit. On the other hand, tourism is vital to the country's progress since it affects not only the economy but also the social and moral values of the population. Businesses centred on providing memorable experiences for tourists are flourishing as a result of a recent emphasis on encouraging entrepreneurship. Furthermore, expansion of tourism businesses can bring economic benefits to any country. Revenue is generated through tourist taxation, foreign exchange is generated, the balance of payment concerns are eased, the economy is diversified, and new jobs are created, especially in rural and distant regions. The conceptual framework is theoretically grounded in institutional and ecosystem perspectives, which argue that entrepreneurial outcomes in tourism are shaped by the interaction between market opportunities, institutional support, and contextual constraints (Bradley *et al.*, 2021). By explicitly linking entrepreneurial orientation with disruptive innovation and socio-economic embeddedness, the study moves beyond linear entrepreneurship-growth models and offers a multi-level extension that explains how tourism entrepreneurship can generate sustainability-oriented outcomes at both firm and destination levels. This perspective complements and advances prior tourism entrepreneurship research by incorporating sustainability as an emergent property of entrepreneurial ecosystems rather than as a predetermined policy goal.

Consistent with the existing literature, we argue that the presence of entrepreneurial opportunities in the tourist industry fosters an entrepreneurial orientation which – when combined with disruptive innovation and socio-economic activities – may pave the way for sustainable tourism development. Numerous studies, such as those by Dominiak and Wantoch-Rekowski (2009), Thapa Karki and Xheneti (2018), and Szirmai *et al.* (2011) demonstrated the correlation between entrepreneurship and economic growth. More than ever before, the innovativeness, risk-taking, proactivity, aggressiveness, and employee autonomy that make up an entrepreneurial orientation prove key to a successful tourist business and a window into the industry's future. Regarding rural development, it is important to have an entrepreneurial approach that prioritises supporting local entrepreneurs so that people may keep their hard-earned money in their own neighbourhoods. Today, what's needed is a setting that promotes the growth of responsible entrepreneurship, with the needs of sustainable development as a starting point. Moreover, while earlier articles such as Wang *et al.* (2022) emphasise the economic benefits of tourism expansion through foreign exchange earnings, tax revenues, and employment generation, the current article advances this perspective by highlighting local value retention and community-based entrepreneurial activity as critical pathways to sustainability. This finding aligns with rural entrepreneurship and community development literature but diverges from growth-centric tourism models by explicitly linking entrepreneurship with social inclusion and environmental responsibility.

Entrepreneurship's potential for good effects on a region's economy, society, and environment provides one rationale for the connection between the tourist industry and sustainable development. Sustainable growth may be achieved through developing tourist entrepreneurship, bolstering culture and identity, diversifying tourism activities (including rural tourism activities), retaining rural residents, and reducing the negative environmental consequences of the tourism industry. Moreover, the EU enterprise policy strategy asserts that businesses, in particular, can aid in sustainable development by adopting corporate social responsibility (CSR), a concept wherein businesses voluntarily incorporate social and environmental concerns into their business operations and their interactions with their stakeholders. Public authorities play a crucial role in encouraging the tourist industry to embrace CSR, especially in terms of encouraging the industry to promote socially and environmentally responsible activities. Entrepreneurship has become a boon to the tourist sector to

protect the environment, benefit local economies, and foster long-term growth in these areas, all of which are essential to the nation's overall success.

While the proposed framework emphasises opportunity-driven tourism entrepreneurship as a pathway to sustainability, it also acknowledges alternative perspectives that question growth-led tourism models. Insights from tourism degrowth and sustainability paradox literature suggest that entrepreneurial expansion may generate trade-offs between economic benefits and environmental or social limits, particularly in fragile destinations. Similarly, community-based entrepreneurship – although often promoted as inclusive – may face constraints related to power asymmetries, capacity gaps, and uneven benefit distribution, which are incorporated as boundary conditions within the framework.

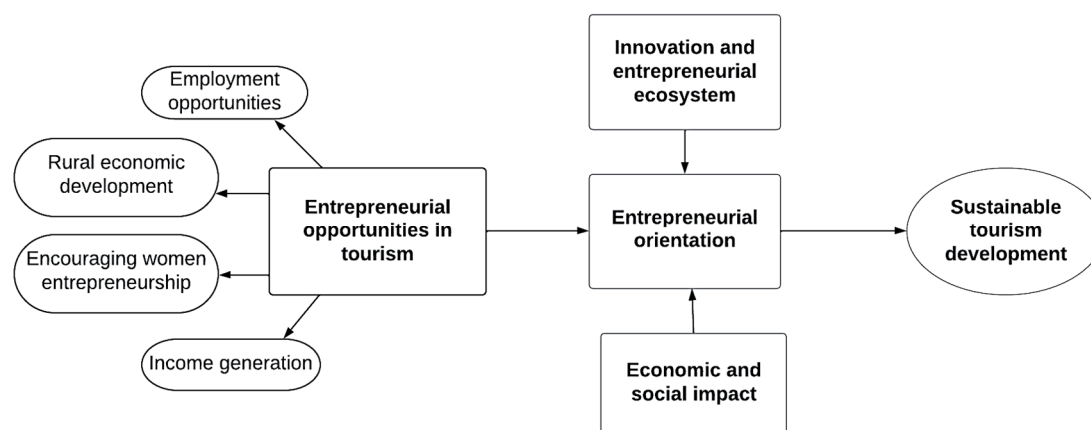


Figure 5. Conceptual framework

Source: own elaboration.

Future Research Directions

Table 1 details the topics that emerged from the analysis and will inform our future research. Given the rising emphasis on sustainability in the tourist sector, future researchers should investigate the relationships between tourism entrepreneurship and local economic growth, as well as examine entrepreneurship as a tool for sustainable development in tourism destinations, analysing the potential of entrepreneurship to establish more sustainable tourism businesses. There is also a need for investigating how to reduce tourism's social and environmental consequences, as well as the role that entrepreneurship and sustainability in the sector play in this process. Further possible areas of study include how technology may help tourist entrepreneurs build more sustainable firms, what it takes to launch a successful sustainable tourism venture, and how much of an impact tourism entrepreneurs can have on local economies. Moreover, researchers should study if and how technological developments affect the initiative and creativity of tourist business owners. Not to mention that the use of AI and data analytics to develop novel tourist enterprises is another area that might benefit from the field of study.

Scholars may also investigate sharing economy prospects and threats, tourist entrepreneurs' access to untapped markets, and innovative approaches to gaining a competitive edge. Future research should determine the extent to which cultural influences affect tourist entrepreneurship, as well as how cultural values and traditions affect the entrepreneurial process and the success of the tourism industry as a whole. This may entail investigating the impact of local communities on tourist entrepreneurship or looking at the ways in which local cultures and traditions affect the growth of tourism businesses. Furthermore, researchers should investigate the resilience and creativity of the tourist industry in the face of the COVID-19 pandemic. To effectively establish policies and strategies to assist tourism entrepreneurship, we need to understand the dynamics of the global tourism sector, visitor motives and values, and the role of governments in regulating and promoting tourism.

Table 1. Future research directions

Research themes	Future research questions
Sustainability perspective	– What new business models may be developed to encourage sustainability and tourist entrepreneurship? – What role do community members play in creating and sustaining tourist projects that prioritise sustainability? – To what extent do entrepreneurs in the tourist industry play a part in advancing environmentally friendly policies and bringing about constructive change?
Economic and social impact	– Does tourism entrepreneurship help boost the local economy? – What effects does tourist entrepreneurship have on society, economy, and culture? – What is the impact of tourism entrepreneurship on local communities, companies, and the environment? – What is the potential for tourist entrepreneurs to create jobs and support economic development?
Entrepreneurial orientation	– What are the difficulties and opportunities for tourist entrepreneurs and the best strategies for conquering them? – What entrepreneurial tactics do entrepreneurs in the tourist industry employ, and what are their success and failure rates? – What is the role of education and training in supporting and growing tourist businesses?
Innovation and entrepreneurial ecosystem	– What effect do technologies like AI and data analytics have on startup businesses in the tourist industry? – What is the significance of technology in the tourist business and its influence on entrepreneurial activities? – How have digital technologies and new media changed the dynamics of business in the tourist industry?
Entrepreneurial opportunities in tourism	– Do government policies, laws, and incentives play a part in encouraging tourism-related business startups?
Sustainable tourism development	– How digital tools may be used to help promote eco-friendly tourism and business ventures? – How may entrepreneurs design and execute ecologically and financially solvent practices for the tourism industry? – How can more inclusive, fair, and sustainable tourism practices be developed, particularly for minority and underprivileged communities?

Source: own study.

CONCLUSIONS

As globalisation proceeds, the significance of tourism to national economies and local communities is grows. This study carries important implications for policymaking and assisting business owners in making ethical and sustainable choices.

The research substantially contributes to existing management theories, synthesising key findings by presenting theoretical and contextual contributions that complement the existing theories. The study integrated entrepreneurial opportunities in tourism with socio-economic factors, including employment generation, rural economic development, women's entrepreneurship, and income generation, thereby expanding existing sustainable tourism theories to encompass inclusive economic development beyond environmental aspects. The inclusion of innovation and the entrepreneurial ecosystem as precursors to entrepreneurial orientation enhances the theoretical comprehension of how systemic and contextual elements influence sustainability-driven entrepreneurial behaviour. By incorporating thoughts on innovation ecosystems and entrepreneurship into sustainability frameworks, this study enhances the philosophy of sustainable tourism. Moreover, the study connected entrepreneurial activities to more general sustainability objectives, particularly in rural and inclusive tourist environments.

Our study details the obstacles that may stand in the way of sustainable development and how they might be overcome. Moreover, the study results present policy implications for managers, policymakers, and academicians in the field of sustainable tourism entrepreneurship. Policymakers should assist the sectors of hospitality and innovation in order for them to develop in the appropriate manner. Our study will help managers face the dynamic challenges that prevail in the sustainable tourism industry. The framework provides essential insights for policymakers, tourism planners, and practitioners by emphasising entrepreneurship as a strategic instrument for attaining sustainable tourist development. The framework posits that cultivating innovation ecosystems, endorsing an entrepreneurial attitude, and facilitating inclusive entrepreneurial possibilities can create employment, improve rural livelihoods, and advance women's involvement in tourism-related enterprises. The findings underscore the necessity for governments to implement focused strategies that enhance entrepreneurial ecosystems and offer institutional support for tourism entrepreneurs.

Possible future outcomes would include the effects of tourism entrepreneurship on sustainable tourism development, tourism trends, economy and society, entrepreneurial orientation, post-pandemic tourism and sustainability perspectives.

This study has certain limitations that should be acknowledged. We relied solely on the Web of Science database, which may exclude relevant studies indexed in other databases. Moreover, we based the study on secondary and conceptual analysis. Thus, future studies could adopt an empirical approach and focus on specific geographical contexts to enhance the robustness and contextual relevance of the findings.

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Authors

The contribution share of authors was equal and amounted to 20% for each of them. Sanchita Bansal – conceptualisation; supervision; validation; visualisation; project administration; review and editing. Priya Nangia – writing the original draft; data curation; formal analysis; investigation; methodology; resources; software. Nisha Chanaliya – writing the original draft; data curation; formal analysis; investigation; methodology; resources; software. Dariusz Cichoń – investigation; supervision; validation; visualisation. Marek Dudek – investigation; supervision; validation; visualisation.

Sanchita Bansal (corresponding author)

Professor of Management at the University School of Management Studies, Guru Gobind Singh Indraprastha University, New Delhi, India. Her research interests include SDGs, entrepreneurial marketing, women entrepreneurship, social entrepreneurship, responsible consumption, women empowerment, and happiness.

Correspondence to: Prof. Sanchita Bansal, University School of Management Studies, Guru Gobind Singh Indraprastha University, New Delhi, India; AGH University, al. Mickiewicza 30, 30-059, Krakow, Poland, Krakow, Poland. e-mail: bansalsanchita@gmail.com

ORCID  <https://orcid.org/0000-0003-3585-5511>

Priya Nangia

Assistant Professor at the Amity School of Business, Amity University, Noida, Uttar Pradesh, India. Her research interests include marketing and responsible consumption.

Correspondence to: dr Priya Nangia, Amity School of Business, Amity University, Uttar Pradesh, Noida, India, e-mail: priyanangia2233@gmail.com

ORCID  <https://orcid.org/0000-0003-0541-5291>

Nisha Chanaliya

Doctoral Candidate at the University School of Management Studies, Guru Gobind Singh Indraprastha University, New Delhi, India. Her research interests include finance, marketing, and development economics.

Correspondence to: Ms. Nisha Chanaliya, University School of Management Studies, Guru Gobind Singh Indraprastha University, New Delhi, India, e-mail: nishachanaliya25@gmail.com

ORCID  <https://orcid.org/0009-0001-7346-571X>

Dariusz Cichoń

Assistant Professor and Coordinator of International Mobility at the Faculty of Management, AGH University of Krakow Poland. His research interests include sustainable development, women entrepreneurship, and smart cities.

Correspondence to: dr Dariusz Cichoń, Faculty of Management, Department of Enterprise Management, AGH University of Krakow, al. Mickiewicza 30, 30-059, Krakow, Poland, e-mail: dcichon@agh.edu.pl

ORCID  <https://orcid.org/0000-0003-4198-1530>

Marek Dudek

Associate Professor and Dean at the Faculty of Management, AGH University of Science and Technology Krakow, Poland. His research interests include digital production and WCM.

Correspondence to: dr hab. Marek Dudek, prof. AGH, Department of Enterprise Management, AGH University of Krakow, al. Mickiewicza 30, 30-059, Krakow, Poland, e-mail: madudek@agh.edu.pl

ORCID  <https://orcid.org/0000-0002-9818-739X>

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The 5Cs framework and entrepreneurial intention: The role of credit management understanding in Thailand

Kawin Magtanaroong, Pinya Magtanaroong, Kunnika Jakor, Piyapan Suwannawach

ABSTRACT

Objective: This article identifies the influence of financial management understanding within the 5Cs framework (character, capacity, capital, collateral, and conditions) on entrepreneurial intention (EI). The article addresses the limited application of the 5Cs framework in explaining entrepreneurial behaviour in developing economies such as Thailand.

Research Design & Methods: We applied a quantitative approach using survey data from 462 respondents in Bangkok and its metropolitan area. We analysed the data using confirmatory factor analysis (CFA) and structural equation modelling (SEM). We assessed instrument reliability and validity and applied procedures to control potential common method bias.

Findings: The proposed model explains entrepreneurial intention effectively. Capital and conditions have positive and significant effects on EI, whereas character, capacity, and collateral are not statistically significant. These findings highlight the importance of financial resources and economic conditions in shaping entrepreneurial decisions in Thailand.

Implications & Recommendations: Improving access to financial capital and maintaining a stable economic environment are essential for encouraging entrepreneurial intention. Policymakers should simplify regulations and provide financial incentives for new ventures. Educational institutions should strengthen training in capital access strategies and financial planning, while financial institutions may reconsider credit evaluation practices to better support potential entrepreneurs.

Contribution & Value Added: This article extends the theory of planned behaviour (TPB) and the resource-based view by incorporating the 5Cs framework into the analysis of entrepreneurial behaviour. It proposes a structural model explaining how financial understanding and economic conditions influence entrepreneurial intention in developing economies and provides insights for policymakers, educators, and financial institutions.

Article type: research article

Keywords: entrepreneurial intention; 5Cs framework; theory of planned behaviour (TPB); resource-based view (RBV); structural equation modelling (SEM); Thailand

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INTRODUCTION

Entrepreneurial intention (EI) has attracted growing attention in entrepreneurship research as a key predictor of entrepreneurial behaviour and economic development (Liñán & Fayolle, 2015). Most studies explain EI through individual-level determinants like attitudes, values, and personal traits, typically using the theory of planned behaviour (TPB), which emphasises perceived behavioural control and attitudes as central drivers of decision-making (Ajzen, 1991). However, explanations based solely on personality or individual competencies may not fully capture EI, particularly in developing economies, where entrepreneurial decisions are also under the influence of external conditions, such as economic

volatility, institutional gaps, and limited access to finance (Stephan *et al.*, 2015; Urbano *et al.*, 2019). Thus, potential entrepreneurs may respond more strongly to financial resources and policy constraints than to personal attributes alone. Therefore, understanding EI in developing economies requires integrating financial and contextual perspectives rather than relying solely on individual traits.

One widely used framework in finance is the 5Cs of credit: character, capacity, capital, collateral, and conditions. Originally, scholars developed this framework to help financial institutions evaluate borrowers' creditworthiness and risk (Altman & Sabato, 2007; Sharma & Singh, 2025). Previous studies suggest that the 5Cs also reflect an individual's financial literacy and financial management ability, shaping access to funding and economic decision-making (Fatoki, 2014a; Wise, 2013; Beck & Demirguc-Kunt, 2006). Despite its importance in financial assessment, the framework has rarely explained entrepreneurial behaviour. However, each component may capture individuals' perceptions of financial resources and capital availability, potentially shaping entrepreneurial intention, especially among individuals with limited resources or experience (Cole *et al.*, 2016; Rocha *et al.*, 2025).

In Thailand, promoting small-scale entrepreneurs and SMEs has become a key strategy for supporting grassroots economic development. Nevertheless, limited access to finance remains a persistent barrier (Lusardi & Mitchell, 2014; Murendo & Mutsonziwa, 2017; Ukil *et al.*, 2025). This situation underscores the need for stronger financial knowledge and management understanding. The 5Cs framework may help potential entrepreneurs assess their financial readiness and improve their chances of obtaining funding. While previous studies have examined financial literacy as a factor shaping financial behaviour, only a limited number of studies have examined financial management understanding within the 5Cs framework as a structural factor explaining entrepreneurial intention. Our study addressed this gap by examining how the five 5Cs dimensions shape entrepreneurial intention in Thailand. Specifically, the study identified which components have the strongest impact on EI and how they shape entrepreneurial decision-making. The article extends both the theory of planned behaviour (TPB) and the resource-based view (RBV) by linking financial resource perception with entrepreneurial cognition at the individual level. The findings should provide practical insights for policy-makers and financial institutions seeking to design effective strategies to support new entrepreneurs in Thailand and other developing economies.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Scholars widely recognise entrepreneurial intention (EI) as a key predictor of entrepreneurial behaviour and an important driver of economic development (Liñán & Fayolle, 2015). One of the most influential frameworks explaining EI is the theory of planned behaviour (TPB) (Ajzen, 1991), which proposes that intention rests on three factors: attitude toward the behaviour, subjective norms, and perceived behavioural control. Empirical studies (Kautonen *et al.*, 2015) confirm that TPB explains EI effectively across many contexts, particularly in developed economies with stable institutional environments. However, evidence from developing economies indicates that entrepreneurial decisions reflect not only individual traits but also structural conditions, particularly access to finance and institutional support (Stephan *et al.*, 2015; Urbano *et al.*, 2019). In such contexts, perceived access to finance can directly shape perceived behavioural control and, thus, entrepreneurial intention (Nguyen, 2020). These findings suggest that although TPB provides a strong theoretical foundation, it may not fully explain entrepreneurial behaviour in environments characterised by resource scarcity and institutional uncertainty. Thus, this study extends the TPB perspective by incorporating resource-based and contextual considerations to better explain EI in emerging economies.

Previous studies have often explained EI through individual attributes like personality traits, knowledge, and skills (Rauch & Frese, 2007). In developed economies, characteristics like self-efficacy and proactiveness frequently emerge as strong predictors of EI (Karimi *et al.*, 2016). By contrast, evidence from developing economies shows that these traits' influence may weaken when institutional structures are unstable and access to resources is constrained (Schlaegel & Koenig, 2014). Recent research also suggests that financial literacy does not necessarily translate directly into entrepreneurial intention but may shape behaviour through mechanisms like saving behaviour or financial confidence (Alshebami & Al

Marri, 2022). Similarly, economics education may raise decision-making quality, subsequently strengthening entrepreneurial intention rather than affecting it directly (Pashaei *et al.*, 2024).

Therefore, recent research has increasingly emphasised the role of resources and institutional environments in shaping EI. Perceived access to finance has been shown to interact with entrepreneurial self-efficacy and capabilities, reinforcing entrepreneurial intention (Svotwa *et al.*, 2022). Other studies highlight institutional support, economic stability, and access to financial capital in fostering entrepreneurial activity (Liñán & Fayolle, 2015; Stephan *et al.*, 2015; Urbano *et al.*, 2019). Institutional voids in developing economies, including policy uncertainty and weak market mechanisms, often push entrepreneurs to rely more heavily on external resources than on personal traits alone (Stephan *et al.*, 2015). Periods of macroeconomic instability, like the COVID-19 pandemic, further demonstrate how economic conditions can reshape risk perception and entrepreneurial intentions (Liñán & Jaén, 2022). Access to financial capital, including start-up funding and support from social or business networks, also strengthens confidence and facilitates entrepreneurial action (Van Gelderen *et al.*, 2006). These findings underscore the value of examining EI from an integrated perspective spanning both resources and institutional conditions.

Within this discussion, the 5Cs of credit framework, *i.e.*, character, capacity, capital, collateral, and conditions, ranks among the most widely used approaches for assessing borrowers' creditworthiness in financial institutions (Altman & Sabato, 2007). Previous research has applied the framework to analyse entrepreneurs' financial behaviour, particularly regarding access to finance and debt management (Fatoki, 2014a; Murendo & Mutsonziwa, 2017). Despite its relevance to financial decision-making, the framework has rarely explained entrepreneurial intention directly. Most EI studies continue to rely primarily on psychological approaches like TPB (Ajzen, 1991) or resource-based perspectives like the resource-based view (RBV) (Barney, 1991). Thus, limited research has examined how the 5Cs framework's five dimensions may structurally shape entrepreneurial intention, particularly in developing-country contexts where financial capital and economic conditions often play a decisive role.

This gap matters particularly in Thailand, where limited access to finance and economic uncertainty may shape entrepreneurial decision-making more strongly than personality traits alone. Applying the 5Cs framework to EI integrates financial readiness and resource perception into entrepreneurial decision-making. This study accordingly examines how the five components of the 5Cs framework shape entrepreneurial intention in Thailand and identifies which dimensions exert the strongest impact.

Based on the literature review and the theoretical foundations of the 5Cs framework, we proposed the following hypotheses:

1. The character dimension reflects credibility, discipline, and responsibility in meeting financial obligations, essential for gaining access to credit (Altman & Sabato, 2007). In entrepreneurial contexts, these qualities may strengthen responsibility and commitment toward starting a business (Rauch & Frese, 2007).

H1: Understanding of character has a positive effect on EI.

2. The capacity dimension refers to the ability to manage financial obligations and plan resources effectively (Frame & White, 2004). Financial knowledge and management capability can boost confidence in starting a business and contribute to venture survival (Wise, 2013).

H2: Understanding of capacity has a positive effect on EI.

3. The capital dimension represents the availability of financial resources necessary for launching a business. Adequate start-up capital can reduce structural barriers and expand opportunities for entrepreneurial activity (Van Gelderen *et al.*, 2006). Assessing financial readiness may also strengthen entrepreneurial confidence (Grégoire & Shepherd, 2012).

H3: Understanding of capital has a positive effect on EI.

4. The collateral dimension refers to assets pledged as guarantees that reduce lenders' risk exposure (Fatoki & Asah, 2011). Though many new entrepreneurs possess limited collateral, understanding its role may help them strategically use available assets to improve access to external finance (Coleman & Robb, 2009; Cowling *et al.*, 2012).

H4: Understanding of collateral has a positive effect on EI.

5. The conditions dimension captures the broader economic and policy environment shaping business opportunities (Boudreaux *et al.*, 2019). Entrepreneurs who understand market dynamics and policy conditions may better adapt to economic changes and initiate new ventures (Papadaki & Chami, 2002).

H5: Understanding of conditions has a positive effect on EI.

RESEARCH METHODOLOGY

We examined the causal relationships between financial capital understanding, represented by the 5Cs framework, and entrepreneurial intention (EI). We employed a quantitative research design and using structural equation modelling (SEM), we tested the conceptual model derived from established theories and prior studies. The process comprised conceptual framework development, instrument design, data collection, and statistical analysis.

Research Model

The research model rests on the 5Cs framework of credit assessment, representing financial capital understanding, with entrepreneurial intention (EI) as the dependent variable. The model assumes that understanding each component of the 5Cs may shape individuals' intentions to start a business. Figure 1 presents the conceptual framework of the study and illustrates the hypothesised relationships among the constructs. We empirically tested these relationships using SEM.

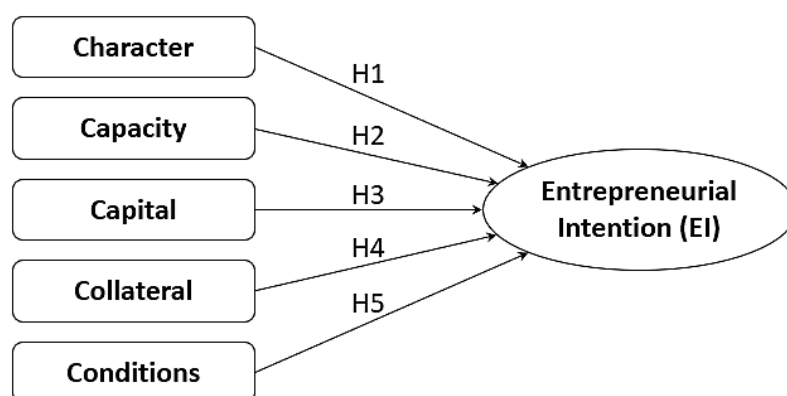


Figure 1. Conceptual model illustrating the relationship between financial capital understanding (5Cs) and entrepreneurial intention

Source: own elaboration.

Sample and Data Collection

The target population comprised working-age individuals in Bangkok and its metropolitan area who expressed interest in or potential for entrepreneurial activity. We used a multistage sampling approach, starting with economically active areas. We collected data through convenience and snow-ball sampling to reach target respondents while ensuring demographic diversity. We conducted the survey between June and September 2025.

The sample size followed the guideline of Krejcie and Morgan's (1970) guideline of at least 384 respondents for a 95% confidence level with a $\pm 5\%$ margin of error. In total, we obtained 462 valid responses, exceeding the recommended threshold and providing an adequate dataset for SEM analysis.

Research Instrument

We collected data using a structured questionnaire developed from the existing literature on the 5Cs framework and entrepreneurial intention (EI). The questionnaire comprised three sections: (1) demographic information; (2) 25 items measuring understanding of the five 5Cs dimensions (five items per construct); and (3) five items measuring entrepreneurial intention. All variables used a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

We adapted entrepreneurial intention items from the widely used scale of Liñán and Chen (2009). Measurement of the 5Cs dimensions drew on credit assessment literature (Altman & Sabato, 2007; Fatoki, 2014b), with wording adjusted to reflect financial management understanding rather than formal credit evaluation. We made minor wording modifications to ensure clarity and contextual suitability for Thai respondents while preserving the original conceptual meaning. A pilot test verified clarity and comprehension of the questionnaire. We assessed reliability via Cronbach's alpha, with most constructs exceeding the commonly accepted threshold of 0.70 (Nunnally & Bernstein, 1994). Values close to 0.70 remained acceptable for exploratory social science research (Hair *et al.*, 2019). Thus, we considered the instrument reliable for further analysis.

Data Analysis

We analysed data via structural equation modelling (SEM) with AMOS to evaluate the fit between the conceptual model and observed data. Following Anderson and Gerbing's (1988) two-step procedure, we first assessed the measurement model through confirmatory factor analysis (CFA) to examine reliability, convergent validity, and discriminant validity. We then estimated the structural model to test the hypothesised relationships. Given the confirmatory nature of this study and its theory-driven hypotheses, we employed covariance-based SEM (CB-SEM) instead of PLS-SEM. Notably, CB-SEM suits testing theoretically specified models, evaluating overall model fit, and validating measurement structures before interpreting structural paths (Byrne, 2016; Hair *et al.*, 2019; Kline, 2023). We treated the 5Cs dimensions and entrepreneurial intention as latent constructs with reflective indicators. The two-step procedure (CFA followed by SEM) ensured both measurement reliability and theoretically consistent interpretation (Anderson & Gerbing, 1988).

We evaluated construct reliability via composite reliability (CR) and average variance extracted (AVE). Although AVE values above 0.50 are typically recommended (Fornell & Larcker, 1981), we conducted additional analyses by examining and removing selected low-loading indicators to improve convergent validity. Thus, our interpretation considered CR values, standardised factor loadings, and the refined measurement model. Table 3 presents the results of the refined measurement model.

We tested discriminant validity using chi-square difference testing. We compared the unconstrained measurement model against models with correlations between construct pairs fixed to unity (Anderson & Gerbing, 1988). A significant chi-square increase indicates that constructs are empirically distinct. Reliability values close to conventional thresholds were deemed acceptable within social science measurement development (Hair *et al.*, 2019).

Control of Common Method Bias (CMB)

We collected data via self-reported questionnaires from a single source, hence common method bias (CMB) could potentially shape the observed relationships among variables (Podsakoff *et al.*, 2003). Therefore, we applied two procedures to assess this risk. Firstly, we conducted Harman's one-factor test by performing exploratory factor analysis (EFA) without rotation. If the first factor explains less than 50% of total variance, serious CMB concerns become unlikely (Podsakoff *et al.*, 2012). Secondly, we applied the common latent factor (CLF) technique in AMOS, introducing a latent factor capturing shared variance across constructs. We compared correlations before and after controlling for the latent factor. If adjusted correlations do not significantly differ from the original estimates, CMB is considered minimal (Fuller *et al.*, 2016; Williams *et al.*, 2010).

Both procedures indicated that common method bias did not substantially affect the data. Thus, we deemed relationships estimated in the structural model reliable.

RESULTS AND DISCUSSION

We analysed 462 valid questionnaires. We used SPSS and AMOS following Anderson and Gerbing's (1988) two-step approach. Firstly, we performed confirmatory factor analysis (CFA) to evaluate the reliability and validity of the measurement model. We used structural equation modelling (SEM) to

test the hypothesised relationships. This section presents the results, beginning with descriptive statistics and measurement validation, then structural model estimation.

Descriptive Statistics

Table 1 presents descriptive statistics for the six constructs: character (CHR), capacity (CAP), capital (CPL), collateral (COL), conditions (CON), and entrepreneurial intention (EI). The mean values ranged from 3.83 to 4.34, indicating generally moderate to high perceptions of these factors among respondents. Standard deviation values ranged from 0.509 to 0.646, suggesting acceptable variability without abnormal dispersion. The correlation matrix shows statistically significant relationships among all constructs at the 0.01 level (two-tailed), with coefficients ranging from 0.435 to 0.715. According to Hair *et al.* (2019), these values represent moderate to strong positive relationships among the variables. Overall, the results indicate that the dataset was appropriate for further reliability and validity testing.

Table 1. Descriptive statistics and correlation matrix of the study variables

Construct	Mean	Std. Deviation	(1)	(2)	(3)	(4)	(5)	(6)
CHR (1)	4.339	0.509	1	–	–	–	–	–
CAP (2)	4.224	0.554	0.715***	1	–	–	–	–
CPL (3)	3.876	0.609	0.496***	0.534***	1	–	–	–
COL (4)	4.006	0.646	0.568***	0.614***	0.654***	1	–	–
CON (5)	3.881	0.574	0.480***	0.494***	0.542***	0.627***	1	–
EI (6)	3.831	0.593	0.435***	0.449***	0.536***	0.525***	0.549***	1

Note. *** Correlation is significant at the 0.01 level (2-tailed)

Source: own study.

Reliability and Validity Testing

We assessed the reliability of the measurement instrument via Cronbach's alpha and composite reliability (CR). As Table 2 shows, Cronbach's alpha values range from 0.697 to 0.788, while CR values range from 0.694 to 0.790. Although some values approach the commonly accepted threshold of 0.70, they remain acceptable for exploratory social-science research (Hair *et al.*, 2019). These results indicate that the instrument demonstrates adequate internal consistency.

We evaluated convergent validity via average variance extracted (AVE) and standardised factor loadings. As Table 2 shows, AVE values range from 0.344 to 0.430, below the conventional threshold of 0.50 suggested by Fornell and Larcker (1981). However, composite reliability values exceed 0.60 for all constructs, indicating acceptable reliability (Hair *et al.*, 2019; Malhotra, 2010). Given that the 5Cs measures were adapted to reflect perceived financial management understanding rather than formal credit evaluation, the constructs may capture broader behavioural perceptions, partly explaining the relatively modest AVE values. Most standardised factor loadings exceed 0.60, supporting the alignment between indicators and their respective constructs.

To address low convergent validity, we examined and removed selected low-loading indicators. Table 3 shows the refined measurement model. The results show a modest improvement in AVE values for several constructs, while maintaining acceptable levels of Cronbach's alpha and composite reliability. Although AVE values remain below the recommended threshold, the improvement suggests stronger convergence among retained indicators. We thus retained the constructs based on acceptable reliability and theoretical consistency (Hair *et al.*, 2019). Although AVE values remain below the conventional threshold (Fornell & Larcker, 1981), this limitation merits consideration when interpreting the results.

We assessed discriminant validity via chi-square difference tests by comparing the unconstrained measurement model with models in which correlations between construct pairs were fixed to unity (Anderson & Gerbing, 1988). A significant chi-square increase indicates that the constructs are empirically distinct. As Table 4 reports, chi-square differences for all construct pairs are statistically significant ($p < 0.001$), confirming adequate discriminant validity.

Table 2. Reliability and convergent validity assessment of the study constructs

Variable name	Cronbach's alpha	CR	AVE	Item	Weights
Character (CHR)	0.720	0.723	0.344	CHR1	0.538
				CHR2	0.603
				CHR3	0.609
				CHR4	0.560
				CHR5	0.617
Capacity (CAP)	0.750	0.760	0.390	CAP1	0.650
				CAP2	0.674
				CAP3	0.695
				CAP4	0.561
				CAP5	0.524
Capital (CPL)	0.697	0.694	0.362	CPL2	0.601
				CPL3	0.636
				CPL4	0.581
				CPL5	0.588
Collateral (COL)	0.788	0.790	0.430	COL1	0.605
				COL2	0.632
				COL3	0.699
				COL4	0.686
				COL5	0.652
Conditions (CON)	0.714	0.717	0.337	CON1	0.568
				CON2	0.626
				CON3	0.577
				CON4	0.584
				CON5	0.544
Entrepreneurial Intention (EI)	0.729	0.730	0.351	EI1	0.561
				EI2	0.597
				EI3	0.588
				EI4	0.585
				EI5	0.630

Source: own study.

Table 3. Refined reliability and convergent validity assessment after item reduction

Variable name	Cronbach's alpha	CR	AVE	Item	Weights
Character (CHR)	0.695	0.697	0.365	CHR2	0.629
				CHR3	0.616
				CHR4	0.562
				CHR5	0.608
				CHR1	0.608
Capacity (CAP)	0.743	0.746	0.425	CAP1	0.657
				CAP2	0.691
				CAP3	0.700
				CAP4	0.549
Capital (CPL)	0.690	0.694	0.363	CPL2	0.600
				CPL3	0.637
				CPL4	0.583
				CPL5	0.587
Collateral (COL)	0.788	0.697	0.430	COL1	0.601
				COL2	0.632
				COL3	0.699
				COL4	0.691
				COL5	0.650

Variable name	Cronbach's alpha	CR	AVE	Item	Weights
Conditions (CON)	0.679	0.682	0.349	CON1	0.572
				CON2	0.628
				CON3	0.573
				CON4	0.590
Entrepreneurial intention (EI)	0.729	0.697	0.351	EI1	0.560
				EI2	0.598
				EI3	0.586
				EI4	0.583
				EI5	0.633

Source: own study.

Overall, the six constructs, *i.e.*, character (CHR), capacity (CAP), capital (CPL), collateral (COL), conditions (CON), and entrepreneurial intention (EI) demonstrate acceptable reliability and validity, supporting the measurement model's adequacy.

Table 4. Chi-square difference between the unconstrained and constrained models

Construct scale pairs		Chi-square difference	p-value
CHR	CAP	223.714	0.000
	CPL	232.292	0.000
	COL	196.782	0.000
	CON	270.027	0.000
	EI	271.765	0.000
CAP	CPL	218.636	0.000
	COL	183.044	0.000
	CON	263.094	0.000
	EI	268.620	0.000
CPL	COL	133.461	0.000
	CON	198.676	0.000
	EI	189.136	0.000
COL	CON	166.382	0.000
	EI	183.665	0.000
CON	EI	223.380	0.000

Source: own study.

Confirmatory Factor Analysis

We conducted confirmatory factor analysis (CFA) to evaluate the measurement model's fit. Results indicate a satisfactory overall fit: CMIN/DF = 1.630, RMSEA = 0.037, and PCLOSE = 1.000, suggesting that the model did not significantly deviate from a perfect fit (Hair *et al.*, 2019). Other indices also exceeded recommended thresholds, including GFI = 0.922, AGFI = 0.906, CFI = 0.943, and TLI = 0.936, while RMR = 0.028 indicated minimal residual error. Additional fit statistics further supported model adequacy. The AIC for the default model (735.883) was lower than those of the saturated model (870.000) and the independence model (474.897), indicating stronger parsimony (Burnham & Anderson, 2004). Similarly, the default model's ECVI (1.596) was lower than the saturated model (1.887) and the independence model (9.707), suggesting the model suits replication. Hoelter's critical N values were 319 at the 0.05 level and 335 at the 0.01 level, both exceeding the recommended threshold of 200 (Byrne, 2016), confirming sample adequacy.

Most factor loadings exceeded 0.50 and proved statistically significant ($p < 0.001$), supporting the reliability and structural validity of the measurement model and confirming its suitability for subsequent structural analysis.

Common Method Bias (CMB) Assessment

Because we collected data through self-reported questionnaires from a single source, we assessed the common method bias (CMB; Podsakoff *et al.*, 2003). We applied two procedures: Harman's one-factor test and the common latent factor (CLF) technique. Harman's test showed the first factor accounted for 26.83% of total variance, below the 50% threshold commonly used to indicate serious CMB concerns (Podsakoff *et al.*, 2012; Fuller *et al.*, 2016). This result suggests that severe single-source bias was unlikely.

We then implemented the CLF approach in AMOS to examine correlations before and after controlling for the latent factor. For example, the correlation between character and capacity showed an uncorrected coefficient of 0.968 and an adjusted coefficient of 0.902. Although magnitude decreased slightly, the direction and statistical interpretation remained unchanged. Similar patterns emerged for other construct pairs, where differences between uncorrected and adjusted correlations were not statistically significant. Although the character-capacity correlation appears high, we report it within the CLF-based CMB diagnostic and serves only as a bias-detection indicator. Our interpretation relies on the CFA/SEM results and discriminant validity tests in Table 4.

Together, the results from both procedures indicate that common method bias did not substantially affect the dataset (Table 5). Thus, we may consider the relationships estimated in the structural model as reliable (Williams *et al.*, 2010).

Table 5. Correlations adjusted for common method bias (CMB)

Construct pairs		Uncorrected correlation	Adjusted correlation	t-Statistic of the adjusted correlation
CHR	CAP	0.968 ***	0.902	1.975
	CPL	0.652 ***	-0.086	-0.425
	COL	0.753 ***	0.409	1.591
	CON	0.654 ***	-0.171	-0.777
	EI	0.583 ***	-0.471	-1.777
CAP	CPL	0.683 ***	0.244	1.501
	COL	0.786 ***	0.546	3.127
	CON	0.658 ***	0.132	0.786
	EI	0.581 ***	-0.127	-0.806
CPL	COL	0.845 ***	0.697	4.009
	CON	0.755 ***	0.399	2.266
	EI	0.77 ***	0.465	2.466
COL	CON	0.838 ***	0.650	3.534
	EI	0.697 ***	0.338	2.180
CON	EI	0.748 ***	0.306	1.672

Note: *** significant at 0.01

Source: own study.

Structural Model Testing

The SEM results show that the proposed model achieved satisfactory fit with the empirical data ($\chi^2/df = 1.630$, CFI = 0.943, RMSEA = 0.037, SRMR = 0.028), meeting recommended thresholds (Hu & Bentler, 1999; Kline, 2023). Structural path analysis indicates that capital ($\beta = 0.561$, $t = 3.268$, $p = 0.001$) and conditions ($\beta = 0.442$, $t = 2.691$, $p = 0.007$) exert positive and statistically significant effects on entrepreneurial intention (EI). By contrast, character ($\beta = 0.274$, $p = 0.679$), capacity ($\beta = -0.210$, $p = 0.766$), and collateral ($\beta = -0.189$, $p = 0.437$) show no statistically significant effects (Table 6).

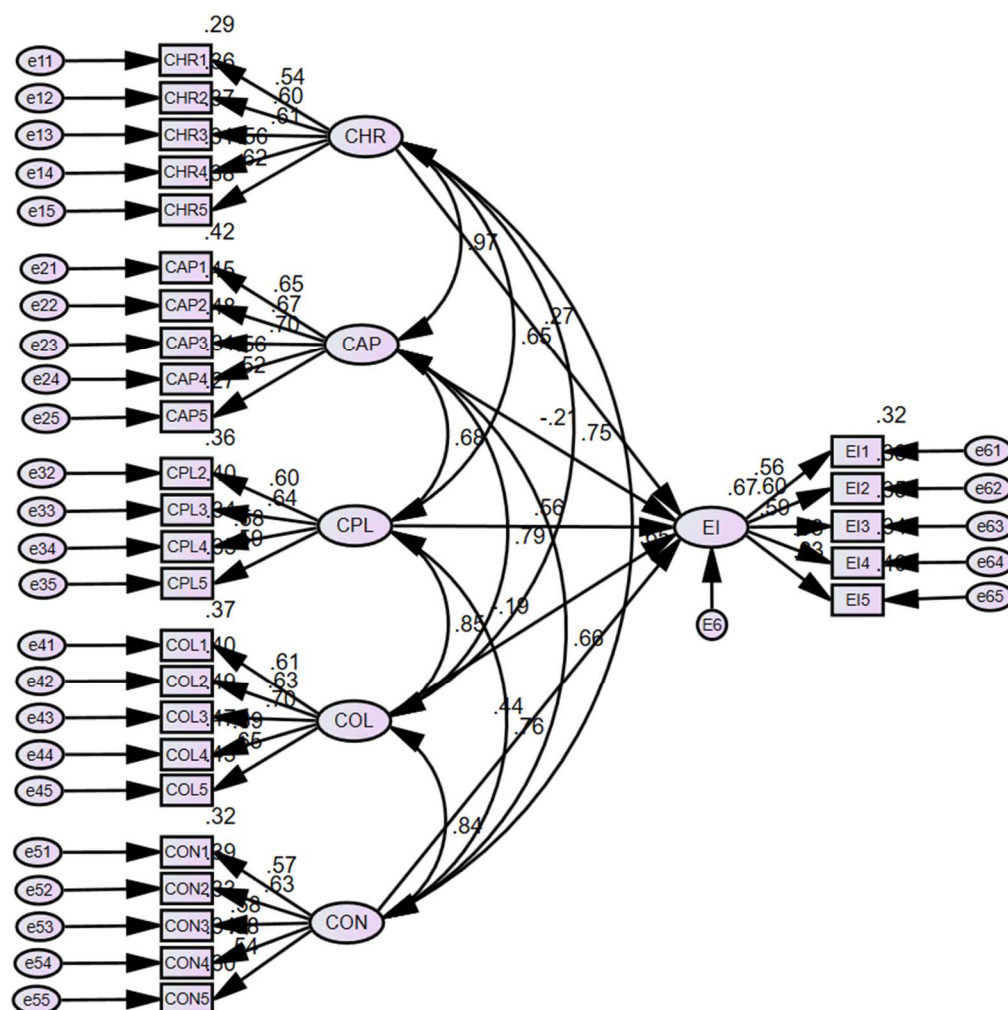
The model explains 66.9% of variance in entrepreneurial intention ($R^2 = 0.669$), exceeding Hair's (2014) threshold and indicating strong explanatory power. Among the predictors, capital shows the strongest effect, followed by conditions, while character, capacity, and collateral are not significant. Hypotheses H3 (capital) and H5 (conditions) are accordingly supported, while H1 (character), H2 (capacity), and H4 (collateral) are not. These findings suggest that financial resources and economic conditions play the most decisive roles in shaping entrepreneurial intention (Figure 2).

Table 6. Structural model estimation results

Construct	Coefficient	Std. deviation	t-Value	p-Value
Character (CHR)	0.274	0.749	0.414	0.679
Capacity (CAP)	-0.210	0.698	-0.298	0.766
Capital (CPL)	0.561	0.151	3.268	0.001***
Collateral (COL)	-0.189	0.195	-0.777	0.437
Conditions (CON)	0.442	0.169	2.691	0.007***

Note: *** Significant at 0.01

Source: own study.


Figure 2. Structural equation model estimation of entrepreneurial intention based on the 5Cs framework

Source: own elaboration.

Discussion

The results confirm that the proposed model effectively explains entrepreneurial intention (EI). Among the five 5Cs dimensions, capital and conditions exert positive and statistically significant effects, while character, capacity, and collateral show no significant influence. These findings indicate that financial resources and the broader economic environment play a more decisive role in shaping entrepreneurial intention than personal traits or collateral-related factors. This pattern aligns with the theory of planned behaviour (Ajzen, 1991), which emphasises perceived control and environmental resources as key drivers of intentional behaviour. Similar conclusions appear in previous studies (Hair, 2014; Kautonen *et al.*, 2015; Karimi *et al.*, 2016), which highlight access to financial resources and supportive economic conditions as key catalysts for entrepreneurial activity.

Although capacity shows no statistically significant effect, its negative coefficient deserves careful interpretation. One possible explanation: stronger awareness of financial obligations and debt management may heighten individuals' sensitivity to financial risk. In this situation, greater financial prudence may reduce willingness to initiate entrepreneurial activity, particularly in uncertain economic environments. Rather than directly fostering new business creation, financial capacity awareness may lead individuals to evaluate liabilities more cautiously, thereby moderating entrepreneurial intention. This aligns with research suggesting that financial literacy can shape entrepreneurial intention indirectly through decision-making and financial confidence rather than through a direct positive relationship (Alshebami & Al Marri, 2022; Pashaei *et al.*, 2024). A similar explanation may apply to the character dimension within the 5Cs framework. In traditional credit evaluation, character reflects financial discipline, reliability, and prudence in fulfilling debt obligations (Altman & Sabato, 2007). Although these attributes are valued from a lender's perspective, they may not always align with the risk-taking orientation commonly associated with entrepreneurial behaviour (Rauch & Frese, 2007). Individuals who strongly internalise financial caution and debt aversion may adopt a more conservative approach toward uncertain opportunities. Strong credit discipline does not necessarily translate into stronger entrepreneurial intention. This tension between financial prudence and entrepreneurial risk-taking offers an additional explanation for the non-significant effect of character observed in this study.

The absence of significant effects for character, capacity, and collateral also contrasts with Darnihamedani and Murphy's (2025) findings, which emphasise the role of institutional and structural factors in shaping entrepreneurial motivation. One explanation lies in the Thai economic context, where access to financial capital and macroeconomic stability may exert more immediate influence on entrepreneurial decisions. Under such conditions, individuals may prioritise tangible financial readiness over personal traits or collateral considerations when evaluating business opportunities. At the same time, we should acknowledge alternative explanations. Operationalising the 5Cs constructs within a behavioural framework may capture financial awareness differently from traditional credit assessment contexts. Cultural attitudes toward risk and debt may also shape how respondents interpret financial capacity and collateral requirements. Therefore, contextual and measurement factors may both contribute to the observed non-significant relationships. Although AVE values improved after item reduction, the relatively modest AVE values for several constructs merit consideration when interpreting the results. While internal consistency remained acceptable, AVE values below 0.50 indicated limited variance explained among some indicators (Fornell & Larcker, 1981). This partly reflects adapting the 5Cs framework from a credit evaluation context to an entrepreneurial cognition perspective, broadening the conceptual scope of dimensions like character and capacity. Thus, these constructs may capture diverse perceptions of financial prudence rather than narrowly defined behavioural traits. This broader interpretation could weaken some structural relationships. However, the overall model demonstrated satisfactory fit and substantial explanatory power, indicating that the main relationships identified in this study remain theoretically meaningful.

Implications

Regarding theoretical implications, this study contributes to entrepreneurship research by adapting the 5Cs framework, originally developed for credit assessment, to explain entrepreneurial behaviour. The results show that capital and conditions significantly shape entrepreneurial intention, highlighting the importance of financial resources and the external business environment. These findings align with the resource-based view (RBV) (Barney, 1991), which holds that competitive advantage depends on access to and effective use of valuable resources. By contrast, the non-significant effects of character, capacity, and collateral indicate that we cannot explain entrepreneurial intention solely by personal traits or debt-management skills. We must also consider broader economic and institutional conditions (Darnihamedani & Murphy, 2025).

The study extends existing theory in two ways. Firstly, it extends TBP by showing that in developing-country contexts, perceived behavioural control reflects external resources and environmental conditions more than individual characteristics (Ajzen, 1991; Kautonen *et al.*, 2015). Secondly, it extends the resource-based view (RBV) by showing that resource understanding and financial manage-

ment capability function as individual-level resources shaping entrepreneurial intention. This perspective links RBV with entrepreneurial cognition by emphasising how individuals interpret and use financial resources when forming entrepreneurial intentions.

The findings provide several implications for policymakers, educational institutions, and financial organisations. For policymakers, interventions should focus on improving practical access to start-up capital rather than relying solely on general entrepreneurship promotion campaigns. Measures like expanding microcredit programmes, simplifying loan applications, reducing collateral requirements for early-stage entrepreneurs, and introducing publicly supported credit guarantee schemes could expand financial accessibility. Stable regulatory frameworks for business registration, taxation, and licensing may also reduce uncertainty and strengthen entrepreneurial feasibility (Urbano *et al.*, 2019).

For educational institutions, entrepreneurship curricula should incorporate more applied financial competencies. Beyond general character development or soft-skill training, programmes could include modules on cash-flow planning, financial risk assessment, funding application preparation, and scenario-based financial decision-making. Prior research indicates that entrepreneurship education becomes more effective when integrating applied financial knowledge with entrepreneurial learning (Nabi *et al.*, 2017). Workshops with real financing cases or partnerships with financial institutions may further enhance students' entrepreneurial readiness.

For financial institutions, the findings suggest reconsidering traditional credit evaluation frameworks for start-ups. Rather than relying heavily on collateral requirements, lenders may consider broader indicators like financial preparedness, adaptability, and business planning capability. Such approaches align with recent discussions emphasising contextual factors in entrepreneurial motivation (Darnihamedani & Murphy, 2025). Advisory services or pre-loan financial coaching could also reduce risk while supporting potential entrepreneurs.

CONCLUSIONS

The study described in this article examined a structural model based on the 5Cs framework to analyse how its components shape entrepreneurial intention (EI). Using data from 462 respondents and applying CFA and SEM, we found that the proposed model achieved satisfactory fit and meaningful explanatory power for EI. The findings show that capital and conditions exert significant positive effects on entrepreneurial intention, while character, capacity, and collateral show no statistically significant relationships. These results highlight the role of financial resources and the broader economic environment in shaping entrepreneurial intention. The findings align with the RBV, which emphasises the role of access to valuable resources and supportive environments in generating competitive advantage (Barney, 1991). They also align with Liñán and Fayolle (2015), who emphasise the importance of structural and resource-based factors in entrepreneurial intention formation. By contrast, the absence of significant effects for individual-level variables supports Darnihamedani and Murphy's (2025) argument that institutional and economic conditions can outweigh personal traits in influencing entrepreneurial decisions.

Overall, this research extends the 5Cs framework beyond its traditional credit-assessment role and applies it to entrepreneurial behaviour to explain why individuals decide to start a business. Within the Thai context, capital and conditions emerged as the most influential factors shaping entrepreneurial intention. The empirical results supported H3 and H5 but not H1, H2, and H4, thus suggesting differences in the relative influence of the five components. The study also extends both TPB and the RBV to the individual level, highlighting how financial resource perceptions and environmental conditions shape entrepreneurial cognition in developing-country contexts. Moreover, the findings provide practical insights for policymakers, financial institutions, and educational organisations by emphasising the value of improving financial accessibility and creating supportive environments that foster entrepreneurial activity.

Limitations and Future Research

Despite providing empirical insights into the relationship between the 5Cs framework and entrepreneurial intention (EI), several limitations merit acknowledgement. Firstly, the quantitative cross-sec-

tional design limited the ability to establish causal relationships. Future studies should adopt longitudinal approaches to examine how entrepreneurial intention evolves and to provide stronger causal evidence (Podsakoff *et al.*, 2012). Secondly, the sample was limited to individuals in Bangkok and its metropolitan area, which may restrict the findings' generalisability. Future research should include broader regional samples or cross-national datasets to enhance external validity. Comparative studies across institutional contexts may yield deeper understanding of how economic environments shape entrepreneurial intention (Liñán & Fayolle, 2015; Stephan *et al.*, 2015). Thirdly, the study relied exclusively on questionnaire data. Although diagnostic tests suggested that common method bias was not severe, survey-based approaches still carry methodological limitations. Future research could incorporate qualitative methods like in-depth interviews or case studies to explore the mechanisms linking the 5Cs components to entrepreneurial intention in greater detail (Yin, 2017). Fourthly, the model did not explicitly incorporate institutional or policy-related structural factors, which previous research has identified as important determinants of entrepreneurial motivation and success (Darnihamedani & Murphy, 2025). Including these factors in future studies may yield a more comprehensive explanation of entrepreneurial intention. Finally, although AVE values improved after item reduction, the relatively modest AVE values observed for several constructs still suggest convergent validity limitations. Despite acceptable composite reliability, AVE values below 0.50 indicate that the variance explained by some indicators was limited (Fornell & Larcker, 1981). This may reflect adapting the 5Cs framework, originally designed for credit risk assessment, to a behavioural research context on entrepreneurial cognition. Therefore, future studies may refine measurement items, reconsider dimensional structures, or adopt mixed-method approaches to strengthen construct validity. Replication across institutional settings may also clarify whether these measurement characteristics are context-specific or inherent to the behavioural operationalisation of the 5Cs framework.

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Authors

The contribution share of authors was equal and amounted to 25% each. KM formulated the research problem, designed the conceptual framework, and selected the research methodology, PM summarised and discussed the results and prepared the research report; KJ processed and analysed the data, developed the research instruments, and evaluated reliability and validity, PS conducted field data collection and managed ethical procedures and data confidentiality.

Kawin Magtanaroong

Lecturer at the Faculty of Business Administration, Rajamangala University of Technology Phra Nakhon, Thailand. His research interests include entrepreneurship, finance, and economics.

Correspondence to: Dr. Kawin Magtanaroong, Department of Finance, Faculty of Business Administration, Rajamangala University of Technology Phra Nakhon, 86 Phitsanulok Road, Suan Chitlada Subdistrict, Dusit District, Bangkok 10300, Thailand, e-mail: kawin.m@rmutp.ac.th

ORCID  <https://orcid.org/0009-0006-2086-7674>

Pinya Magtanaroong (corresponding author)

Lecturer at the Faculty of Business Administration, Rajamangala University of Technology Phra Nakhon, Thailand. Head of the Department of Entrepreneurship. Her research interests include entrepreneurship, and management.

Correspondence to: Dr. Pinya Magtanaroong, Department of entrepreneurship, Faculty of Business Administration, Rajamangala University of Technology Phra Nakhon, 86 Phitsanulok Road, Suan Chitlada Subdistrict, Dusit District, Bangkok 10300, Thailand, e-mail: pinya.m@rmutp.ac.th

ORCID  <https://orcid.org/0009-0008-9729-2252>

Kunnika Jakor

Lecturer at the Faculty of Business Administration, Rajamangala University of Technology Phra Nakhon, Thailand. Her research interests include entrepreneurship, finance, and management.

Correspondence to: Ms. Kunnika Jakor, Department of Finance, Faculty of Business Administration, Rajamangala University of Technology Phra Nakhon, 86 Phitsanulok Road, Suan Chitlada Subdistrict, Dusit District, Bangkok 10300, Thailand, e-mail: kunnika.j@rmutp.ac.th

ORCID  <https://orcid.org/0009-0007-3918-5865>

Piyapan Suwannawach

Lecturer at the Faculty of Business Administration, Rajamangala University of Technology Phra Nakhon, Thailand. His research interests include information systems and computer science.

Correspondence to: Mr. Piyapan Suwannawach, Department of Information System, Faculty of Business Administration, Rajamangala University of Technology Phra Nakhon, 86 Phitsanulok Road, Suan Chitlada Subdistrict, Dusit District, Bangkok 10300, Thailand, e-mail: piyapan.s@rmutp.ac.th

ORCID  <https://orcid.org/0009-0005-0396-1565>

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Use of Artificial Intelligence

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Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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High-tech adoption and innovation in manufacturing firms: Evidence from an Italian industrial area

Noemi Giampaoli

ABSTRACT

Objective: The objective of this article is to empirically assess the relationship between firm characteristics, local innovation networks, and the level of high-tech adoption among manufacturing firms located in the Italian provinces of Fermo and Ascoli Piceno, *i.e.*, two territories characterised by long-standing manufacturing traditions but differing sectoral specialisations. It focuses on the role of firm-level characteristics and local innovation ecosystems. I explored how firms in traditional industrial areas engage with new high-tech solutions, and which factors enable or hinder technological upgrading. By providing micro-level evidence from a central Italian economy, the article offers useful insights for industrial areas facing similar structural and technological challenges.

Research Design & Methods: The study adopted a mixed-methods approach combining firm-level financial data for 2022 with a web scraping activity and a cross-sectional survey conducted in December 2023 on manufacturing firms located in Fermo and Ascoli Piceno. The web scraping provided firms' contact information, and the survey yielded 128 valid responses with information on technology adoption, perceived barriers, and innovation behaviour; I used firm-level data for the econometric analysis.

Findings: Results revealed a heterogeneous landscape of high-tech adoption across firms. While some firms, mainly big-sized, were actively implementing these technologies, a large share of small enterprises remained at early stages of high-tech adoption. Barriers included financial constraints, skill shortages, and uncertainty about returns. Conversely, firms operating within technological districts have already implemented, and are further advancing, the integration of several high-tech solutions into their manufacturing processes.

Implications & Recommendations: The findings suggest the need for targeted regional and industrial policies supporting high-tech readiness among firms. Policy actions should focus on enhancing managerial and technical capabilities, facilitating access to financing, and promoting inter-firm collaborations to foster technological diffusion. These recommendations are particularly relevant for traditional manufacturing regions and peripheral industrial areas, where firms face barriers to technological transformation.

Contribution & Value Added: This article contributes to the literature on technological transformation and Industry 4.0 by offering original evidence from a local manufacturing system. The study advances understanding of how territorial, sectoral, and firm-specific characteristics shape high-tech adoption, providing valuable insights for both scholars and policymakers engaged in supporting modernisation in local industries.

Article type: research article

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INTRODUCTION

In recent years, the diffusion of new technologies and high-tech innovation has profoundly reshaped the competitive landscape of firms across both advanced and emerging economies. The paradigms of technological transformation and Industry 4.0 have radically changed production processes, organisational structures, and value creation mechanisms (Kiel *et al.*, 2017; Müller *et al.*, 2018; Ancillai *et al.*,

2023). Notably, the paradigms encompass such technologies as the Internet of Things (IoT), artificial intelligence (AI), cloud computing, digital technologies, and additive manufacturing. The introduced transformations exceed technological upgrading, representing a structural shift in how firms design, deliver, and capture value (Teece, 2010; Chesbrough, 2010). Consequently, technological capability has become a key determinant of firms' competitiveness, resilience, and growth potential.

However, despite the growing consensus on the strategic role of technologies, adoption patterns of high-tech remain highly uneven, particularly across territories and firm sizes. Small and medium-sized enterprises (SMEs), which dominate the industrial fabric of most European regions, often approach high-tech adoption cautiously and fragmentarily, owing to limited financial, managerial, and human resources (Cugno *et al.*, 2022; Morais & Ferreira, 2020). These differences raise concerns about potential technological divides within regional production systems. Likewise, all things being equal, smaller economies or contexts may face additional barriers to technological innovation.

The COVID-19 pandemic further accelerated the need for technological adaptation, revealing both the strengths and vulnerabilities of manufacturing ecosystems (Cugno *et al.*, 2022). While advanced technologies ensured business continuity through automation and remote operations, they also exposed persistent structural gaps, particularly in traditional or low-tech sectors. Understanding how regional firms approach high-tech innovation therefore becomes crucial for designing effective industrial and innovation policies.

To achieve this goal, I adopted a strategy that combines balance-sheet information for 2022 with data collected through a survey administered in December 2023. I obtained firms' contact details through a web-based data collection procedure, enabling the administration of the questionnaire, which yielded 128 valid responses on technological adoption, perceived constraints, and innovation practices. Then, I exploited these data within an econometric framework that explores how firms' characteristics, such as size, sector, ownership, and localisation, and the local context shape technological behaviours and innovation readiness.

Empirical evidence reveals a heterogeneous level of high-tech adoption among regional manufacturing firms. While several companies, especially bigger ones, are experimenting with advanced technologies such as cloud systems, IoT, and digital platforms, many smaller firms still rely on traditional production processes and report limited technological readiness. The results confirm a dual structure within the local industrial ecosystem: a minority of technologically advanced firms and a majority lagging in technological upgrading. Furthermore, the analysis highlights that firms' perceived barriers to high-tech adoption relate mainly to financial constraints, lack of skilled personnel, and uncertainty about return on investment. Simultaneously, firms that belong to technological districts have already adopted high-tech solutions and report positive effects in terms of the number of technologies already implemented.

The article contributes to the ongoing debate on technological transformation and regional innovation systems. Indeed, while extensive research has explored national or sectoral drivers of Industry 4.0, fewer studies have focused on territorial-level analyses of technological diffusion, particularly in traditional manufacturing areas. By focusing on a specific regional ecosystem, this research highlights the role of contextual factors, such as local districts and digital innovation hubs, in shaping high-tech adoption pathways, both in the two provinces analysed and in other comparable contexts.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

High-tech transformation is a multifaceted process reshaping how firms generate and capture value through the integration of new technologies into business operations and strategies (Teece, 2010; Foss & Saebi, 2017). The Industry 4.0 framework emphasises the convergence of advanced technologies, including IoT, AI, robotics, digitalisation, and data analytics, as drivers of efficiency, innovation, and competitive advantage (Kiel *et al.*, 2017; Müller *et al.*, 2018). Recent studies highlight that the adoption of these technologies not only enhances productivity but also triggers organisational and strategic renewal, often leading to business model innovation (BMI) (Ancillai *et al.*, 2023; Björkdahl, 2020).

However, empirical evidence shows highly heterogeneous diffusion of these technologies across firms. For example, the literature highlights that firm size plays a crucial role in shaping technological

adoption patterns. Larger enterprises typically benefit from economies of scale, more structured organisational processes, and easier access to financial resources, which facilitate investments in complex digital technologies (Kohtamäki *et al.*, 2019; 2020). In contrast, SMEs face significant barriers to digitalisation, including financial constraints, lack of internal expertise, and uncertainty about the expected returns on investment (Cugno *et al.*, 2022; Morais & Ferreira, 2020). Scholars have conceptualised this imbalance as a ‘digitalisation paradox’ (Gebauer *et al.*, 2020), in which the potential of digital transformation remains underexploited among smaller firms.

In this study, I measured firm size as the number of employees. Building on past literature, I expected that firms with greater organisational and financial resources would be more likely to engage in high-tech adoption.

H1: Larger firms (*i.e.*, firms with more employees) are more likely to adopt high-tech than smaller firms.

Beyond firm-level determinants, the territorial and institutional context also shapes firms’ technological behaviour. Regional innovation systems, industrial districts, and local collaborative networks can provide access to knowledge spillovers, shared resources, and specialised competencies, which can significantly reduce the costs and risks associated with technological upgrading (Asheim & Isaksen, 2002; Belussi & Sedita, 2010). Firms embedded in such innovation networks benefit from proximity to other firms, research institutions, and support organisations, which enhances learning processes and facilitates the diffusion of new technologies. In contrast, firms that are not embedded in these collaborative environments may face greater difficulties in accessing external knowledge and innovation-related resources. In the analysis, I captured this dimension through firms’ participation in technological districts, research centres, and digital innovation hubs. Accordingly, I expected firms integrated within local innovation networks to exhibit higher levels of high-tech adoption.

H2: Firms embedded in technological districts exhibit higher levels of high-tech adoption than firms not involved in such networks.

Finally, internal capabilities shape firms’ ability to adopt and use advanced technologies effectively. Managerial quality, strategic orientation towards innovation, and the availability of skilled human capital can enhance firms’ capacity to identify, evaluate, and implement new technological solutions (Chen & Huang, 2009; Caloghirou *et al.*, 2018).

H3: Firms with greater innovation orientation and managerial capabilities are more likely to overcome barriers to technological transformation.

RESEARCH METHODOLOGY

Sample

I conducted the empirical analysis using a structured data collection process that combined administrative and survey-based information. Firstly, I identified key technological domains and measurable indicators of high-tech development, focusing on the adoption of advanced technologies, software tools, digitalised processes, and e-commerce. Building on these dimensions, I designed a dedicated online survey to collect information on firms’ engagement with high-tech activities, perceived benefits and challenges, collaborative initiatives, and perspectives on future technological development.

Furthermore, I constructed a firm-level dataset using the AIDA database (Bureau van Dijk, 2023), which provided comprehensive financial, registry, and sectoral information on Italian companies. The initial population comprised 16 457 firms located in the provinces of Fermo and Ascoli Piceno. After restricting the sample to active limited liability companies operating in the manufacturing sector and excluding firms without complete financial data for 2022 or those in liquidation, the dataset consisted of 1 383 firms.

To ensure that this dataset remained representative of the overall population, I verified its consistency in firm size, age, and growth dynamics, confirming that the selected firms adequately reflect the structural characteristics of the manufacturing base in the two provinces.

For each firm, I collected detailed information, including structural characteristics, sector, legal status, ownership, district membership, key financial indicators, and employee data.

To facilitate survey administration, I implemented a web scraping procedure to retrieve firms' contact information, which I conducted in full compliance with data protection and privacy regulations.

Specifically, the web scraping targeted firms' official websites as listed in the AIDA database and retrieved publicly available contact information, primarily email addresses used for business communication. The scraping focused on standard website sections (*e.g.*, 'homepage,' 'contacts,' 'about,' 'company information') and did not involve social media platforms or third-party directories. I retained firms if I identified at least one valid and active email address associated with the firm. At that stage, I excluded firms with inactive websites, missing contact pages, or invalid email addresses, thus reducing the sample from 1 383 to 697 eligible firms. While this restriction may introduce a selection bias towards firms with a stronger technological presence, it reflects the practical requirements of online survey administration and the increasing diffusion of corporate websites even among small and medium-sized manufacturing firms. Moreover, the analysis focused on limited liability companies, which are more likely to display a minimum level of high-tech engagement than unipersonal entrepreneurial activities.

I distributed the online survey, implemented via Microsoft Forms, individually to all eligible firms in December 2023. Participation was voluntary and respondents could withdraw at any stage. Of the 697 firms contacted, 141 responded, and 128 firms provided valid consent and completed the questionnaire, resulting in an effective response rate of 18.4%. These 128 firms constituted the final analysed sample.

This final sample was composed predominantly of limited liability companies (S.R.L., 83%), with a substantial presence of family-owned firms (45%). Most firms were Italian-owned (58%), while the remainder was foreign-owned or had undisclosed ownership. Sectoral analysis, based on ATECO classification, showed a diversified manufacturing structure with 19 sectors represented (Table 1).

Table 1. Companies' distribution based on the ATECO code in Fermo and Ascoli Piceno in the year 2022

ATECO description	ATECO code	Freq.	%
Food industries	10	10	7.81%
Beverage industry	11	9	7.03%
Textile industries	13	6	4.69%
Packaging of clothing items; packaging of leather and fur items	14	6	4.69%
Manufacture of leather goods and the like	15	23	17.97%
Wood and wood and cork products industry (excluding furniture); manufacture of articles of straw and plaiting materials	16	2	1.56%
Manufacture of paper and paper products	17	11	8.59%
Printing and reproduction of recorded media	18	4	3.13%
Manufacture of chemical products	20	8	6.25%
Manufacture of articles of rubber and plastics	22	4	3.13%
Manufacture of other non-metallic mineral processing products	23	1	0.78%
Manufacture of metal products (excluding machinery and equipment)	25	13	10.16%
Manufacture of computers and electronic and optical products; electro-medical apparatus, measuring apparatus and clocks	26	4	3.13%
Manufacture of electronic equipment and non-electrical household equipment	27	4	3.13%
Manufacture of NCA machinery and equipment	28	7	5.47%
Manufacture of motor vehicles, trailers and semi-trailers	29	6	4.69%
Furniture manufacturing	31	6	4.69%
Other manufacturing industries	32	2	1.56%
Repair, maintenance and installation of machines and equipment	33	2	1.56%
Total	—	128	100%

Note: distribution of the sample of enterprises responding to the survey.

Source: own study.

The most common sectors were leather and related products (18%), fabricated metal products (10%), and paper and paper products (9%), while several niche sectors were represented by only

one or two firms. Territorial coverage was balanced between the two provinces, with 66 firms in Fermo and 62 in Ascoli Piceno, and more than half of the municipalities across the two provinces included in the survey (see Figure 1 for a geographic distribution).

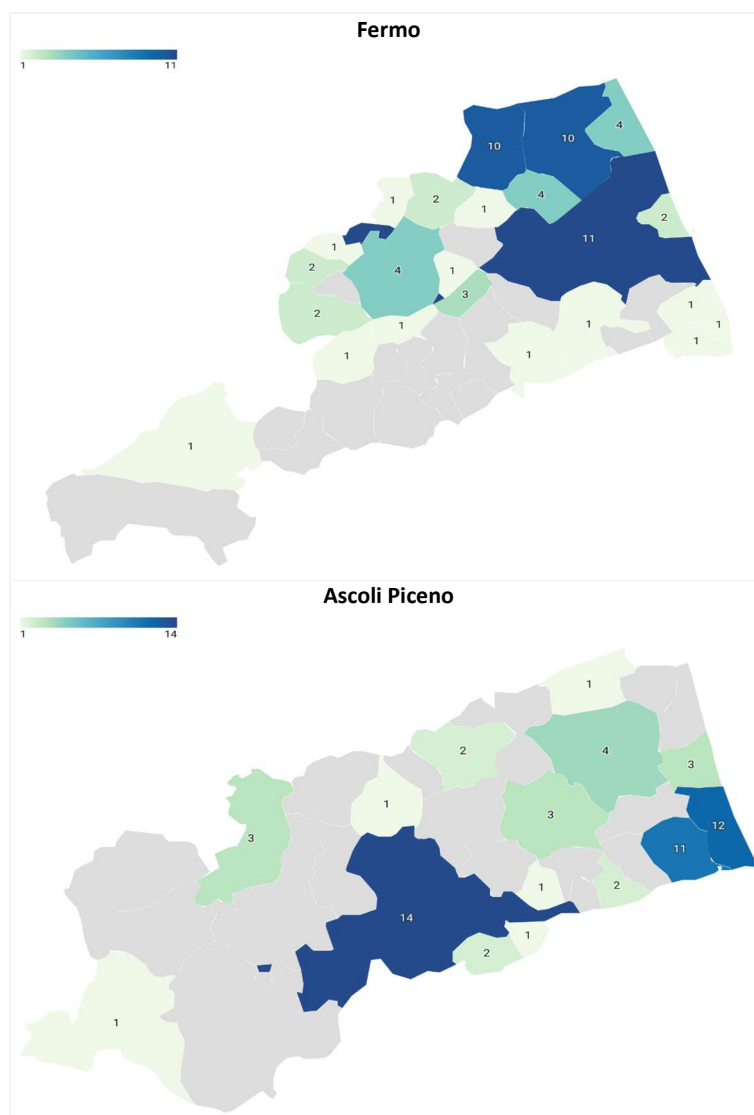


Figure 1. Territorial coverage of the sample surveyed for the two provinces of Fermo and Ascoli Piceno in December 2023

Source: own elaboration.

Overall, the dataset provided a representative and detailed view of manufacturing firms in the two provinces, enabling an in-depth analysis of high-tech adoption patterns and the factors influencing technological engagement at the firm level.

Variables

From the survey, I retrieved the dependent variables that captured the degree of technological adoption within firms. Firstly, I identified a list of fourteen technologies that fell under the category of high-tech and could be relevant to investigate within firms. These technologies were as follows: (1) cloud; (2) industrial Internet or Internet of Things (IoT); (3) simulation; (4) horizontal and vertical integration; (5) cybersecurity systems and cyber-physical systems; (6) additive manufacturing; (7) Big Data analysis; (8) augmented reality; (9) advanced manufacturing solutions and robotics; (10) artificial intelligence

(AI); (11) machine learning; (12) blockchain; (13) wearable, sensors and smart devices; (14) electronic commerce (E-commerce). A detailed description of each technology is provided in Appendix.

In detail, to capture the level of penetration, I formulated a multiple-choice question with four possible answers for each technology. The question ‘According to you, for each of the following high-tech technologies, what is the degree of actual implementation in your company?’ offered the following options, as previously described: (a) not implemented / not of interest; (b) of interest / not yet implemented; (c) planned within the next five years; (d) implemented.

Depending on the answer, the firm was assigned a score ranging from 0 to 3, where 0 corresponded to ‘not implemented/not of interest’ and 3 corresponded to ‘implemented.’ This made it possible to create a quantitative measure that captures, on the one hand, the level of hi-tech penetration and the actual implementation of one or more specific technologies, and on the other, highlights potential delays in adoption or particular technologies of interest, among other aspects.

This synthetic metric allowed me to classify both technologies and firms. In fact, if a technology has been implemented by all 128 firms, the maximum score for that technology would be 384. Conversely, if a firm had already adopted all the technologies, it would obtain a score of 42. Figure 2 presents a summary of the scores received by enterprises by type of technology.

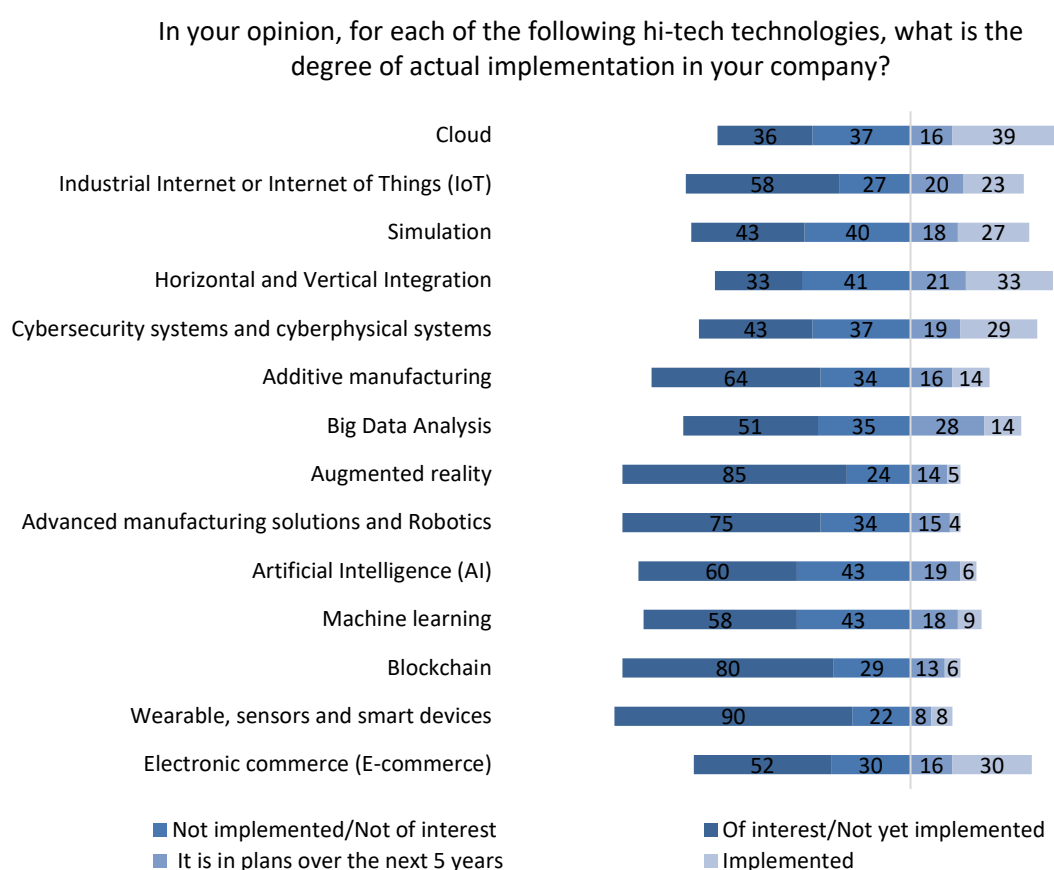


Figure 2. High technologies and penetration level for the surveyed firms in December 2023

Source: own elaboration.

Based on the answer from the survey, HighTech was a discrete variable representing the total score assigned to each firm based on the number of technologies adopted and their level of implementation. Since each technology could take a value ranging from 0, indicating that the technology was not implemented, to 3, denoting full implementation, higher values reflected broader and more advanced technological adoption. WeightedHighTech expressed the same measure in relative terms by dividing the total score by 42, which represents the maximum achievable value if all fourteen technologies were

fully implemented (14×3). This rescaled indicator facilitates comparison across firms of different technological profiles. To capture threshold effects, I also constructed two dummy variables. *D_HighTech* took the value of one if the total technological score (*HighTech*) exceeded the average score achieved by the companies in the sample (i.e., above 13), and zero otherwise. Similarly, *D_WeightedHighTech* equalled one if the weighted score (*WeightedHighTech*) was above 0.5 – corresponding to over 50% of the maximum potential technological adoption level – and zero otherwise.

In the empirical analysis, I controlled for several firm-level characteristics that may influence the outcomes of interest. I measured firm size by the number of employees, capturing differences in scale and organisational capacity (*Size*). I defined liabilities as the ratio of financial debts to total turnover, providing an indication of the firm's financial leverage (*Liabilities*). I measured tangible assets as the share of tangible fixed assets over total assets, reflecting the firm's capital intensity (*Tangible assets*). I calculated firm age as the number of years since the firm's establishment and it served as a proxy for experience and market maturity (*Age*).

In addition to these controls, I included several potential determinants of firm performance and behaviour. The cost per employee variable represented the average labour cost per worker, expressed in thousands of euros, and captures differences in labour quality or intensity (*Cost_employee*). I also considered three dummy indicators capturing firms' participation in innovation-related networks: *Tech_District* equalled one if the firm belonged to a technological district, *Research_Center* equalled one if it was part of a research centre, and *Dig_Inn_Hub* equalled one if it was associated with a digital innovation hub, with all three set to zero otherwise. Furthermore, *Family* was a dummy variable equal to one when the firm's global ultimate owner (GUO) is an individual or family, and zero when ownership was corporate or institutional. Finally, *Foreign* equalled one if the GUO was a foreign entity and zero if it was Italian. Table 2 shows a descriptive summary of these variables.

Table 2. Descriptive statistics of the enterprises in the sample in 2022-2023

Variable	Obs.	Mean	Std. Dev.	Min	Max
Size	128	41.62	89.27	0.00	560.00
Liabilities	128	1.11	1.94	0.00	10.12
Tangible assets	128	0.20	0.20	0.00	0.92
Age	128	25.50	15.87	2.00	93.00
Cost_employee	128	34.41	15.94	0.00	66.85
Tech_District	128	0.12	0.32	0.00	1.00
Research_Center	128	0.12	0.32	0.00	1.00
Dig_Inn_Hub	128	0.07	0.26	0.00	1.00
Family	128	0.45	0.50	0.00	1.00
Foreign	128	0.42	0.50	0.00	1.00
HighTech	128	13.22	7.67	0.00	35.00
WeightedHighTech	128	0.31	0.18	0.00	0.83
D_HighTech	128	0.50	0.50	0.00	1.00
D_WeightedHighTech	128	0.19	0.39	0.00	1.00

Source: own study.

Empirical Strategy

Using this empirical strategy, I tested whether specific firm attributes were more strongly associated than others with the level of high-tech adoption, and whether these characteristics could help explain why some firms adopt these technologies while others do not.

This relationship is inherently complex and multifaceted; theoretically, we may expect a bidirectional interaction. On the one hand, firm characteristics may influence the extent of high-tech adoption: firms investing heavily in research and development or employing highly skilled workers are more likely to implement advanced technologies. On the other hand, the adoption of high-tech solutions may reshape firm characteristics by inducing investments in employee training, organisational

restructuring, or process innovation. Several studies have investigated this interplay between technological adoption and firm attributes. For instance, Spitsin *et al.* (2022) examines how the performance and growth of high-tech firms affect their financial structures, showing that better-performing and faster-growing firms tend to exhibit stronger financial positions. Cavalcante (2013) focuses on how new technologies can reshape business models, highlighting that technological adoption often entails substantial structural and organisational adjustments.

Building on insights from this literature (Cavalcante, 2013; Spitsin *et al.*, 2022) and on the empirical properties of the data, I performed a quantitative analysis to empirically assess the link between high-tech adoption and firm characteristics using two complementary econometric specifications. This dual approach allowed me to capture both the intensity of technology adoption and the likelihood of being a relatively high adopter. I estimated the first model using a linear ordinary least squares (OLS) specification, defined as:

$$HighTech_{i,t} = \alpha_i + \beta_i * D_{i,t} + \gamma_i * C_{i,t} + \alpha_{ateco} + \alpha_{nuts3} + \varepsilon_{i,t} \quad (1)$$

in which $HighTech_{i,t}$ is a discrete index measuring the intensity of high-tech adoption, defined as the sum of fourteen technology-specific scores. Although discrete, this variable exhibits a sufficiently wide support and variability to be treated as approximately continuous, allowing the use of OLS as a parsimonious and easily interpretable benchmark. OLS estimates capture the average marginal effect of firm characteristics on the overall intensity of technology adoption. $D_{i,t}$ is the vector containing the main explanatory variables (or drivers) of interest, while $C_{i,t}$ includes a set of firm-level control variables. The model also includes fixed effects for the 2-digit industry classification (α_{ateco}) and for province (α_{nuts3}), which help control for unobserved heterogeneity across industries and territorial contexts. Finally, $\varepsilon_{i,t}$ denotes the error term. I clustered standard errors at the firm level.

To complement the analysis, I estimated a non-linear Probit model:

$$D_HighTech_{i,t} = \beta_i * D_{i,t} + \gamma_i * C_{i,t} + \alpha_{ateco} + \alpha_{nuts3} + \varepsilon_{i,t} \quad (2)$$

In this case, the main independent variables, controls, and fixed effects remain the same as in the OLS model. The dependent variable, $D_HighTech_{i,t}$, corresponds to the probability that a firm, given its characteristics, has a high-tech level equal to or above the observed average score. This specification permits focusing on the extensive margin of adoption by modelling the probability that a firm reaches a relatively high level of technological intensity. Estimating both OLS and Probit models ensured robustness of the results across alternative functional forms and provided complementary insights into the determinants of high-tech adoption. To mitigate potential endogeneity problems, I lagged all independent variables by one year and took them at 2022 values.

RESULTS AND DISCUSSION

Firstly, the results of both the linear and Probit regressions suggest that some firm-level characteristics were clearly associated with a higher high-tech score.

Table 3 reports the results of the OLS regressions investigating the relationship between firm characteristics and the degree of high-tech adoption. Columns (1) to (3) use the total high-tech score as the dependent variable, while Columns (4) to (6) replicate the analysis using the weighted high-tech score, which represents an alternative operationalisation of technological adoption intensity. As expected, rescaling the dependent variable did not alter the qualitative relationships between the regressors and the outcome. Across almost all specifications, the coefficients were consistent in both magnitude and significance, suggesting the consistency of the results even with the inclusion of provincial (NUTS3) and sectoral (ATECO) fixed effects.

Among the control variables, firm size showed a positive and statistically significant association with the level of high-tech adoption in all specifications. Thus, larger firms were more likely to adopt a broader set of advanced technologies. The effect, although modest in magnitude, was highly robust across specifications, implying that scale advantages may facilitate investment in complex technological solutions. Similarly, liabilities, measured as financial debts over turnover, showed a positive and statistically significant coefficient in the baseline OLS specifications: firms with a more leveraged

financial structure were not necessarily constrained in their innovative capacity; rather, they might have used financial leverage strategically to fund technological investments. However, this effect weakens and becomes insignificant once sectoral and provincial fixed effects are included. This pattern suggests that we should interpret the positive association between liabilities and high-tech adoption with caution, as it may reflect unobserved sectoral or territorial characteristics rather than a firm-level driver of technological adoption.

Turning to the determinants, the cost per employee variable was also positive and significant, indicating that firms with higher labour costs – often a proxy for more qualified or specialised workers – were more likely to score higher in high-tech adoption. This finding aligns with the idea that human capital quality is a critical enabler of technological upgrading. Indeed, companies offering higher wages can attract and retain more qualified talent, which in turn can contribute to high-tech development.

I observed the strongest effect for the Tech_District variable. Belonging to a technological district increased the high-tech adoption score by approximately 6 to 8 percentage points, a large and highly significant effect across all model specifications. This result highlights the importance of spatial and network-related factors in fostering technological diffusion. Firms embedded in technological districts likely benefited from knowledge spillovers, local collaboration networks, and institutional support, all of which enhance their probability of adopting advanced technologies. The effect remained significant and stable even after controlling for regional and sectoral heterogeneity, confirming that the impact of local innovation ecosystems operated beyond industry- or region-specific dynamics.

On the other hand, the presence of a Research_Center affiliation exerted a positive and significant influence in the baseline specifications, although its magnitude decreased and became insignificant once fixed effects were introduced. This suggests that while research collaborations can promote technology adoption, their effect may be partially captured by sectoral or regional differences in innovation intensity. In contrast, other variables such as Tangible assets, Age, Family ownership, and Foreign ownership did not display statistically significant relationships with technological adoption. These null results suggest that the firm's asset structure, age profile, and ownership type are less critical in explaining the probability of adopting advanced technologies once other factors are controlled for.

Overall, the results suggest that high-tech adoption is primarily driven by factors related to firm size, financial and human resources, and, most importantly, by the firm's integration within technological districts. These findings support the hypothesis that local innovation ecosystems play a crucial role in shaping firms' technological trajectories, amplifying the benefits of knowledge sharing and collaborative dynamics (Table 3).

Table 4 reports the results of the Probit estimations, where the dependent variable was a dummy indicator equal to one when the firm's high-tech adoption score was above the sample average. Columns (1)-(3) refer to the unweighted version of the dependent variable (D_HighTech), while Columns (4)-(6) use the weighted measure (D_Weighted HighTech). The consistency of the results across the OLS and Probit specifications strengthens the findings' reliability and serves as a meaningful robustness check, indicating that results are not driven by the choice of functional form.

The estimated coefficients confirm that firm size remains a strong and statistically significant determinant of the probability of being classified as a high-tech adopter. Larger firms were significantly more likely to score above the average threshold of technological implementation, underscoring once again the role of firm scale and organisational capacity in enabling the diffusion of advanced technologies.

The Tech_District variable retained its central role and continued to exhibit a positive and significant effect across all model specifications. Belonging to a technological district increased the probability of being a high-tech firm. This result strongly supports the hypothesis that local innovation ecosystems play a crucial role in shaping technological behaviour: firms embedded in such districts are more likely to benefit from proximity to knowledge sources, local collaboration opportunities, and institutional support for innovation.

Moreover, the presence of a Research_Center affiliation was also positively and significantly associated with high-tech adoption, with marginal effects comparable in size to those of technological districts. While research centres do not appear to be significant in increasing the overall high-tech score,

this result suggests that collaboration with research institutions can meaningfully enhance firms' technological capabilities, likely by facilitating access to scientific knowledge and specialised expertise, ultimately improving the likelihood of having more technologies than average.

Table 3. Results from the OLS model for the 128 firms in 2022-2023

Variables	(1) HighTech	(2) HighTech	(3) HighTech	(4) Weighted HighTech	(5) Weighted HighTech	(6) Weighted HighTech
Size	0.0158*** (0.0047)	0.0157*** (0.0047)	0.0140* (0.0072)	0.0004*** (0.0001)	0.0004*** (0.0001)	0.0003* (0.0002)
Liabilities	0.5676** (0.2814)	0.5696** (0.2806)	0.3340 (0.3413)	0.0135** (0.0067)	0.0136** (0.0067)	0.0080 (0.0081)
Tangible assets	0.3214 (3.0158)	0.3469 (3.0228)	2.1191 (3.6635)	0.0077 (0.0718)	0.0083 (0.0720)	0.0505 (0.0872)
Age	-0.0706 (0.0969)	-0.0721 (0.0988)	-0.0678 (0.0958)	-0.0017 (0.0023)	-0.0017 (0.0024)	-0.0016 (0.0023)
Age ²	0.0017 (0.0012)	0.0017 (0.0012)	0.0014 (0.0011)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
Cost_employee	0.0880** (0.0435)	0.0883** (0.0436)	0.0961* (0.0516)	0.0021** (0.0010)	0.0021** (0.0010)	0.0023* (0.0012)
Tech_District	7.7416*** (1.8988)	7.7351*** (1.8993)	6.3166*** (2.0092)	0.1843*** (0.0452)	0.1842*** (0.0452)	0.1504*** (0.0478)
Research_Center	2.8794* (1.4982)	2.8743* (1.5114)	1.6678 (1.6802)	0.0686* (0.0357)	0.0684* (0.0360)	0.0397 (0.0400)
Dig_Inn_Hub	2.0812 (1.3561)	2.0687 (1.3829)	2.3612 (1.9640)	0.0496 (0.0323)	0.0493 (0.0329)	0.0562 (0.0468)
Family	-2.3896 (1.6537)	-2.3893 (1.6599)	-1.4750 (1.8925)	-0.0569 (0.0394)	-0.0569 (0.0395)	-0.0351 (0.0451)
Foreign	-1.0605 (1.7052)	-1.0556 (1.7223)	0.1181 (1.9865)	-0.0252 (0.0406)	-0.0251 (0.0410)	0.0028 (0.0473)
Constant	9.2764*** (2.5968)	9.2280*** (2.6338)	4.9152 (4.3762)	0.2209*** (0.0618)	0.2197*** (0.0627)	0.1170 (0.1042)
Observations	128	128	128	128	128	128
R ²	0.2592	0.2592	0.4465	0.2592	0.2592	0.4465
Nuts3 FE	NO	YES	YES	NO	YES	YES
Sector FE	NO	NO	YES	NO	NO	YES

Note: Results from the OLS estimation. Dependent variables: *HighTech* (columns 1-3) and *Weighted HighTech* (columns 4-6). Independent variables are at time $yr=2022$. Provincial and sectoral fixed effects are included in the saturated model (columns 3 and 6).

Source: own study.

Finally, other control variables, such as financial leverage (Liabilities), Tangible assets, Age, and ownership structure (Family, Foreign), remained statistically insignificant. Their lack of significance suggests that once network participation and firm scale are accounted for, these factors do not exert a meaningful marginal effect on the probability of adopting high technologies.

Overall, the Probit model corroborated the main findings from the OLS estimations. The probability of being a high-tech firm increased significantly with firm size, higher-quality human capital, and especially with the firm's integration into innovation-oriented ecosystems such as technological districts and research centres. These results highlight the central role of local knowledge networks and collaborative environments in fostering technological upgrading among firms, confirming that spatial and relational proximity are key drivers of high-technology adoption.

The results are consistent with previous studies highlighting firm size as a key determinant of high-tech adoption (Müller *et al.*, 2018; Kohtamäki *et al.*, 2019). Similar to existing evidence on SMEs, larger firms appeared better equipped to absorb the costs and organisational complexity associated with high-tech. Moreover, the strong effect of technological districts confirmed the relevance of regional

innovation system theories (Asheim & Isaksen, 2002; Belussi & Sedita, 2010), suggesting that local knowledge spillovers and institutional proximity significantly shape firms' technological trajectories. In this respect, the findings extend prior research by providing micro-level evidence on how territorial embeddedness operates even within relatively small and traditional manufacturing contexts. Finally, compared to studies focusing on national or sectoral drivers of high-tech, this article emphasises the importance of place-based factors and district participation, supporting the view that high-tech transformation is not solely a firm-level decision but a context-dependent process.

Table 4. Results from the Probit model for the 128 firms in 2022-2023

Variables	(1) D_HighTech	(2) D_HighTech	(3) D_HighTech	(4) D_Weighted HighTech	(5) D_Weighted HighTech	(6) D_Weighted HighTech
Size	0.0012** (0.0006)	0.0012** (0.0006)	0.0016*** (0.0006)	0.0007*** (0.0003)	0.0007*** (0.0003)	0.0008** (0.0004)
Liabilities	0.0424** (0.0175)	0.0430** (0.0175)	0.0331 (0.0209)	-0.0020 (0.0144)	-0.0029 (0.0137)	-0.0197 (0.0198)
Tangible assets	0.1084 (0.1877)	0.1114 (0.1893)	0.1221 (0.2080)	-0.0410 (0.1518)	-0.0474 (0.1511)	0.1332 (0.1953)
Age	-0.0016 (0.0060)	-0.0020 (0.0061)	-0.0010 (0.0070)	-0.0036 (0.0049)	-0.0033 (0.0051)	-0.0068 (0.0061)
Age ²	0.0001 (0.0001)	0.0001 (0.0001)	0.0000 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001* (0.0001)
Cost_employee	0.0090*** (0.0025)	0.0091*** (0.0025)	0.0116*** (0.0027)	0.0016 (0.0021)	0.0015 (0.0020)	0.0031 (0.0028)
Tech_District	0.5423*** (0.1548)	0.5388*** (0.1529)	0.2170* (0.1622)	0.1832** (0.0855)	0.1854** (0.0859)	0.3219** (0.1483)
Research_Center	0.2214** (0.1022)	0.2218** (0.1027)	0.2545** (0.1153)	0.1693** (0.0775)	0.1707** (0.0775)	0.3088** (0.1350)
Dig_Inn_Hub	0.2260 (0.1515)	0.2183 (0.1552)	0.1823 (0.1416)	-0.1223 (0.1199)	-0.1243 (0.1179)	-0.3590 (0.1855)
Family	-0.1169 (0.1042)	-0.1179 (0.1044)	-0.0014 (0.1139)	-0.0562 (0.0770)	-0.0563 (0.0764)	-0.0601 (0.1023)
Foreign	0.0155 (0.1053)	0.0148 (0.1053)	0.2124* (0.1167)	-0.0847 (0.0830)	-0.0853 (0.0825)	-0.0215 (0.1043)
Observations	128	128	107	128	128	95
Pseudo R ²	0.2794	0.2797	0.3899	0.1700	0.1710	0.2593
Nuts3 Control	NO	YES	YES	NO	YES	YES
Sector FE	NO	NO	YES	NO	NO	YES

Note: Results from the Probit estimation. Dependent variables: *D_HighTech* (columns 1-3) and *D_Weighted HighTech* (columns 4-6). Independent variables are at time *yr=2022*. Provincial and sectoral fixed effects are included in the saturated model (columns 3 and 6).

Source: own study.

CONCLUSIONS

I analysed the level of high-tech adoption among firms located in the provinces of Fermo and Ascoli Piceno, based on a unique dataset that combines information from the AIDA database and a dedicated survey administered directly to 128 companies. I focused on the implementation of fourteen specific technologies.

The empirical evidence, based on OLS and Probit models, clarified the determinants of high-tech adoption and provided support for all three research hypotheses. Firstly, the results indicate that firm size and human capital intensity emerge as key drivers of high-tech adoption: larger firms and those with higher labour costs per employee, used as a proxy for skilled and qualified personnel, exhibited a significantly higher probability of adopting advanced technologies. Secondly, firms characterised by a stronger innovation orientation and managerial capabilities are better able to overcome barriers to

technological transformation, suggesting that organisational and cognitive resources complement structural factors in shaping adoption behaviour (H1 and H3).

Thirdly, the presence within technological districts and collaboration with research centres emerge as positive and significant determinants of high-tech adoption (H2). These results underscore the importance of spatial and relational proximity: firms embedded in innovation-oriented ecosystems are more likely to access knowledge flows, institutional resources, and collaborative opportunities that foster technological upgrading. Conversely, variables related to firms' financial structure, tangible assets, or ownership type showed no significant relationship with high-tech adoption once network effects and firm size are controlled for.

These findings yield clear policy insights. Firstly, strengthening local innovation ecosystems appears essential: policies should promote the creation and consolidation of technological districts, university-industry collaborations, and applied research networks, which are proven to facilitate technological diffusion. Secondly, public programmes should prioritise human capital development, both by fostering specialised training and by incentivising firms to attract and retain skilled workers. Finally, targeted financial instruments, such as innovation vouchers, tax incentives, and co-funded R&D programmes, could help reduce the cost barriers that currently prevent many firms from adopting advanced technologies.

Overall, the diffusion of high-tech innovation depends on a coordinated, multi-actor strategy. Firms, universities, research centres, and public institutions must act jointly to create an enabling environment for technological upgrading. Only through such an integrated approach, *i.e.*, combining organisational effort, human capital investment, and institutional support, will firms in peripheral regions be able to overcome existing structural constraints and fully exploit the opportunities offered by technological transformation.

Beyond the specific local context analysed, the results offer relevant insights for a broader set of traditional manufacturing regions characterised by similar features, such as fragmented industrial structures, limited technological capabilities, and relatively weak innovation systems. In such contexts, place-based industrial and innovation policies that combine local support, skills upgrading, and inter-firm collaboration are likely to be especially effective in fostering technological upgrading. As a result, the evidence provided in this study can inform policymakers designing strategies to support industrial modernisation in peripheral areas and traditional manufacturing regions, not only in the two provinces but elsewhere as well.

The study is not without limitations. As a survey-based analysis, it may suffer from response bias. Moreover, the relatively small and geographically concentrated sample limited the results' generalisability. Future research should expand the sample to validate these findings across different contexts, assess sector-specific pathways and study the impact of policy interventions on reducing barriers to high-tech. Finally, future research should incorporate longitudinal data to capture dynamic patterns of technological adoption over time.

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Appendix 1: List and description of the main high technologies (high-tech)

List and description of the main high technologies (high-tech)

High-Tech	Description
Cloud	It allows storage and access to computer data and resources via the Internet rather than local devices or physical servers. Resources are hosted and managed by cloud providers and can include storage, computing, software, and more. This allows the management of large amounts of data.
Industrial Internet or Internet of Things (IoT)	It refers to the connection of industrial devices, machinery and systems via the Internet to enable data collection, sharing, and analysis. This allows for more efficient monitoring and control of industrial processes by embedding the internet within 'intelligent' objects.
Simulation	It is the creation of models or representations of real systems in order to study their behaviour or test hypotheses. It is used in particular to simulate processes between connected machines and to optimise processes.
Horizontal and vertical integration	The first refers to the integration of different processes within a company, while the second refers to the integration of processes in different production phases or supply chains.
Cybersecurity systems and cyberphysical systems	The first relates to technologies and practices to protect computer systems from threats and attacks, while the second relates to physical systems integrated with computer components that can be controlled and monitored via digital networks.
Additive manufacturing	Also known as 3D printing, it is a manufacturing process that creates objects by adding material layer by layer, rather than removing it from a solid block. In general, it refers to the use of digital development software for the production of customised objects.
Big Data analysis	It is the process of examining, cleaning, analysing, and interpreting large data sets (big data) to obtain useful information, identify patterns, and support business decisions.
Augmented reality	It overlays digital elements, such as images, onto a real-world view, often through devices such as glasses or viewers, to enrich the user experience.
Advanced manufacturing solutions and robotics	It represents the use of advanced technologies in industrial production, including robotics, automation, intelligent systems and process digitalisation. It mainly refers to the use of interconnected and programmable collaborative robots based on needs.
Artificial intelligence (AI)	It refers to the simulation of human intelligence by computers or computer systems to perform complex tasks such as speech recognition, problem solving and learning to support business.
Machine learning	It is a branch of AI that focuses on the development of algorithms that allow computers to learn from data and improve performance over time without being explicitly programmed.
Blockchain	It is an online recording technology that allows the creation of a public, secure, immutable and decentralised ledger of transactions, often used for financial transactions or smart contracts.
Wearable, sensors and smart devices	It refers to wearable or embedded devices with sensors and connectivity capabilities to collect biometric, environmental or other data and interact with other devices or networks.
Electronic commerce (E-commerce)	Abbreviated as 'electronic commerce,' it refers to the buying and selling of goods and services on the Internet, often through platforms and e-commerce websites.

Source: own elaboration.

Author**Noemi Giampaoli**

Research Fellow at the Department of Economics and Social Sciences, Polytechnic University of Marche, Italy. Her research interests include international economics, digital innovation, firms' structure, entrepreneurship, and regional dynamics.

Correspondence to: Noemi Giampaoli, Polytechnic University of Marche, Department of Economics and Social Sciences, P.le Martelli 8, 60100 Ancona, Italy; Money and Finance Research Group (MoFiR); e-mail: n.giampaoli@staff.univpm.it

ORCID  <https://orcid.org/0000-0002-6329-8436>

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Use of Artificial Intelligence

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Conflict of Interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Moderating effects of work environment on the leadership–organisational commitment relationship

Katarzyna Łucjan, Dawid Szostek, Adam P. Balcerzak, Elżbieta Rogalska

ABSTRACT

Objective: The objective of this article is to identify the moderating role of the company industry, company size, the company department, and employees' work position in the relationship between leadership style and organisational commitment. The article fills a gap in the literature on the relationship between leadership style and organisational commitment. Although there are many studies on this topic, the literature has not yet examined this relationship in terms of its moderation by characteristics of work and position.

Research Design & Methods: This article is based on an empirical study conducted on a sample of professionally active Poles. We analysed the obtained data using structural equation modelling (SEM).

Findings: The main findings show that transactional leadership strongly affects organisational commitment among employees of larger organisations in the engineering, technology, and information technology (IT) industries.

Implications & Recommendations: Transactional leaders most strongly influence organisational commitment among lower-level employees. In contrast, transformational leaders most strongly influence organisational commitment among higher-level employees. These results have practical implications for organisations, which allows them to increase organisational commitment and thus improve their outcomes.

Contribution & Value Added: Transformational leadership most substantially affects organisational commitment among employees working in smaller organisations and organisations in the services and medicine industries. Furthermore, the study also proved that workplace characteristics are essential for this relationship. Therefore, employees in administration and support departments show greater organisational commitment when a transformational leader manages them, while employees in operations and logistics departments show greater commitment when a transactional leader manages them.

Article type: research article

Keywords: leadership style; organisational commitment; human resources management; transactional leader; transformational leader

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INTRODUCTION

For years, academic research has focused on leadership style and organisational commitment (Sosik *et al.*, 1997; Eagly & Johnson, 1990; Devlin, 1978; Jamal, 1974). The growth of these areas means they continue to be the most popular research topics (Fernandes *et al.*, 2025; Riadi *et al.*, 2025; Saripudin & Perkasa, 2024; Milhem *et al.*, 2024).

In recent years, the importance of managerial attitudes and the broadly defined quality of human capital was occasionally questioned in light of rapid and fundamental technological changes associated with the proliferation of artificial intelligence (AI). The initial wave of AI-driven business expansion appeared to focus primarily on technological advancement, with expectations that it

could reduce the importance of human capital engagement (Lazaroiu *et al.*, 2025; Balcerzak *et al.*, 2025a; Balcerzak & Valaskova, 2024).

Studies addressing the organisational and human resource management challenges arising from the expansion of AI in business contexts point to significant structural and operational transformations (see Balcerzak *et al.*, 2025b; 2026b). However, the most recent empirical research examining the key determinants of successful AI implementation, particularly in terms of enhancing organisational effectiveness and productivity growth, continues to emphasise the critical role of human capital (Yu & Qi, 2025; Yu, 2025; Balcerzak *et al.*, 2026a). Therefore, despite the challenges posed by profound technological transformation, human resources remain the most valuable asset within the firm. Within this context, hiring a new employee includes both financial and non-financial costs for the employer. Thus, caring for current employees and reducing turnover has become a priority (Nalla, 2025; Holúbek *et al.*, 2025; Eger & Žižka, 2024). The subject concepts link these two approaches. Caring for employees is leaders' responsibility (Huang *et al.*, 2021) and organisational commitment links the employees with the organisation (Benkarim & Imbeau, 2021).

The success of the entire organisation depends on the leadership style, and, in particular, employee satisfaction (Skopak & Hadzaihmetovic, 2022), their engagement (Thanh & Quang, 2022), brand growth (Binu Raj, 2022), and final financial results (Le *et al.*, 2023). On the one hand, a leader who makes conscious decisions in human resource management contributes significantly to the organisation's success (Kessi *et al.*, 2025). On the other hand, using the wrong tools can lead to employee retention (Asianab, 2023), decline in the quality of the organisation's performance (Bayati *et al.*, 2025), and cost increases (Dur *et al.*, 2021).

Despite a wide range of studies on both leadership style and organisational commitment (Yahaya *et al.*, 2016; Donkor *et al.*, 2021; Oyewobi, 2024; Waseel *et al.*, 2025), we still lack investigations into the work environment context in this relationship. Specifically, when it comes to the company industry, company size, company department, and the employees' work position. However, these variables can significantly moderate the relationship between leadership style and organisational commitment. For example, company industry and company size naturally determine communication within the organisation and the type of tasks performed (Tkalac Verčič *et al.*, 2024; Barnes *et al.*, 2023). Furthermore, small organisations achieve better results through decentralised communication, while large organisations achieve better results through centralised communication (Ding *et al.*, 2023).

As an active participant in the communication process between the employee and the organisation, the leader can, through their actions, improve or deteriorate the organisation's results (Li *et al.*, 2023). Employees' perception of internal communication also depends on their department. Communication practices should be adapted to the specific organisational unit (Fuciu & Serban, 2024). Moreover, looking even more closely, even to the individual employee, the position an employee occupies determines what kind of leader they may need. For example, a transformational leader can effectively mitigate the negative effects of task ambiguity on job satisfaction, but only for employees who hold formal management positions. Other employees are not susceptible to this effect (Nielsen *et al.*, 2022).

Nevertheless, despite the extensive literature, to the best of our knowledge, especially regarding Central European institutional and managerial environment, no study has thus far examined variables related to organisational characteristics and work position characteristics as moderators of the relationship between leadership style and organisational commitment. Some articles address these variables individually, but not as moderators of the aforementioned relationship (Tkalac Verčič *et al.*, 2024; Nielsen *et al.*, 2022).

The literature reveals a gap in considerations of the relationship between leadership style and organisational commitment moderated by the work environment. Thus, we focused on this relationship. Despite a wide range of studies, our study is the first to show that the work environment constitutes an essential factor, indicating that a properly selected leadership style guarantees high organisational commitment. The application of the guidelines noted in the article by organisations will lead to increased organisational commitment and, ultimately, to improved outcomes.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Leadership Styles Theory

Leadership style is an important research topic and frequently features in organisational structure studies. Some of the most popular styles are transformational leadership and transactional leadership, which are contrast with each other. Nevertheless, both a transformational leader and a transactional leader can exhibit transformational behaviours, and a transactional leader can exhibit transactional behaviours, adapting to the situation (*e.g.*, a combination of transactional rewarding and transformational motivating) (Wojciechowska-Dzięcielak & Szumowski, 2021).

Many consider a transactional leader to be someone who manages a team by using a system of rewards and punishments. In this case, relationships with employees are based on an exchange of benefits – a reward for a task. Such leaders often appear authoritarian, task-oriented, and lacking empathy and flexibility. They strictly supervise and manage the team's tasks (Dong, 2023). A transactional leader is essential in formalised structures where a traditional, hierarchical management style prevails. Transactional leadership enables error control and ensures task predictability, which can be a key factor in achieving success in traditional organisations (Garzón Lasso *et al.*, 2024). Moreover, a transactional leader shows a strong correlation with task performance effectiveness and works well in the implementation of specific, measurable tasks (Gemeda & Lee, 2020).

On the contrary, a transformational leader is someone who focuses on the needs and motivations of team members. They approach them individually, not using a system of rewards and punishments to motivate them, but through personal influence, charisma, and by example. They build emotional bonds with the team, offering employees autonomy and self-fulfilment (Dong, 2023). Transformational leaders are well-suited to organisations implementing innovations. Their ability to stimulate creative and innovative thinking in the team allows for the development of innovative solutions (Rashwan & Ghaly, 2022; Le, 2020).

The transactional style maintains knowledge within an organisation through a system of rewards and structured processes. Meanwhile, the transformational style more positively affects knowledge creation and sharing (Eniola & Adeola, 2025). However, both leadership styles positively affect employee performance (Yapa *et al.*, 2024; Qalati *et al.*, 2022).

Thus far, researchers investigated the links between leadership style and work system, showing that transformational leadership affects the organisational commitment of on-site employees more substantially. In contrast, transactional leadership affects the organisational commitment of remote employees more significantly (Łucjan *et al.*, 2023). Other studies revealed that transformational leadership is the most preferred style of team management due to its positive impact on employee motivation, trust, and organisational commitment (Alshammari & Yambao, 2025). However, the area of moderating the relationship between leadership and organisational commitment by company industry, company size, company department, and employees' work position remains underexplored. Existing studies often treat these variables as additions rather than as key moderators. Furthermore, research in this area remains limited. However, there are indications that these are areas that should be considered when selecting a leadership style in an organisation (Garzón Lasso *et al.*, 2024; Dong, 2023; Garzón Lasso *et al.*, 2020).

According to the above-mentioned theory, transactional leadership may be necessary in traditional, hierarchical structures, but it will not support innovation in organisations (Garzón Lasso *et al.*, 2024; Rashwan & Ghaly, 2022). Leaders who use transactional behaviour can be successful in organisations that deal with technology and IT-related areas. This is due to the monitoring, control, and evaluation of activities occurring in such organisations. Moreover, the rewarding style used by transactional leaders positively affects the motivation of IT employees, who then feel understood and recognised (Wang *et al.*, 2021). Transformational leadership most strongly affects knowledge creation in the technology and healthcare sectors. Meanwhile, transactional leadership is best at retaining this

knowledge in the technology and finance sectors. Leadership style has proven key to knowledge management within the company. This allows organisations to consciously influence the process of knowledge creation and improvement (Eniola & Adeola, 2025).

The characteristics of the company industry may determine which leadership style will be most effective. The manufacturing industry appears more likely to achieve its goals when a democratic style is used instead of an autocratic, paternalistic, or laissez-faire style (Wei & Vasudevan, 2022). The transformational style is significant for the hotel industry during a crisis. It supports the development of innovation, commitment, and a culture of learning (Burton & Dickinger, 2025). Ethical leadership, which has common elements with transformational leadership (*e.g.*, caring for others and morale), directly influences the job satisfaction of restaurant employees and also reduces their stress levels (Yasir & Javed, 2024).

Company Size

Another factor determining the need for a specific leadership style is the company size. According to the results of a 2024 study, each leadership style has particular effects. In small and medium-sized enterprises, the transformational style motivates employees. The transformational style translates into employee job satisfaction, while the transactional style focuses on increasing productivity, but with the side effect of stress and burnout. The transactional style ignores employee needs, emotions, and well-being, which may even lead to lower morale among employees of small and medium-sized enterprises (Karácsony & Czibula, 2020; Berisha *et al.*, 2024). However, these findings are contradicted by an article suggesting that both transactional and transformational styles are better accepted and more effective in small enterprises, where community values, close relationships, and mutual support dominate. However, the transformational style shows a slightly stronger correlation with the effects of such an organisation (Cantermi & Lizote, 2022).

Large organisations differ from small organisations in terms of structure. Above all, the projects' complexity and an extensive hierarchy require carefully planned management. In large organisations, a transactional style can be successfully applied, which supports clear expectations, a top-down reward system, and necessary monitoring. However, the effect of transactional leadership may also depend on other factors, such as the project type or the organisation's cultural context (Abbas & Ali, 2023). Interestingly, a slightly older study shows that the larger the organisation, the lower the propensity to take risks, the more conservative the behaviour, and the lower the tendency to strengthen employee autonomy within the organisation. It is due to the difficulty of controlling such a large structure and the need to maintain a wide span of control. The importance of a directive style, which allows for control over the organisation, increases, while the significance of employee-oriented leadership decreases (Marx, 2017).

Company Department

Regardless of its size, every organisation has departments (formalised or informal) that differ in terms of their scope of tasks and the qualifications required of their employees. On the one hand, an organisation may run a strictly task-oriented department, characterised by repetitive tasks and requiring precise supervision, for which a transactional leader would be an excellent management solution. On the other hand, there are also departments where autonomy, innovation, and creativity are essential in everyday activities. These departments will then be better supervised by a transformational leader (Sunarsi *et al.*, 2021; Wang *et al.*, 2021; Garzón Lasso *et al.*, 2024).

However, there are situations in which a particular department requires different behaviours from a single leader, like in the sales department, where people-oriented leadership can increase loyalty and sales results. In contrast, task-oriented leadership can effectively resolve customer issues by establishing and following effective procedures (Kulat *et al.*, 2023).

Although few recent studies discuss the importance of departments for leader-employee relationships, a survey of university departments found that departments involved in development, teaching, research, and knowledge transfer are more likely to use elements of transformational leadership. On the other hand, administrative departments employ the transactional style (Chin *et al.*, 2024). Another, slightly older study showed that departments such as medical, fleet management, activities, and office

management, where cooperation and communication are essential, prefer the democratic leadership style. The operational departments that perform specific tasks, such as supply or finance, tend to favour the autocratic style. They need quick action and a clearly defined direction (Bhargavi & Yaseen, 2016).

Employee Work Position

Employee preferences regarding leadership style also affect the employee's work position. It turns out that the transformational style can boost job satisfaction for employees who formally act as leaders. In people without a formal leadership position, the effect of the transformational style was significantly weaker (Nielsen *et al.*, 2022). Meanwhile, a position with a clearly defined description and well-defined tasks responds best to transactional leadership (Al Rawas & Jantan, 2023).

The employee's work position in the organisational hierarchy also has a significant impact. A study in nursing departments showed that the higher the position in the hierarchy, the stronger the influence of transformational leadership on the department's perceived effectiveness. Thus, the level of hierarchy moderates the impact of leadership style on work performance. The effectiveness of leadership style does not depend only on the leader but also on the employee's work position (Stordeur *et al.*, 2000). A more recent article (Aras & Jufri, 2022) claims that there are no significant differences in preferred leadership styles across hierarchical levels. Despite this, the influence of transformational leaders on job satisfaction and organisational citizenship behaviour (OCB) was greater in groups of leaders than in groups of line employees.

Organisational Commitment in Different Work Environments

Organisations aspire to achieve competitive advantage, which depends partly on the commitment of the entire team to the organisation's results (Szostek *et al.*, 2020, 2025; Parmar *et al.*, 2022). On the one hand, committed employees are more loyal and productive, and the customer service they provide is of a higher standard. On the other hand, uncommitted employees deteriorate the organisation's performance (Canavesi & Minelli, 2022; Szostek *et al.*, 2023; 2022a; 2022b). One of the most popular typologies of organisational commitment is the division into affective commitment (AC), which refers to employees who are emotionally attached to their organisation, continuance commitment (CC), which characterises employees who continue to work out of fear of the potential costs of leaving and therefore treat remaining in the organisation as a duty, and normative commitment (NC), which refers to employees who feel a specific obligation to continue working in the organisation (Meyer & Allen, 1991).

Employee-supervisor relationships inform every working day. The leader can significantly affect employee commitment and the results of their work. Moreover, empirical research has shown that leadership style affects the type of employees' organisational commitment (Łucjan *et al.*, 2023; Najafabadi *et al.*, 2025). Factors such as work-related stress will harm organisational commitment. It is the leader who can contribute to its reduction if they adopt the right strategy, take the right actions, and behave in an appropriate way (Wojtczuk-Turek, 2024; Yasir & Javed, 2024).

Studies show that the division between public and private enterprises is significant for employee commitment. Public employees show higher continuance commitment, while private sector employees show higher levels of affective and normative commitment (Todorović *et al.*, 2024; Łucjan *et al.*, 2023; Nguyen & Nguyen, 2021). It is worth exploring this division by examining specific industries in terms of commitment and how the leadership style used affects it. Thus far, we know that for the IT industry the most important predictors of employee organisational commitment are issues related to work environment and support from supervisors (Nguyen *et al.*, 2024). On the other hand, effective organisational communication, training, rewards, and recognition can help build organisational commitment in a manufacturing company. However, the leadership style, which naturally influences other issues of importance to employees, turns out to be crucial. Ultimately, leadership style positively impacts all commitment types (AC, CC, NC) (Sampe *et al.*, 2023; Pham, 2022). These are issues worth developing and exploring in greater depth.

There are also studies that, taken together, allow us to deduce conclusions regarding the distinction between commitment and the size of the organisation and the work position. For example, in small and medium-sized enterprises, external rewards influence all three types of commitment (AC,

NC, CC), while team support most influences NC, and working conditions only influence AC and NC. In turn, CC is more strongly associated with job involvement and the constraints' perception. By continuously monitoring influencing factors, an organisation can consciously manage employees' commitment (Hadziahmetovic & Pozega, 2024; Shankar *et al.*, 2015). In large companies, high-performance HR practices (HPHRPs) positively impact all three types of commitment. The HPHRPs are high-quality HR practices based on the belief that properly treated employees will be key to organisational competitive advantage. Related high-commitment HR practices (HCHRP) that strongly support commitment affect employees' emotional bond with the organisation. This effect grows rather among key specialists than among other employees, which means that leaders are more likely to identify with the organisation when HCHRP are applied to them (Kwon *et al.*, 2010; Yang & Mostafa, 2024).

As discussed in this chapter, theory and available research findings suggest that the company industry, company size, the company department, and the employee's work position constitute important factors influencing the relationship between leadership style and organisational commitment. Hence, we proposed four hypotheses:

- H1:** The industry of the company moderates the relationship between leadership style and organisational commitment.
- H2:** The size of the company moderates the relationship between leadership style and organisational commitment.
- H3:** The company department moderates the relationship between leadership style and organisational commitment.
- H4:** The employee's work position moderates the relationship between leadership style and organisational commitment.

Figure 1 presents the framework of the hypotheses in the our investigation.

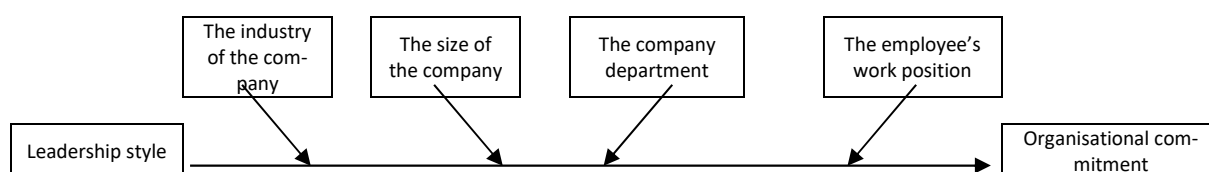


Figure 1. Visualisation of hypotheses

Source: own elaboration.

RESEARCH METHODOLOGY

Sampling Methods and Participant Characteristics

We collected the data in the form of 259 correctly completed questionnaires in February and March 2025 via an internet survey. We used nonprobability sampling, supported by a snowball technique. We posted the questionnaire on social media (Facebook) in groups that bring together professionals and

Table 1. Demographic profile of the test sample

Sex	F	162	62.5%
	M	97	37.5%
Age	18-25	59	22.8%
	26-33	115	44.4%
	34-65	85	32.8%
Work position	Assistant/Junior Specialist	27	10.42%
	Expert	21	8.11%
	Specialist	145	55.98%
	Manager	55	21.24%
	Owner	9	3.47%
	Other	2	0.77%

Source: own study.

people active in the labour market. Although access to the survey was open, the inclusion criterion for the analysis was the respondent's current professional activity. This yielded data from people with real-world experience. Table 1 presents the short demographic profile of the test sample.

Measurement Scales and Analysis Strategy

We used the model by Meyer and Allen (1991) to collect data on organisational commitment presented on the scale operationalised by Lee *et al.* (2001). (See Appendix A.) The scale presented items AC1-AC6, which defined affective commitment, items CC1-CC6, which described continuance commitment, and items NC1-NC6, which related to normative commitment. We measured employees' perspective of leadership style using the scale presented in Appendix B, composed by Jensen *et al.* (2019). The scale included items TFL1-TFL7, which represent the perception of transformational leadership, and items TCL1-TCL12, which represent the perception of transactional leadership. On both scales, inverted values are underlined in the appendices. The five-point Likert-type scale measured all items (1=strongly disagree, 5=strongly agree).

We processed the collected data using SEM. This method is widely used in management due to its suitability for measuring latent phenomena. This method considers multiple dependent variables, allowing for the control of error measurements and the assessment of both direct and indirect relationships, thus providing a complete and accurate overview of the analysed relationships. The method also provides greater flexibility than standard regression analysis (Balcerzak & Pietrzak, 2016; Chang & Ku, 2023; Anthonius *et al.*, 2025; Wach *et al.*, 2023; Waqas *et al.*, 2025; Teng & Wu, 2025).

RESULTS AND DISCUSSION

Model Verification

We analysed the collected data using IBM SPSS Statistics and IBM SPSS Amos v. 29. The confirmatory factor analysis allowed for selecting variables with the highest factor loadings. It proved vital for subsequent SEM calculations. Table 2 presents latent variables and their observable variables with Cronbach's alpha statistics and average variance extracted (AVE).

Table 2. Cronbach's alpha and AVE statistics of variables

Latent variables	Measurable variables (Components)	Cronbach's alpha internal consistency	AVE convergent validity
Affective commitment (AC)	AC2, AC3, AC4, AC5	0.867	0.755
Continuance commitment (CC)	CC1, CC2, CC3, CC5	0.775	0.746
Normative commitment (NC)	NC2, NC3, NC4, NC5	0.827	0.877
Transformational leadership (TFL)	TFL1, TFL2, TFL3, TFL6	0.923	0.502
Transactional leadership (TCL)	TCL1, TCL2, TCL4, TCL6	0.925	0.504

Source: own study.

We used the heterotrait-monotrait ratio of correlations (HTMT) to calculate discriminant validity. Table 3 presents the results of those calculations.

Table 3. Heterotrait-monotrait ratio of correlations (HTMT)

Variable	TCL	TFL	CC	NC	AC
TCL	–	–	–	–	–
TFL	0.630	–	–	–	–
CC	0.266	0.234	–	–	–
NC	0.346	0.335	0.113	–	–
AC	0.368	0.331	0.118	0.158	–

Source: own study.

Cronbach's alpha above 0.7 appeared for most of the variables, indicating that the questionnaire was reliable and accurately explored the phenomena in question. An AVE greater than 0.5 ensured relevance and that the tool used diagnosed the specified criterion well, and only this criterion. In addition, as we can see in Table 3, all HTMT values were less than 0.9, so there were no discriminant validity problems. Thus, the observable variables measured the corresponding latent variables.

Hypothesis Testing

Table 4 presents the results of the SEM factor analysis of the external model. All measurable variables describing latent variables had statistically significant factor loadings. We put '-' for items for which the p-value could not be verified.

Table 4. External SEM model estimation results

Relationship	Parameter	Evaluation of parameter	P
TCL6 ← Transactional leadership	α_1	0.788	0.000
TCL4 ← Transactional leadership	α_2	0.869	0.000
TCL2 ← Transactional leadership	α_3	0.916	0.000
TCL1 ← Transactional leadership	α_4	0.898	-
TFL6 ← Transformational leadership	α_5	0.756	0.000
TFL3 ← Transformational leadership	α_6	0.757	-
TFL2 ← Transformational leadership	α_7	0.962	0.000
TFL1 ← Transformational leadership	α_8	0.957	0.000
AC2 ← Affective commitment	α_9	1.073	0.000
AC3 ← Affective commitment	α_{10}	0.914	-
AC4 ← Affective commitment	α_{11}	0.932	0.000
AC5 ← Affective commitment	α_{12}	0.808	0.000
NC2 ← Normative commitment	α_{13}	0.588	0.000
NC3 ← Normative commitment	α_{14}	0.654	0.000
NC4 ← Normative commitment	α_{15}	0.795	-
NC5 ← Normative commitment	α_{16}	0.777	0.000
CC2 ← Continuance commitment	α_{17}	0.858	-
CC1 ← Continuance commitment	α_{18}	0.522	0.000
CC3 ← Continuance commitment	α_{19}	0.792	0.000
CC5 ← Continuance commitment	α_{20}	0.618	0.000

Source: own study.

The following tables present further results. Tables that contain information on the relationships between variables also have some bolded rows, which mark the statistical significance of the relationship based on the calculated p-values (assuming $p \leq 0.05$).

Concerning the hypothesis **H1** (The industry of the company moderates the relationship between leadership style and organisational commitment), Table 5 shows the results of the moderation hypothesised in H1. As we may see from the obtained results, most β parameters were statistically significant in all subgroups. The exceptions were the TCL→AC relationship in production, service, and medical organisations, the TCL→NC relationship in marketing and production organisations, and the TCL→CC relationship in service and medical organisations. In marketing and production organisations, TFL has the most substantial impact on AC and NC, and TCL on CC. In sales organisations, TCL had the strongest impact on AC, and TFL on NC and CC. Among service and medical organisations, TFL had a strong impact on all commitment types. Notably, in the production and sales groups, the model was not the best fit ($RMSEA > 0.1$), likely due to the small size of these subgroups, hence, the results for these organisations should be treated with caution. In summary, the impact of TCL on organisational commitment was most dominant in organisations related to engineering, technology, and IT, while TFL had the most substantial impact on services and medicine.

Table 5. Results of internal SEM model estimation in subgroups by the industry of the company

Relationship	Parameter	Engineering, technology, IT			Marketing			Production			Sales			Services and medicine		
		Evaluation of standardised parameter	P	S.E.	Evaluation of standardised parameter	P	S.E.	Evaluation of standardised parameter	P	S.E.	Evaluation of standardised parameter	P	S.E.	Evaluation of standardised parameter	P	S.E.
TCL → AC	β1	0.418	0.015	0.210	0.747	0.000	0.165	0.354	0.115	0.290	0.569	0.005	0.216	0.353	0.060	0.208
TCL → CC	β2	0.310	0.048	0.202	0.159	0.228	0.132	0.437	0.086	0.342	0.595	0.006	0.239	0.474	0.017	0.235
TCL → NC	β3	0.555	0.002	0.244	0.932	0.000	0.198	0.662	0.022	0.467	0.739	0.000	0.268	0.373	0.058	0.220
TFL → AC	β4	0.112	0.000	0.111	0.865	0.000	0.085	0.738	0.000	0.269	0.547	0.000	0.178	0.780	0.000	0.163
TFL → CC	β5	0.211	0.002	0.067	0.505	0.000	0.085	0.532	0.000	0.159	0.779	0.000	0.138	0.610	0.000	0.078
TFL → NC	β6	0.378	0.000	0.085	0.633	0.000	0.132	0.646	0.000	.0185	0.767	0.000	0.135	0.750	0.000	0.129
Measures of model fit		IFI = 0.906			IFI = 0.956			IFI = 0.782			IFI = 0.831			IFI = 0.933		
		RMSEA = 0.095			RMSEA = 0.063			RMSEA = 0.188			RMSEA = 0.167			RMSEA = 0.085		

Source: own study.

Concerning the hypothesis **H2** (The size of the company moderates the relationship between leadership style and organisational commitment), Table 6 below shows that parameters β_4 - β_6 were statistically significant in each subgroup. Parameter β_1 was significant only for organisations with 2-50 and 251-499 employees, and β_2 and β_3 for organisations with 2-50 and 500+ employees. In the smallest organisations, TCL has the strongest impact on NC, and TFL on AC and CC. In medium-sized organisations (51-499), TFL has a strong impact on commitment. In the largest organisations (500+), TCL dominates, but TFL has a significant impact on AC. The results indicate that in organisations with up to 499 employees, TFL has a more substantial impact on organisational commitment, while TCL has a stronger impact on commitment in the largest organisations.

Table 6. Results of internal SEM model estimation in subgroups by the size of the company

Relationship	Parameter	Number of employees in the organisation											
		2-50			51-250			251-499			500+		
		Evaluation of standardised parameter	P	S.E.	Evaluation of standardised parameter	P	S.E.	Evaluation of standardised parameter	P	S.E.	Evaluation of standardised parameter	P	S.E.
TCL → AC	β1	0.447	0.000	0.146	0.019	0.989	0.854	0.695	0.000	0.306	0.078	0.903	0.561
TCL → CC	β2	0.497	0.000	0.200	0.232	0.467	0.183	0.043	0.879	0.324	0.405	0.023	0.106
TCL → NC	β3	0.760	0.000	0.145	0.650	0.355	0.515	0.325	0.370	0.319	0.594	0.000	0.106
TFL → AC	β4	0.812	0.000	0.132	0.739	0.000	0.183	0.746	0.000	0.236	0.759	0.000	0.132
TFL → CC	β5	0.549	0.000	0.116	0.492	0.000	0.106	0.330	0.000	0.085	0.343	0.000	0.063
TFL → NC	β6	0.721	0.000	0.124	0.618	0.000	0.125	0.481	0.000	0.113	0.573	0.000	0.090
Measures of model fit	IFI = 0.928			IFI = 0.982			IFI = 0.912			IFI = 0.915			
	RMSEA = 0.098			RMSEA = 0.043			RMSEA = 0.095			RMSEA = 0.099			

Source: own study.

Concerning the hypothesis **H3** (The company department moderates the relationship between leadership style and organisational commitment), Table 7 shows the results of the moderation from hypothesis 3. As we can see from the bolded rows, the impact of TFL on each type of organisational commitment was significant in all subgroups. In the case of the relationship between TCL and organisational commitment, it achieved statistical significance only for parameter 3 in operations, logistics, and production departments. Moreover, TCL had the strongest impact on the departments of operations and logistics, leading to NC. Transformational leadership had the strongest impact on AC in production departments, and on both CC and NC in administration and support departments. Overall, the transactional leader has the strongest impact on operational and logistics departments, while the transformational leader has the strongest impact on administrative and support departments. However, the results in the operations and support departments should be considered with caution due to $RMSEA > 0.100$, which is most likely due to the small sample size in this subgroup.

Concerning the hypothesis **H4** (The employee's work position moderates the relationship between leadership style and organisational commitment), Table 8 shows the the results of the calculations within H4. As we can see, only parameter β_1 did not achieve statistical significance for the subgroups: specialist, manager/management, and expert, and parameter β_2 for the subgroups: manager/management and expert. The remaining parameters are statistically significant. TCL has the greatest impact on organisational commitment among employees with the lowest position – assistant/junior specialist – with the greatest impact on AC. Transformational leadership has the strongest impact on AC in the manager/management group and, subsequently, on CC and NC in the expert group. Looking at the results for hypoth-

esis 4 in general, we may conclude that transactional leadership works better among employees with lower positions, while transformational leadership works better for higher-level employees.

Table 7. Results of internal SEM model estimation in subgroups by the company department

Relationship	Parameter	Administration and support			Operations and logistics			Production			Marketing and sales		
		Evaluation of standardised parameter	P	S.E.	Evaluation of standardised parameter	P	S.E.	Evaluation of standardised parameter	P	S.E.	Evaluation of standardised parameter	P	S.E.
TCL → AC	β1	-0.116	0.995	0.985	0.091	0.987	0.969	0.014	0.989	0.854	-0.003	0.056	0.715
TCL → CC	β2	0.714	0.168	0.405	0.272	0.584	0.468	0.733	0.110	0.303	0.287	0.133	0.169
TCL → NC	β3	0.493	0.114	0.556	0.740	0.000	0.223	0.664	0.003	0.275	0.762	0.859	0.889
TFL → AC	β4	0.785	0.000	0.175	0.789	0.000	0.225	0.800	0.000	0.206	0.773	0.000	0.102
TFL → CC	β5	0.733	0.000	0.064	0.569	0.000	0.123	0.729	0.000	0.104	0.562	0.000	0.053
TFL → NC	β6	0.840	0.000	0.125	0.722	0.000	0.166	0.777	0.000	0.148	0.762	0.000	0.069
Measures of model fit	IFI = 0.918			IFI = 0.795			IFI = 0.910			IFI = 0.969			
	RMSEA = 0.097			RMSEA = 0.169			RMSEA = 0.098			RMSEA = 0.060			

Source: own study.

Table 8. Results of internal SEM model estimation in subgroups by the work position

Table of Results of Internal SEM Model Estimation in Subgroups by the Work Position													
Relationship	Parameter	Specialist			Manager / management			Assistant / Junior Specialist			Expert		
		Evaluation of standardised parameter	P	S.E.	Evaluation of standardised parameter	P	S.E.	Evaluation of standardised parameter	P	S.E.	Evaluation of standardised parameter	P	S.E.
TCL → AC	β1	0.358	0.151	0.246	0.073	0.899	0.496	0.969	0.000	0.266	-0.983	0.473	0.929
TCL → CC	β2	0.505	0.008	0.191	0.763	0.519	0.335	0.859	0.000	0.184	0.799	0.531	0.396
TCL → NC	β3	0.753	0.000	0.110	0.668	0.003	0.253	0.802	0.000	0.142	0.826	0.000	0.214
TFL → AC	β4	0.744	0.000	0.095	0.786	0.000	0.151	0.731	0.000	0.246	0.695	0.000	0.192
TFL → CC	β5	0.381	0.000	0.049	0.384	0.000	0.066	0.379	0.001	0.120	0.765	0.000	0.144
TFL → NC	β6	0.541	0.000	0.064	0.632	0.000	0.099	0.553	0.000	0.156	0.793	0.000	0.151
Measures of model fit	IFI = 0.953			IFI = 0.926			IFI = 0.923			IFI = 0.949			
	RMSEA = 0.069			RMSEA = 0.093			RMSEA = 0.098			RMSEA = 0.094			

Source: own study.

Although it is valuable to conduct another investigation with a larger sample, considering the above results, we present the hypotheses summary in Table 9 below.

Table 9. Hypotheses summary

Hypothesis	Decision
1	Confirmed
2	Confirmed
3	Confirmed
4	Confirmed

Source: own study.

Discussion

Theoretical Implications

We examined the role of moderators, *i.e.*, the industry of the company, the size of the company, the company department, and the employee's work position, in the relationship between leadership style and organisational commitment. Previous studies showed the existence of relationships between leadership style and organisational commitment (Łucjan *et al.*, 2023) and this study filled the gap in research on the role of the mentioned variables.

All hypotheses were confirmed. According to hypothesis 1, the company industry moderates the relationship between leadership style and organisational commitment. As it turns out, transactional leaders strongly influence organisational commitment among employees in engineering, technology, and IT organisations. This result confirms the conclusions of previous studies that employees in the technical and IT sectors feel understood and motivated by transactional leadership (Eniola & Adeola, 2025; Wang *et al.*, 2021). The results of H1 also show that transformational leaders had the strongest influence on services and medicine. This is consistent with the claim that transformational leaders have the greatest influence on knowledge creation in the technology and health sectors (Eniola & Adeola, 2025).

According to hypothesis 2, the size of the company shapes the relationship between leadership style and organisational commitment. As it turns out, in smaller organisations (up to 499 employees), commitment is most strongly influenced by a transformational leader, while in organisations with 500+ employees, a transactional leader dominates. This may be based on the theory that larger organisations require greater formalisation of communication, supervision, and control, which allows for effective resource management (Abbas & Ali, 2023). Meanwhile, a transformational leader can effectively motivate employees in smaller organisations by considering their needs, emotions, and well-being (Karácsony & Czibula, 2020; Berisha *et al.*, 2024).

When considering hypothesis 3, as well as the moderating role of departments within an organisation, we can observe that transformational leaders have the strongest influence on administrative and support departments. In contrast, transactional leaders have the strongest influence on operational and logistics departments. Sunarsi *et al.* (2021), Wang *et al.* (2021), Chin *et al.* (2024), and Garzón Lasso *et al.* (2024) also support these results. Transformational leadership offers employees autonomy, innovation, and creativity, while TCL offers precise supervision that guarantees the perfect execution of repetitive tasks. It is the operational departments that conduct the day-to-day activities of the organisation, which usually do not differ significantly from each other. These are certain algorithms and patterns that streamline its main operation, and whose supervision by a transactional leader can contribute to increased commitment. On the other hand, in administrative and support departments, autonomy in everyday life may be necessary, as such employees deal with various issues and are responsible for resolving specific situations correctly. Although this conclusion contradicts the conclusion of an earlier study, according to which transactional behaviours work better in administrative departments (Chin *et al.*, 2024), a transformational leader can provide the necessary support and atmosphere to increase commitment.

Not only the industry, the size, the department of the company, but also the hierarchy of the work position in the organisation is important for the preferred leadership style, as confirmed by hypothesis 4. A transactional leader can achieve the best results among assistants and juniors, and a transformational leader among higher-level employees such as managers, board members, or experts. This result

confirms that employees who formally hold leadership roles prefer their superiors to be transformational leaders who give them autonomy and care about their sense of importance, understanding, trust, and empathy (Nielsen *et al.*, 2022). On the other hand, among lower-level employees, where positions are rather clearly described and tasks to be performed are clearly defined, a transactional leader who controls the performance of these tasks will work better (Al Rawas & Jantan, 2023).

Considering the results of this and previous studies, organisations should pay particular attention to the relationship between leaders and employees. As it turns out, the industry of the company itself determines which leadership style will make employees more committed, which will translate into better results for the organisation. Organisations with up to 499 employees and traditional, hierarchical organisations should focus on a transactional leadership style, while larger organisations and those that focus on innovation and creativity should focus on a transformational style. Moreover, a division within the organisation can be applied. Among autonomous departments that require creative thinking and solving a variety of tasks, a transformational leader will work better, while departments with an orderly, repetitive list of tasks will achieve greater organisational commitment with a transactional leader. The most detailed division is the employee's work positions. As it turns out, lower-level employees will require a transactional leader to achieve better organisational commitment, while higher-level employees will require a transformational leader. Bearing in mind the essence of these distinctions, an organisation can relatively quickly increase commitment among its employees.

Managerial Implications

In view of our study results and those of previous studies, organisations should pay particular attention to the quality of the relationship between leaders and employees, as it constitutes a key mechanism shaping organisational commitment and, consequently, the overall performance. Importantly, the findings indicate that there is no universally optimal leadership style; instead, its effectiveness depends on contextual factors such as industry, organisational size, departmental specificity, and employee position. Therefore, managers should adopt a contingent approach to leadership, consciously adjusting their behaviours to the characteristics of the work environment.

From a practical perspective, organisations should implement differentiated leadership strategies at multiple levels. At the macro level, industry conditions should guide leadership development programmes. For example, in engineering, technology, and IT sectors, greater emphasis should be placed on transactional mechanisms such as clear goal-setting, performance monitoring, and reward systems, whereas in service- and knowledge-intensive contexts, organisations should invest in developing transformational competencies, including vision-building, empowerment, and inspiration. Similarly, organisational size should inform leadership structures: smaller and medium-sized firms benefit from relational and motivational approaches, while large, complex organisations require more formalised and control-oriented leadership practices.

At the meso level, HR policies should reflect intra-organisational diversity. Introducing differentiated leadership standards across departments can significantly enhance effectiveness. Operational and logistics units, characterised by routine and standardisation, should be managed through transactional leadership, ensuring efficiency and predictability. In contrast, administrative, support, and innovation-oriented units should be led by transformational leaders who foster autonomy and creativity.

Finally, at the micro level, leadership should be aligned with employees' hierarchical position. Lower-level employees benefit from structured guidance and clear expectations typical of transactional leadership, whereas higher-level employees, such as experts and managers, require greater autonomy, trust, and developmental support provided by transformational leaders. Implementing such a multi-level, adaptive leadership approach enables organisations to more precisely manage employee commitment and achieve sustainable improvements in performance.

CONCLUSIONS

The study filled the gap in detailed empirical research on the relationship between leadership style and organisational commitment. The main purpose of this article was to investigate the moderating

role of the company industry, company size, company department, and employees' work position in the relationship between leadership style and organisational commitment. The study showed that leadership style should be selected individually in each organisation, because its characteristics and the employee's work position determine the most effective leadership style for achieving a specific level of commitment among employees. A transformational leader will work better in creative, innovative organisations with up to 499 employees. More specifically, based on this study, we know that departments in an organisation that are autonomous and require a creative approach (e.g., administration) will achieve better organisational commitment thanks to a transformational leader, while departments with clearly defined, repetitive tasks (e.g., departments of operations or departments of logistics) will achieve better organisational commitment thanks to a transactional leader. The final division in the moderation was the employee's work position. Employees who work at lower levels, such as juniors or assistants, should be managed by a transactional leader, while a transformational leader should manage higher-level employees (experts, managers, and executives). In conclusion, this study provided very important and specific guidelines for the development of quality and management science, as well as practical implications for organisations operating in Central and Eastern Europe.

Limitations

There are some limitations to the described study. The first is the relatively limited subgroup size, which was reflected in high RMSEA in some models. Further research should be conducted on larger groups.

The sampling was non-random, so it cannot be representative and the results cannot be generalised. However, the diversity of the sample in terms of demographics and employment characteristics undoubtedly contributed to the increased value of the survey. Nevertheless, further studies should include a larger sample.

The final limitation is the subjectivity that respondents may have had in answering the questionnaires. Perhaps some valuable variables might have been omitted, but this approach allowed for the use of the structural equation model.

However, despite the limitations discussed above, the authors remain assured of the value the study provides for science. The study brings very valuable findings that can also be successfully applied to HR practice among organisations.

Future Studies

Future research, including the study of the scope of leadership style and organisational commitment, should primarily include a larger sample to improve the model's quality. Moreover, future research could examine other types of leadership styles, absent from this study, such as participative, charismatic, servant, or authoritarian. The inclusion of other leadership styles could shed new light on the perception of a leader's impact on organisational outcomes. Furthermore, future research could investigate latent employee traits such as submissiveness, self-confidence, or openness to interpersonal relationships. Such an advanced study would provide a new perspective to the management of organisations by showing how interactions between employee personality traits and leadership style affect the level of organisational commitment and long-term organisational results.

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Appendix A: Scale of the three-component model of organisational commitment

		1	2	3	4	5
AC1	I would be very happy to spend the rest of my career with this organisation.					
AC2	I really feel as if this organisation's problems are my own.					
AC3	I do not feel a strong sense of belonging to my organisation.					
AC4	I do not feel emotionally attached to this organisation.					
AC5	I do not feel like part of a family at my organisation.					
AC6	This organisation has a great deal of personal meaning for me.					
CC1	Right now, staying with my organisation is a matter of necessity as much as desire.					
CC2	It would be very hard for me to leave my organisation right now, even if I wanted to.					
CC3	Too much of my life would be disrupted if I decided I wanted to leave my organisation now.					
CC4	I feel that I have too few options to consider leaving this organisation.					
CC5	If I had not already put so much of myself into this organisation, I might consider working elsewhere.					
CC6	One of the few negative consequences of leaving this organisation would be the scarcity of available alternatives.					
NC1	I do not feel any obligation to remain with my current employer.					
NC2	Even if it were to my advantage, I do not feel it would be right to leave my organisation now.					
NC3	I would feel guilty if I left my organisation now.					
NC4	This organisation deserves my loyalty.					
NC5	I would not leave my organisation right now because I have a sense of obligation to the people in it.					
NC6	I owe a great deal to my organisation.					

Source: own elaboration based on Lee *et al.* (2001).

Appendix B: Scale of employees' perception of leadership

		1	2	3	4	5
TFL1	My leader concretises a clear vision for the organisation's future.					
TFL2	My leader communicates a clear vision of the organisation's future.					
TFL3	My leader makes a continuous effort to generate enthusiasm for the organisation's vision.					
TFL4	My leader has a clear sense of where he or she believes our organisation should be in 5 years.					
TFL5	My leader seeks to make employees accept common goals for the organisation.					
TFL6	My leader strives to get the organisation to work together in the direction of the vision.					
TFL7	My leader strives to clarify for the employees how they can contribute to achieving the organisation's goals.					
TCL1	My leader rewards the employees' performance when they live up to the leader's requirements.					
TCL2	My leader rewards the employees depending on how well they perform their jobs.					
TCL3	My leader points out what employees will receive if they do what is required.					
TCL4	My leader lets employees' effort determine the rewards received.					
TCL5	My leader gives individual employees positive feedback when they perform well.					
TCL6	My leader actively shows his or her appreciation of employees who do their jobs better than expected.					
TCL7	My leader generally does not acknowledge individual employees even though they perform as required.					
TCL8	My leader personally compliments employees when they do outstanding work.					
TCL9	My leader gives negative consequences to the employees if they perform worse than their colleagues.					
TCL10	My leader makes sure that there are consequences for employees if they do not consistently perform as required.					
TCL11	My leader takes steps to deal with poor performers who do not improve.					
TCL12	My leader gives negative consequences to his or her employees if they do not perform as the leader requires.					

Source: own elaboration based on Jensen *et al.* (2019).

Authors

The contribution share of authors was as follows: KŁ – 40%, DS – 20%, APB – 20%, ER – 20%.
KŁ – conceptualisation, literature writing, methodology, results, calculations, DS – conceptualisation, discussion, APB – conceptualisation, results, conclusions, discussion, ER – results, conclusions, discussion.

Katarzyna Łucjan

Doctoral Student at Nicolaus Copernicus University in Toruń in Poland. Her research interests include counterproductive work behaviours and human resource management.

Correspondence to: Katarzyna Łucjan, Wydział Nauk Ekonomicznych i Zarządzania, ul. Gagarina 13a, 87-100 Toruń, Poland; e-mail: katarzynalucjan2@gmail.com

ORCID  <https://orcid.org/0000-0002-0610-1318>

Dawid Szostek

Associate Professor at the Faculty of Economics and Management in Nicolaus Copernicus University in Toruń in Poland. His research interests include counterproductive work behaviours, human resource management, and organisational management.

Correspondence to: dr hab. Dawid Szostek, prof. UMK, Nicolaus Copernicus University, Katedra Zachowań Organizacyjnych i Marketingu, ul. Gagarina 13a, 87-100 Toruń, Poland, e-mail: dawidsz@umk.pl

ORCID  <https://orcid.org/0000-0001-6743-854X>

Adam P. Balcerzak (corresponding author)

Associate Professor at the Faculty of Economics in University of Warmia and Mazury in Olsztyn in Poland; and Associate Professor at the Faculty of Business and Economics in Brno University of Technology in Czechia. His research interests include organisational challenges under AI proliferation pressure and counterproductive work behaviours.

Correspondence to: dr hab. Adam P. Balcerzak, prof. UWM, University of Warmia and Mazury, Katedra Rynku i Konsumpcji, ul. pl. Cieszyński 1/327; 10-720 Olsztyn; Poland, e-mail: a.balcerzak@uwm.edu.pl

ORCID  <https://orcid.org/0000-0003-0352-1373>

Elżbieta Rogalska

Assistant Professor at the Faculty of Economics in University of Warmia and Mazury in Olsztyn in Poland. Her research interests include managerial economics, counterproductive work behaviours and human resource management.

Correspondence to: dr Elżbieta Rogalska, University of Warmia and Mazury, Katedra Ekonomii, ul. R. Prawocheńskiego 3/103, 10-720 Olsztyn, e-mail: elzbieta.rogalska@uwm.edu.pl

ORCID  <https://orcid.org/0000-0003-4995-5791>

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Use of Artificial Intelligence

We declare that this manuscript was prepared without the use of AI or generative AI tools.

Conflict of Interest

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Towards a sociotechnical framework and maturity model for artificial intelligence-driven supply chain due diligence

Marcel Welsen, Łukasz Sułkowski

ABSTRACT

Objective: The objective of this article is to develop an integrated sociotechnical framework and a diagnostic maturity model for artificial intelligence-driven supply chain due diligence. It addresses the implementation gap under escalating mandatory regulations by demonstrating how technological capabilities, ethical governance, and cultural adaptation interact, shape each other, and must be developed together.

Research Design & Methods: We employed a theory-building approach and conducted a purposive literature synthesis. We applied thematic analysis, grounded in institutional theory, stakeholder theory, and the technology-organisation-environment framework to develop an integrated framework and maturity model, illustrated via analysis of European e-commerce sustainability disclosures.

Findings: We identified three critical sociotechnical interfaces (tech-ethics, ethics-culture, and tech-culture) and derived three formal propositions from the analysis. We propose, organisational readiness may function more as a coefficient than an additive factor, where the substantive effectiveness of technological tools depends on cultural commitment. A distinct ‘institutional governance gap’ emerges from the illustrative application.

Implications & Recommendations: Organisations, including small and medium-sized enterprises and entrepreneurial ventures operating within mandatory due diligence supply chains, should move beyond technocentric approaches to assess artificial intelligence (AI) readiness simultaneously across operational, institutional, global, and strategic layers. The maturity model enables systematic capability gap identification.

Contribution & Value Added: We propose a diagnostic maturity model and formal propositions that bridge the gap between legal theory and organisational implementation. These contributions are conceptual and require empirical validation.

Article type: conceptual article
Keywords: artificial intelligence; supply chain due diligence; Corporate Sustainability Due Diligence Directive; EU AI Act; sociotechnical framework; TOE framework; organisational readiness
JEL codes: M14, M16, O33

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INTRODUCTION

Mandatory due diligence legislation marks a paradigm shift in corporate accountability across global value chains (Wilhelm, 2024), with AI increasingly central to its implementation (Shahzadi *et al.*, 2024). The EU Corporate Sustainability Due Diligence Directive (CSDDD), agreed in June 2024 with member state transposition required by July 2027, requires companies to identify and address adverse human rights and environmental impacts across global value chains (European Commission, 2024a, 2025b). In Germany, authorities enacted similar obligations under the Supply Chain Due Diligence Act (LkSG), in force since January 2023, although they have also suspended reporting obligations from 2025 onward due to the upcoming CSDDD (Sinnig & Zetzsche, 2025; Bundesregierung, 2025). This shift demonstrates

the broader trend towards foreign corporate accountability (Rühmkorf, 2023). Early adopters gain legitimacy advantages while laggards face institutional exclusion (Campbell, 2007). To manage such complex requirements, organisations deploy AI systems for supplier monitoring and risk assessment (Shahzadi *et al.*, 2024; Yang *et al.*, 2023). However, the deployment of AI itself is now regulated. The European Union (EU) Artificial Intelligence Act (Regulation 2024/1689) has established risk-based requirements for AI systems, with AI used in employment and worker management classified as ‘high-risk’ (European Commission, 2024b). Organisations that deploy AI for due diligence face overlapping compliance obligations as these frameworks converge. This creates demands to satisfy simultaneously technological, ethical, and cultural requirements (de Oliveira Serra, 2025; Sinnig & Zetzsche, 2025).

AI technologies, such as machine learning, natural language processing (NLP), and predictive analytics all promise to automate supplier data analysis, identify risk patterns, and generate audit-ready documentation (Agrawal *et al.*, 2024; Nweje & Taiwo, 2025; Shahzadi *et al.*, 2024; Shamsuddoha *et al.*, 2025; Yang *et al.*, 2023). Moreover, AI adoption can enhance Environmental, Social, and Governance (ESG) performance (Lin & Zhu, 2025; Vann Yaroson *et al.*, 2025). We argue that there is a gap in the literature on how organisations possess AI tools while lacking readiness to deploy them ethically within complex regulatory environments. This gap reflects the following paradox: The CSDDD demands rigorous evidence, yet data remains qualitative, unstructured, and fragmented across supplier tiers (Brintrup *et al.*, 2023). The volume of information exceeds human processing capabilities and creates a gap between expanding responsibility and capacity to translate data into compliance decisions.

Notably, the existing research examines these AI challenges in isolation: technological capabilities (Shahzadi *et al.*, 2024; Yang *et al.*, 2023), organisational culture (Cannas *et al.*, 2024; Samuels, 2024), and ethical governance (Batool *et al.*, 2025; Stahl & Eke, 2024). This fragmentation obscures the fact that these dimensions dynamically shape one another. Despite growing scholarly attention to both AI governance and mandatory due diligence, research integrating these domains remains scarce.

Recent work addresses these areas only separately. Trindade *et al.* (2025) studied CSDDD design principles but did not address AI implementation challenges. Akbarighatar *et al.* (2023) developed a sociotechnical AI maturity model but did not apply it to mandatory due diligence contexts. Culot *et al.* (2024) reviewed AI in supply chain management but did not engage with emerging regulatory frameworks. Currently, no research integrates institutional theory, stakeholder theory, and the technology–organisation–environment (TOE) framework to explain how organisations respond to the convergent pressures of the CSDDD and EU AI Act.

Single-theory explanations also prove insufficient. Firstly, institutional theory explains why organisations must respond to regulatory pressures (DiMaggio & Powell, 1983), but cannot explain why firms facing identical pressures respond differently and lack mechanisms for priority-setting among competing demands. Secondly, stakeholder theory explains how organisations navigate competing demands (Mitchell *et al.*, 1997), but does not predict implementation success without attention to technological and organisational capabilities. Thirdly, the TOE framework captures why capability variation leads to different outcomes (Tornatzky & Fleischer, 1990), but does not account for the coercive and normative pressures that mandate a response in the first place. The central theoretical contribution lies in reconceptualising organisational readiness as a coefficient instead of an additive factor: technological investments are multiplied and cultural commitment is not just added. This explains why identical AI systems produce divergent outcomes across organisations. The argument is that if cultural commitment is low, even large tech investments bring little benefit; if cultural commitment is high, smaller investments can yield greater impact.

We addressed the literature gaps with our integrated framework by combining all three lenses and revealing dynamics invisible to any single theory, especially the compliance paradox, where structural conformity masks operational divergence (Meyer & Rowan, 1977). The primary objective of this article is to develop an integrated sociotechnical framework for AI-driven supply chain due diligence, synthesising institutional theory, stakeholder theory, and the TOE framework. We derived formal propositions from this framework that specify the interaction mechanisms across dimensions and we developed a diagnostic maturity model that enables systematic readiness assessment. Two research questions guided these contributions:

- RQ1:** How do technological capabilities, ethical governance, and cultural adaptation interact through the integrated lens of institutional theory, stakeholder theory, and the TOE framework in the context of AI-driven due diligence?
- RQ2:** How might organisations systematically assess readiness across all three dimensions?

RESEARCH METHODOLOGY

Research Design

We adopted a theory-building approach combining purposive literature synthesis with illustrative case analysis. We began with a literature synthesis to integrate disparate insights (Snyder, 2019), aligning with critical review methodology that provides interpretive analysis to reveal theoretical gaps and develop new frameworks (Paré *et al.*, 2015). Such synthesis is well-suited for an emerging topic where the goal is to combine ideas rather than exhaustively cover all literature. We focused on the intersection of AI and supply chain due diligence – a space of regulation, technology, and ethics. Adopting a problematising review (Alvesson & Sandberg, 2020), we challenged the assumption that technological, ethical, and cultural dimensions can be addressed in isolation. We aimed to develop a conceptual theory, following the approach of prior EBER conceptual studies that synthesise theory and derive propositions (Butkeviciene & Sekliuckiene, 2022). We synthesised institutional theory, stakeholder theory, and TOE framework perspectives into one integrated sociotechnical model and derived formal propositions from the analysis. We complemented this theoretical development with an illustrative analysis of three prominent European e-commerce firms (Amazon, 2025; Otto Group, 2025; Zalando SE, 2025) to demonstrate the framework's applicability in practice. Based on multiple cases, we conducted analytical replication to strengthen theory development by revealing patterns across firms (Eisenhardt & Graebner, 2007; Yin, 2018). We purposefully selected these firms for their market significance and their exposure to emerging due diligence regulations (Bundesministerium für Justiz, 2021; European Commission, 2024a). For each company, we collected recent sustainability reports (2024-2025) and analysed these documents against the AI due-diligence-maturity model criteria. We coded each report to assess the firm's technological capabilities, ethical governance structures, and cultural readiness, using our maturity indicators as a coding scheme (see coding protocol in Appendix B). This analysis provided an illustrative demonstration of the framework rather than a basis for generalisation. It provides real-world context for our theoretical propositions. We acknowledge that our case selection was limited to one industry. Therefore, future studies should examine additional industries and more varied firm types to further test and refine the framework's applicability.

Literature Selection and Analysis

We searched major databases (Web of Science, Scopus, Google Scholar) using Boolean queries. Representative search strings (Scopus) included: TITLE-ABS-KEY (('supply chain' W/3 'due diligence') AND ('AI' OR 'machine learning')) OR TITLE-ABS-KEY (('supply chain due diligence' OR 'ESG monitoring') AND 'artificial intelligence' AND 'cross-cultural' AND 'technology adoption'). To improve reproducibility, we applied the following inclusion criteria: (1) focus on peer-reviewed articles, regulatory documents or primary corporate disclosures published between 2020-2025; (2) focus on AI applications in supply chain management, due diligence, or ESG compliance; (3) engagement with one of our theoretical foundations (institutional theory, stakeholder theory, or TOE framework) or with AI governance frameworks. Exclusion criteria included: (1) purely technical AI articles without organisational or managerial implications; (2) opinion pieces or practitioner reports without empirical or theoretical grounding; (3) non-English sources. The first author screened titles and abstracts against these criteria, with borderline cases discussed between authors.

Following systematic screening protocols, we filtered the initial pool of approximately 200 articles down to 89 sources based on strict inclusion criteria for relevance to AI in supply chain due diligence and regulatory compliance. Peer-reviewed publications constituted the majority, supplemented by regulatory documents and corporate disclosures. We prioritised conceptual rigour alongside relevance to con-

text and citation impact. This agrees with other literature reviews recently published in related domains (Culot *et al.*, 2024; Samuels, 2024). In addition, we included foundational works on institutional theory (Campbell, 2007; DiMaggio & Powell, 1983), stakeholder theory (Freeman, 2010; Mitchell *et al.*, 1997), and the technology–organisation–environment framework (Tornatzky & Fleischer, 1990).

We conducted thematic analysis for literature selection (Braun & Clarke, 2006) aligned with established guidelines for conceptual research (Snyder, 2019). This involved three stages. Firstly, open coding for identifying emergent themes across the technological, ethical, and cultural dimensions. Secondly, thematic mapping to connect these patterns with constructs from institutional, stakeholder and TOE theories. Thirdly, integrative synthesis for developing the unified framework and maturity model. With this systematic analysis, we ensured that our framework was grounded in the literature and that the themes from different streams of research coherently informed our sociotechnical perspective.

LITERATURE REVIEW AND THEORY DEVELOPMENT

Institutional Pressures and Regulatory Transformation

The CSDDD demonstrates a paradigm shift from voluntary corporate social responsibility to legally required due diligence obligations (Leite *et al.*, 2024; Welsen, 2025; Wilhelm, 2024). Organisations face coercive pressures to implement AI systems that will monitor suppliers, identify adverse impacts, and generate compliance documentation (Buhmann & Feld, 2024). This creates three institutional dynamics reshaping organisational responses.

Firstly, normative isomorphism develops as AI ethics standards take shape (DiMaggio & Powell, 1983; Reis & Pinheiro Junior, 2025; Rudko *et al.*, 2025; Singh, 2024), with industry associations promoting explainable AI and creating mimetic pressures (El Mimouni & Bouhdadi, 2025; Kabir *et al.*, 2025). Artificial intelligence functions both as a product and driver of institutional forces.

Secondly, regulatory uncertainty remains, because member states have time until July 2027 to transpose the Directive (European Commission, 2025a), with staggered implementation afterwards (European Commission, 2024a, 2025b). While early movers face higher costs, they gain legitimacy; late adopters risk penalties and reputational deficits (Campbell, 2007).

Thirdly, institutional logic conflict occurs when efficiency-oriented AI clashes with transparency requirements (Milosevic *et al.*, 2023). Algorithms that maximise efficiency may obscure labour rights violations. This creates tensions that no technology can resolve. Empirical research supports these dynamics. Mishra *et al.* (2024) find that coercive pressure influences blockchain adoption, with institutional pressures accounting for substantial variance in adoption decisions among 222 supply chain professionals. These pressures intensify through regulatory convergence. The EU AI Act classifies AI for employment and worker management as ‘high-risk,’ requiring conformity assessments and human oversight or control (European Commission, 2024b). Furthermore, AI for supplier risk assessment likely falls within this classification, creating overlapping obligations with the CSDDD and reinforcing the urgency for explainable AI as a legal requirement (de Oliveira Serra, 2025; Sinnig & Zetsche, 2025).

Stakeholder Demands and Competing Legitimacy Claims

Stakeholder theory demonstrates how organisations navigate competing demands from constituencies with varying power, legitimacy, and urgency (Mitchell *et al.*, 1997). Artificial intelligence systems must address regulators, investors, consumers, and affected communities simultaneously (Marano *et al.*, 2024), with each shaping design and implementation. This agrees with the concept of stakeholder salience, according to which the urgency of regulatory mandates like the CSDDD combines with the legitimacy of human rights advocates to force a redesign of AI architectures (European Commission, 2024a; Mitchell *et al.*, 1997). When stakeholder power shifts towards mandatory accountability, the Tech-Ethics interface necessitates a move from opaque ‘black-box’ systems to interpretable models (Kabir *et al.*, 2025).

Contemporary applications expand this foundation. Birkstedt *et al.* (2023) identified how diverse stakeholder groups hold conflicting expectations regarding AI transparency and fairness, while Papagiannidis, Mikalef, and Conboy (2025) developed a responsible AI governance framework

that operationalises stakeholder engagement, demonstrating how organisations can integrate stakeholder concerns into AI deployment.

Critical tensions emerge: regulators demand explainability while firms protect proprietary algorithms (Batoool *et al.*, 2025; Radanliev, 2024); investors seek standardised metrics while due diligence requires contextual judgement (Gustafsson *et al.*, 2023a); finally, fairness definitions vary culturally (Han *et al.*, 2025; Roy & Mukherjee, 2022). This complexity reveals why technological capabilities alone prove insufficient.

An AI system may generate documentation satisfying auditors while failing to prevent human rights abuses. Effective systems may produce embarrassing findings, creating incentives to constrain scope (Abhulimen & Ejike, 2024). The challenge lies in aligning incentives with substantive rather than symbolic compliance.

Technology–organisation–environment Dynamics

The TOE Framework (Tornatzky & Fleischer, 1990) structures analysis across technological readiness, organisational capabilities, and environmental context. Our synthesis revealed that organisational readiness matters more than technological sophistication, consistent with meta-analytic evidence (Pinto *et al.*, 2025), large-scale empirical studies (Arroyabe *et al.*, 2024), and systematic reviews (Romeo & Lacko, 2025; Sánchez *et al.*, 2025).

The technological dimension encompasses advances enabling AI to process supplier databases, identify risk patterns, and generate compliance reports (Brintrup *et al.*, 2023; Shahzadi *et al.*, 2024). Machine learning can detect emission anomalies (Brintrup *et al.*, 2023), predict disruptions (Wong *et al.*, 2022), and analyse disclosures (Li *et al.*, 2024). Natural language processing enables the extraction of relevant information from unstructured supplier communications, audit reports, and media coverage. However, technology availability does not guarantee effective deployment. Data quality challenges persist, and algorithmic bias can systematise discrimination (Akinrinola *et al.*, 2024; Bahangulu & Owusu-Berko, 2025; Belenguer, 2022; Faheem, 2024; Hofmann *et al.*, 2024).

The organisational dimension proves decisive. Cross-functional integration (Cannas *et al.*, 2024), new competencies in algorithm governance (Batoool *et al.*, 2025), and cultural transformation (Samuels, 2024) determine success. Empirical studies validate this: Ioakeimidou *et al.* (2024), Sánchez *et al.* (2025), and Hughes *et al.* (2026) demonstrate that organisational factors outweigh technological sophistication.

The environmental dimension shapes adoption urgency. Firms covered by the CSDDD face legal liability, creating incentives for AI investment (Buhmann & Feld, 2024). Small and medium-sized enterprises (SMEs) experience indirect pressure without proportionate resources, creating asymmetric burdens that threaten viability while creating opportunities for compliance-as-a-service (Gustafsson *et al.*, 2023a). Early adopters gain advantages; late adopters risk legitimacy deficits (Campbell, 2007).

These three perspectives work together but not without tension. Institutional theory emphasises conformity: organisations facing the same pressures should respond similarly. Stakeholder theory suggests that different stakeholder configurations produce different responses. The TOE framework implies that organisational capabilities vary widely and shape implementation outcomes. We addressed the tension by treating the theories as complementary lenses rather than competing explanations. Institutional pressures create the context, stakeholder demands shape choices within that context, and organisational capabilities determine whether those choices succeed. This multi-level complementarity aligns with Herold's (2018) demonstration that institutional theory and stakeholder theory operate at different analytical levels and can be integrated when examining sustainability-related organisational practices. We extend this by adding the TOE framework as a third level. Each theory operates within specific boundary conditions. Institutional theory is most applicable when regulatory pressure is high and compliance norms are crystallising, which are the conditions present in the current CSDDD context. When different parties have valid but contradictory expectations, *e.g.*, authorities demand open data while firms protect their trade secrets, stakeholder theory becomes essential. The TOE framework applies when adoption success varies even when the external pressure is similar, directing attention to internal capabilities. In our framework, we integrated these theories where their bound-

ary conditions overlap: the mandatory due diligence context features high regulatory pressure (activating institutional theory), competing stakeholder demands (activating stakeholder theory), and variable implementation success (activating the TOE framework). The integration of these three perspectives demonstrates a dynamic that is invisible to single-theory analyses: structural isomorphism with operational divergence. Organisations converge (becoming similar) when having similar AI governance structures (satisfying institutional pressures), while they diverge (becoming different) for the implementation (reflecting stakeholder priorities and capabilities) – a compliance paradox where apparent conformity masks substantive variation that determines whether due diligence achieves real or merely symbolic compliance. This compliance paradox aligns with Meyer and Rowan's (1977) concept of institutional decoupling, wherein organisations adopt formal structures for legitimacy while actual practices diverge from espoused policies.

The Integrated Sociotechnical Framework

This integration shows three dimensions that mutually shape one another: technological capabilities, ethical governance, and cultural adaptation (Akbarighatar *et al.*, 2023; Dey *et al.*, 2023; El Mimouni & Bouhdadi, 2025). The tech-ethics interface captures how ethical demands drive technology choices. The ethics-culture interface shows how cultural context shapes fairness standards. The tech-culture interface reveals how organisational culture determines technological effectiveness. Figure 1 shows the integrated framework with three interfaces. This structure challenges step-by-step implementation models. Organisations cannot first adopt technology, then consider ethics, and then adapt to culture. All three dimensions demand simultaneous attention.

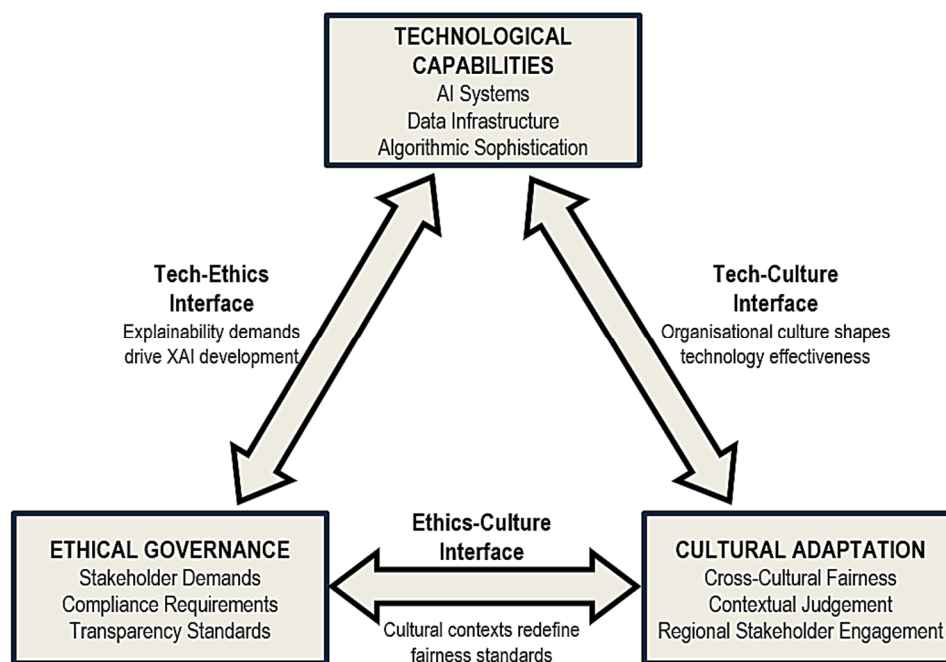


Figure 1. Integrated sociotechnical framework for AI-driven supply chain due diligence

Source: own elaboration.

The integrated framework suggests three critical interfaces where dimensions interact, each warranting detailed examination. The tech-ethics interface concerns how ethical demands and technological architectures mutually shape one another. The ethics-culture interface addresses how cultural contexts redefine fairness standards. The tech-culture interface examines how organisational culture determines technology effectiveness.

Sections 3.5-3.7 elaborate on each interface through our integrated theoretical lens, developing formal propositions that specify the interaction mechanisms (addressing RQ1). Section 3.8 then presents the maturity model (addressing RQ2).

Navigating the Tech-ethics Interface: The Explainability Imperative

Organisations confront the explainability paradox (RQ1). Regulations demand transparency, yet AI often operates opaquely (Batool *et al.*, 2025). The EU AI Act requires high-risk systems to enable oversight and maintain traceability (European Commission, 2024b). Machine learning predicts disruptions accurately, yet stakeholders demand understandable conclusions (Kabir *et al.*, 2025). Under the EU AI Act (Art. 13), ‘transparency’ is not merely an ethical preference but a legal mandate for high-risk systems. This creates a shift in procurement logic: organisations should prioritise ‘global interpretability’ (understanding the whole model) and ‘local interpretability’ (understanding a specific supplier risk score) over marginal gains in predictive accuracy. In a CSDDD audit, a ‘black box’ prediction, no matter how accurate, may count as legal liability, instead of an asset. This tension reflects a fundamental accuracy-interpretability trade-off extensively documented in the machine learning literature: complex models such as deep neural networks and ensemble methods provide accurate predictions but work in ways that humans cannot easily understand. By contrast, interpretable models sacrifice accuracy for transparency (Batool *et al.*, 2025; Chang & Bau, 2025). This evidence demonstrates that ethical demands fundamentally reshape technological architectures.

Practice shows a dual response. Technically, organisations adopt explainable AI using LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations), creating audit trails satisfying requirements (Chang & Bau, 2025; Stahl & Eke, 2024; Teixeira *et al.*, 2025). Organisationally, firms establish governance committees ensuring human oversight (Batool *et al.*, 2025). Explainability constitutes both a technical property and an organisational capability.

Systematic reviews confirm explainable artificial intelligence’s (XAI) centrality for regulatory compliance (Chang & Bau, 2025; Kabir *et al.*, 2025), though empirical business management studies examining AI deployment specifically in mandatory due diligence contexts remain scarce. The tech-ethics interface demonstrates mutual influence. Ethical demands reshape technological choices, driving interpretable architectures even when opaque alternatives perform better. Simultaneously, technological capabilities expand ethical possibilities – NLP enables monitoring at previously impossible scales (Marano *et al.*, 2024). Technology and ethics resist independent optimisation.

From this analysis, we derived proposition 1 (tech-ethics interface): Ethical demands for transparency reshape technological architectures, driving organisations towards interpretable AI models even when opaque algorithms offer superior predictive accuracy.

Reconciling the Ethics-culture Interface: Contextual Fairness

The CSDDD’s global scope creates cultural challenges that technology alone cannot resolve (RQ1, RQ2). Organisations must assess labour practices across countries with different norms (Han *et al.*, 2025). Fairness frameworks developed in Europe may get things wrong in two ways. They may flag acceptable local practices as violations. Or they may treat harmful practices as acceptable local customs. Research shows that people in different cultures understand AI fairness differently (Barnes *et al.*, 2024; Han *et al.*, 2025). Large language models also show cultural biases (Brauner *et al.*, 2024; Starke *et al.*, 2022; Tao *et al.*, 2024; Yuan *et al.*, 2025). The cultural variation literature suggests areas where such differences may arise: working hours considered excessive in Europe may be standard elsewhere; collective bargaining may operate differently across regions; community-based hiring practices may be flagged as nepotism by AI systems trained on Western standards. We believe that those illustrative examples align with Roy and Mukherjee’s (2022) finding that national culture shapes corporate ESG disclosure more than economic factors. Yuan *et al.* (2025) demonstrate that ChatGPT exhibits systematic cultural biases in interpersonal decision-making tasks, while Tao *et al.* (2024) find that cultural prompting can reduce but not eliminate such biases. These findings suggest that AI systems deployed for global due diligence require not merely technical debiasing but an ongoing cultural calibration informed by local stakeholders.

Organisations navigate this through participatory governance. Firms establish regional committees including suppliers, civil society, and workers’ advocates (Marano *et al.*, 2024). These provide cultural context for interpreting outputs. Effective due diligence requires contextual judgement enabled by AI, not replaced by it (Chaudhary, 2024).

From this analysis, we derived proposition 2 (ethics-culture interface): Algorithmic fairness standards are culturally contingent, requiring local stakeholder engagement to prevent the normalisation of harmful practices or the misinterpretation of acceptable local norms.

Leveraging the Tech-culture Interface: Organisational Readiness as Primary Determinant

Organisational culture predicts AI effectiveness better than technical sophistication (Cannas *et al.*, 2024; Milosevic *et al.*, 2023). Evidence suggests that organisations with strong commitment achieve better AI outcomes than technically advanced firms lacking such commitment (Cannas *et al.*, 2024; Neumann *et al.*, 2024). Technology amplifies existing tendencies rather than transforming them.

This logic suggests that organisational readiness may function rather as a coefficient than an additive factor. If cultural commitment is low, the substantive impact of even sophisticated technology remains minimal. Artificial intelligence does not create a due diligence culture. It scales the one that already exists. This coefficient logic draws on resource complementarity theory (Amit & Schoemaker, 1993), which establishes that strategic resources generate value through synergistic combination rather than independent contribution. Empirical research supports this pattern. Neumann *et al.* (2024) state that internal capabilities prove far more influential for AI adoption than external support. Studying 280 Vietnamese SMEs, Dey *et al.* (2023) found that AI capabilities enhance supply chain resilience only when supported by appropriate cultural and governance mechanisms – AI adoption alone proved insufficient. Similarly, Hughes *et al.* (2026) demonstrate that organisational factors consistently outweigh technological sophistication in determining generative AI adoption success. The same technology produces different outcomes depending on organisational values: committed firms invest in supplier improvement while cost-focused firms may simply switch suppliers without solving the problem (Abhulimen & Ejike, 2024). Best practice favours cultural transformation before technological deployment. Organisations establish committees, develop protocols, and create incentives rewarding ESG outcomes before deploying AI at scale (Shahzadi *et al.*, 2024). The tech-culture interface inverts conventional logic: cultural readiness determines technological effectiveness, not the reverse.

From this analysis, we derived proposition 3 (tech-culture interface): Organisational readiness acts as a primary determinant of AI effectiveness, in which technology may function as a coefficient that amplifies existing cultural tendencies rather than transforming them independently of context. Together, propositions 1-3 address RQ1 by specifying the mutual influence mechanisms across dimensions through the integrated theoretical lens, revealing interaction effects invisible to single-theory approaches.

Practical Implications: The AI Due-diligence-maturity Model

Research shows that AI maturity, not just technical sophistication, predicts whether organisations succeed with AI (Hansen *et al.*, 2024). Several maturity models already exist in related areas. Akbarighatar *et al.* (2023) developed a sociotechnical AI maturity framework focused on responsible AI. Vann Yaroson *et al.* (2025) examined responsible AI capabilities in supply chains. Sadiq *et al.* (2021) and Colangelo *et al.* (2022) addressed AI maturity for data management and production systems. However, none of these models addresses the specific needs of mandatory due diligence compliance under the CSDDD and EU AI Act. Our model differs from these existing frameworks in three key respects. Firstly, while Akbarighatar *et al.* (2023) generally focus on responsible AI practices, our model specifically targets mandatory due diligence contexts where regulatory convergence (CSDDD and EU AI Act) creates unique compliance challenges. Secondly, unlike Sadiq *et al.* (2021) and Colangelo *et al.* (2022) who emphasise technical maturity, our model foregrounds the institutional and cultural layers that our theoretical framework identifies as primary determinants of effectiveness. Thirdly, our four-layer structure (operational, institutional, global, strategic) operationalises the compliance paradox, enabling organisations to diagnose why structural conformity may coexist with operational divergence.

We built on earlier work, including the corresponding author's prior analysis of organisational responses to sustainability directives (Welsen, 2025), as well as recent validation studies of readiness assessment approaches (Elhady & Shohieb, 2025). Our AI due-diligence-maturity model has four organisational layers. Three layers map directly to the framework dimensions: the operational layer addresses technological capabilities, the institutional layer covers ethical governance structures, and the

global layer reflects cultural adaptation across borders. The fourth layer, namely the strategic one, captures leadership commitment as a cross-cutting enabler that determines whether the other three dimensions achieve substantive rather than symbolic compliance. The four maturity levels, *i.e.*, crawl, walk, run, fly, follow common maturity model practice (Sadiq *et al.*, 2021). They represent progress from initial ad-hoc approaches (crawl), through developing awareness (walk), to integrated practice (run), and finally optimised strategic leadership (fly). By structuring the assessment across four layers and four maturity levels, we provide diagnostic granularity that enables targeted interventions.

We operationalised this multidimensional progression in the AI due-diligence-maturity model. Table A1 in the Appendix provides a detailed breakdown of maturity levels and indicators across the four layers, capturing the progression from reactive compliance to strategic leadership. Maturity progression differed across firm types. Platform multinational enterprises (MNEs) may advance rapidly; SMEs may go directly to Level 3 through AI-as-a-service or require extended early phases. For resource-constrained firms, the maturity model suggested a potential 'leapfrog' strategy. By adopting AI-as-a-service compliance tools, an SME might bypass level 2 (walk) and advance directly to level 3 (run), provided that the firm's institutional governance mechanisms are established in parallel. This leapfrog potential extends Steinmueller's (2001) concept of technology leapfrogging to organisational contexts, enabling resource-constrained organisations to bypass in-house AI development through platform-based solutions. This re-frames mandatory due diligence as a catalyst for digital professionalisation rather than an entry barrier.

Organisations should assess maturity against size-appropriate benchmarks. This model requires empirical validation beyond the illustrative application presented here; we offer it as a theoretically grounded but exploratory diagnostic tool inviting future empirical testing. Until validated, the model functions as a conceptual framework for structuring analysis rather than a prescriptive assessment instrument. The three-firm analysis in Section 4.1 demonstrates applicability but cannot establish validity. Future research should test the model across larger samples and diverse industry contexts.

Progression follows iterative improvement logic (Deming, 1982). Organisations may use the model as a preliminary self-assessment tool for identifying potential gaps across layers, though practitioners should note that the model requires empirical validation before prescriptive application. A firm strong in technology but weak in culture should prioritise stakeholder engagement; a firm with governance but limited capacity should invest in infrastructure. The model enables targeted development.

DISCUSSION

This section applies the integrated framework and maturity model developed in Section 3 to examine AI-driven due diligence in practice. Section 4.1 presents an illustrative analysis of three European e-commerce firms, explores the framework's applicability, and reveals patterns across cases. Section 4.2 discusses the significance of these findings for theory and practice.

Illustrative Application

To demonstrate the practical applicability of the proposed maturity model, we conducted systematic qualitative content analysis of sustainability reports from Amazon (2025), Otto Group (2025), and Zalando SE (2025). Otto Group and Zalando operate under LkSG; Amazon faces indirect pressure through European operations and forthcoming CSDDD obligations. We coded the documents for explicit mentions of AI, machine learning, and algorithmic systems, applying conservative coding rules where capabilities were not inferred from absence of evidence. Pattern-matching analysis tested observed evidence against the three theoretical propositions. Appendix B summarises the coding protocol and key evidence; complete evidence matrices are available from the corresponding author upon request.

The analysis revealed pronounced variation across firms. At the operational layer, Amazon demonstrated explicit AI deployment across sustainability functions, including 'AI-powered robots to automate sorting recyclable materials' (p. 20), predictive leak detection (p. 24), and 'AI machine learning to determine the safest and most efficient packaging' (p. 22). Otto Group deployed 'AI-powered forecasting tools, including demand forecasting and return rate prediction' (p. 81) and op-

erated an ‘AI Forecasting solution since 2019’ (p. 81). Zalando’s reports contain no explicit mention of AI, machine learning, or algorithmic systems for due diligence purposes.

Table 1. Summary of AI due-diligence maturity assessment: Three European e-commerce firms (2024-2025)

Firm	Business model	Operational	Institutional	Global	Strategic	Overall
Amazon	Hybrid	Fly	Run	Fly	Fly	Fly
Otto Group	Hybrid	Run	Walk	Crawl	Walk	Walk
Zalando	Platform/Hybrid	Crawl	Crawl	Crawl	Crawl	Crawl

Source: own study based on systematic content analysis of publicly available sustainability reports (2024-2025).

A pronounced institutional governance gap emerged. Only Amazon achieved ISO/IEC 42001 certification for responsible AI (p. 49) and maintained board-level oversight where committees ‘reviewed the Company’s approach to responsible AI development and AI governance’ (p. 47). Otto Group provided AI awareness training to ‘around 17 000 white-collar employees’ (p. 80) but lacked formal AI governance structures. Zalando demonstrated comprehensive sustainability governance but no AI-specific policies or roles.

Pattern-matching analysis suggested differential proposition support. Proposition 1 (tech-ethics) found preliminary support only in Amazon’s certification-driven approach, suggesting that the transparency-architecture relationship operates primarily in technology-intensive contexts. Proposition 2 (ethics-culture) received universal support: all three firms deployed multi-language stakeholder tools, suggesting that global governance requires culturally accessible interfaces regardless of AI maturity. Proposition 3 (tech-culture) received the strongest cross-case support: Zalando’s explicit acknowledgement of data quality limitations suggests that organisational readiness may function as a coefficient – technology cannot bypass foundational data gaps. Several validity limitations apply. The assessment relied exclusively on public disclosures, which may have understated actual capabilities. The coding was conducted by the researchers who developed the model. As a safeguard against author bias, conservative coding rules required explicit textual evidence and treated absence as absence of capability; this rule produced the lowest maturity assessment for the firm employing the corresponding author. The illustrative analysis demonstrated exploratory framework application but did not constitute validation. Nevertheless, the analysis revealed an important gap between operational AI deployment and institutional governance warranting further investigation.

Discussion of Findings

The preceding illustrative analysis addressed both research questions and revealed patterns warranting further reflection. Regarding RQ1, the three interfaces demonstrate that technological capabilities, ethical governance, and cultural adaptation do not merely coexist but actively reshape one another. The tech-ethics interface shows that regulatory demands for transparency alter AI architectural choices, even when opaque models offer superior performance. The ethics-culture interface reveals that fairness cannot be universally defined but requires continuous local calibration. The tech-culture interface inverts conventional assumptions: rather than technology driving organisational change, cultural readiness determines whether technological investments yield substantive outcomes.

Regarding RQ2, the AI due-diligence-maturity model provides a diagnostic tool for systematic readiness assessment. The illustrative application to European e-commerce firms demonstrates both the model’s applicability and a concerning finding: even firms with advanced operational AI capabilities exhibit significant institutional governance gaps. This pattern, *i.e.*, operational sophistication without corresponding governance maturity, exemplifies the compliance paradox identified in our theoretical framework. Organisations may satisfy surface-level regulatory requirements while lacking the governance structures necessary for substantive due diligence.

These findings carry implications for both theory and practice. Theoretically, they suggest viewing AI-driven due diligence as fundamentally sociotechnical rather than purely technological. The coefficient logic of proposition 3 that organisational readiness multiplies rather than adds to technological

capability suggests that investments in AI systems without parallel investments in governance and culture may yield minimal returns. The illustrative analysis also provides partial support for proposition 1 (in Amazon's transparency-driven architecture choices) and proposition 2 (in all firms' multi-language stakeholder tools). Practically, the findings indicate that organisations facing CSDDD compliance should resist the temptation to pursue technology-first strategies. The institutional governance gap observed across all three firms, regardless of their operational maturity levels, suggests that this is a systemic challenge, which requires deliberate attention.

CONCLUSIONS

Research Results Summary

Addressing RQ1, our integrated framework synthesising institutional theory, stakeholder theory, and the TOE framework demonstrates that dimensions operate as mutually constitutive interfaces: tech-ethics (transparency demands drive XAI adoption), ethics-culture (fairness standards are culturally contingent), and tech-culture (organisational culture determines technology effectiveness). The three derived propositions specify these interaction mechanisms, revealing effects invisible to single-theory approaches and reconceptualising compliance as a sociotechnical transformation. Addressing RQ2, we propose the AI due-diligence-maturity model across four layers (operational, institutional, global, strategic) with four maturity levels (crawl to fly). This enables identification of capability gaps and prioritised development. Appendix A provides the full operationalisation.

Theoretical Contributions

The compliance paradox identified in our framework, where structural conformity masks operational divergence, explains why the illustrative analysis revealed institutional governance gaps even among firms demonstrating operational AI maturity. This insight anchors our four theoretical contributions.

Firstly, we demonstrated mutual influence across dimensions that the existing research treats as related but separate, showing how changes in one dimension reshape possibilities in others. Prior sociotechnical work on AI (Akbarighatar *et al.*, 2023; Dey *et al.*, 2023) recognises that technology and organisation interact, but does not specify how this interaction occurs in mandatory due diligence contexts. Our framework identifies three interfaces (tech-ethics, ethics-culture, tech-culture) as the specific sites where dimensions shape one other. Ethical demands drive technological architectures, which enable new ethical possibilities, which encounter cultural variation requiring further adaptation. This extends sociotechnical theory from general recognition of interdependence to specification of interaction mechanisms.

Secondly, we integrated institutional theory, stakeholder theory, and the TOE framework within a unified framework. These lenses typically compete for explanatory primacy. We argue for their complementarity: institutional theory explains regulatory pressures, stakeholder theory illuminates competing demands, and the TOE framework structures analysis of barriers and enablers. Integration reveals dynamics invisible to single-theory approaches.

Thirdly, our AI due-diligence-maturity model extends recent advances in measuring organisational readiness. Dey *et al.* (2023) found that AI capabilities enhance organisational agility only when supported by cultural and governance mechanisms, confirming our mutual influence thesis. By structuring assessment across four layers with four maturity levels, we provide diagnostic granularity that enables targeted interventions.

Fourthly, we advanced the understanding of regulatory transformation as a sociotechnical process. The CSDDD literature largely focuses on legal compliance and liability frameworks (Buhmann & Feld, 2024; Gustafsson *et al.*, 2023b). We argue that compliance requires simultaneous technological, organisational, and cultural transformation. Legal obligations catalyse sociotechnical change whose outcomes depend on organisational responses. Regulatory effectiveness depends not merely on legal design but on organisational capacity for adaptation.

Final Reflections and Limitations

This research reconceptualised AI in supply chain due diligence as a sociotechnical challenge rather than a purely technological solution. By showing that technological capabilities, ethical governance, and cultural adaptation dynamically shape one another, we challenged assumptions in both academic literature and practitioner discourse. Organisations cannot address CSDDD compliance through technology alone. Effective AI-driven due diligence requires transformation across all three dimensions, with cultural readiness often more important than algorithmic sophistication. The integrated framework synthesises fragmented perspectives into a unified model, while the maturity model provides diagnostic tools for systematic readiness assessment.

Several limitations qualify our contributions. Firstly, this conceptual framework requires empirical validation through systematic case studies. Secondly, our purposive literature review cannot claim to be comprehensive. Thirdly, applicability may vary across industries with different supply chain complexities. Fourthly, while we emphasised SME relevance, our illustrative analysis focused on large MNEs. Fifthly, rapidly evolving AI technology and regulations mean that specific details may have changed before the article's publication. The illustrative analysis provides early evidence of framework usefulness but cannot support statistical generalisation; it does reveal an important gap between technical deployment and institutional governance warranting further study.

Sixthly, we based the above analysis exclusively on publicly available sustainability reports. Actual AI capabilities may exceed what is disclosed in these documents. The conservative coding approach (explicit AI/ML/Algorithm terms only) may understate deployment, particularly for Zalando, where advanced digital tools are utilised but not explicitly labelled as AI-driven. The assessment was conducted by the researchers who developed the maturity model. Seventhly, as a conceptual article, the propositions require empirical testing through quantitative studies with larger samples to establish generalisability.

The main implication is important and clear: technology alone cannot resolve fundamental tensions between efficiency and accountability, or between symbolic compliance and substantive impact. Moreover, AI-driven due diligence will succeed only when organisations recognise that algorithms are tools enabling human judgement, not substitutes for it. The challenge lies not in building more sophisticated AI but in building organisational cultures capable of using AI wisely. Such cultures treat compliance as an opportunity rather than a burden, engage stakeholders as partners, and understand technology as an amplifier of values rather than a replacement for them. For entrepreneurial firms and SMEs in supply chains subject to mandatory due diligence, this finding suggests potential pathways. While our illustrative analysis focused on large MNEs, the framework implies that strong commitment and stakeholder relationships may partially compensate for limited technological resources – a proposition requiring empirical testing with SME samples.

Research Agenda

Future research should pursue three directions. Empirically, scholars should investigate how organisations navigate the three interfaces through comparative case studies. Longitudinal research could test whether cultural transformation before technological deployment produces better outcomes. Quantitative studies could examine whether advancement in one maturity layer enables or constrains progress in others. The CSDDD implementation period beginning July 2027 offers an opportunity to study regulatory transformation in real time (Sinnig & Zetzsche, 2025).

Theoretically, researchers should examine boundary conditions. Does mutual influence operate differently in highly versus lightly regulated industries? Do firm size, ownership structure, or governance quality moderate relationships between dimensions? These investigations would refine framework applicability. Furthermore, SMEs face different resource constraints than large MNEs (Sánchez *et al.*, 2025). They may need collaborative compliance models or AI-as-a-service approaches to meet requirements. Understanding whether entrepreneurial firms achieve compliance through innovative mechanisms would inform regulatory design for diverse organisational forms.

Methodologically, scholars should operationalise the maturity model by developing Likert-scale items from the Appendix A indicators, testing inter-rater reliability with coders blind to firm identity,

and validating constructs against compliance outcomes such as audit findings and supplier remediation rates. Such instruments would enable systematic comparison across organisations and jurisdictions. The concurrent CSDDD and AI Act implementation creates a natural experiment for examining how overlapping regulations shape AI adoption.

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APPENDIX A: AI DUE DILIGENCE MATURITY MODEL – DETAILED INDICATORS

This model enables organisations to assess AI readiness for supply chain due diligence, based on Welsen (2025).

Table A1. AI due-diligence-maturity model: Indicators across four organisational layers and maturity levels

Organisa-tional layer	Level 1. Crawl (ini-tial & ad-hoc)	Level 2. Walk (de-veloping & aware)	Level 3. Run (inte-grated & proactive)	Level 4. Fly (optimised & strategic)
1. Operational (day-to-day processes, workflows, and tools)	Data are siloed and require manual ex-traction. The use of AI is experimental and lacks formal risk checks or ethi-cal guidelines in workflows.	Standalone AI tools are used for spe-cific tasks. Basic bias checks and data quality proto-cols are introduced but applied incon-sistently.	Artificial intelligence risk assessments and ethical reviews are a standard, required part of the project lifecycle. Data govern-ance is automated and robust.	A predictive, AI-driven sys-tem illuminates the multi-tier supply chain. Generative AI acts as a ‘co-pilot’ for ex-perts, with continuous, auto-mated monitoring for perfor-mance and ethical drift.
2. Institu-tional (inter-nal govern-ance, policies, roles, and training)	Compliance is a manual, checklist-based exercise. No formal AI policies or dedicated gov-ernance roles exist.	An ethics commit-tee is formed. The first AI governance policies are writ-ten, but enforce-ment is ad-hoc. Awareness training is offered.	A robust, cross-func-tional AI governance framework is estab-lished with clear roles (e.g., AI Ethics Of-ficer). Training is man-datory for relevant teams.	AI governance is fully inte-grated into the enterprise GRC (governance, risk, com-pliance) framework. Ethical performance is a formal key performance indicator (KPI), continuously audited and re-ported.
3. Global (cross-border coordination and adapta-tion)	Each country or business unit oper-ates in isolation. There is no central coordination of AI compliance, creat-ing inconsistency and risk.	Headquarters be-gins issuing basic global AI guide-lines. Subsidiaries in high-regulation zones (e.g., EU) re-act to local laws, but knowledge is not shared.	A unified global AI governance program exists, balancing cen-tral standards with re-quired local adapta-tion. Best practices are actively shared across the MNEs net-work.	The firm uses its global foot-print as a strategic ad-vantage, leveraging insights from advanced regulatory markets to pre-emptively raise standards worldwide. Responsible AI is required of global partners and suppli-ers.
4. Strategic (top-manage-ment over-sight and business strategy)	Top management is largely unaware or uninvolved in AI governance; it is viewed purely as a technical IT issue.	Leadership recog-nises AI compliance as a necessary cost and risk-mitigation issue. Budgeting is reactive, often fol-lowing an incident or new regulation.	Leadership actively di-rects AI governance as a key part of corpo-rate responsibility. Responsible AI is inte-grated into strategic planning and resource allocation.	The Board of Directors pro-vides active oversight. Re-sponsible AI is a core part of the corporate brand and a source of competitive ad-vantage, shaping new busi-ness models and market en-try decisions.

Note: The levels are grounded in our prior work (Welsen, 2025). The operational layer progresses from data challenges (Shahzadi *et al.*, 2024) to AI-driven platforms. The institutional layer matures from reactive postures (Brintrup *et al.*, 2023) to robust governance (Batoool *et al.*, 2025). The global layer addresses cross-border requirements (Gustafsson *et al.*, 2023a; Wilhelm, 2024). The strategic layer evolves to a point where responsible AI becomes a competitive advantage (Hansen *et al.*, 2024).

Source: own study based on Welsen (2025).

APPENDIX B: ILLUSTRATIVE ANALYSIS CODING PROTOCOL

This appendix documents the systematic approach that we used for the illustrative maturity assessment presented in Section 4.1

B.1 Documents analysed

Amazon (2025): 2024 Amazon Sustainability Report Otto Group (2025): Annual Report 2024/25 – Sustainability Strategy Zalando SE (2025): Carbon Disclosure Project (CDP) Questionnaire 2025, Corporate Sustainability Reporting Directive (CSRD) Digest 2024, Sustainability Progress Report 2023

B.2 Coding approach

We systematically searched the documents for explicit mentions of AI, machine learning, and algorithmic systems across four organisational layers. Conservative coding rules were applied: (1) only explicit AI/ML/Algorithm terminology was coded; (2) general digitalisation or non-AI automation was excluded; (3) capabilities were not inferred from absence of evidence; (4) when uncertain about maturity level, the lower level was assigned. Pattern matching analysis then tested observed evidence against the three theoretical propositions.

B.3 Evidence summary by company (2024-2025) Table B.3

Amazon Layer	Evidence	Page	Maturity Level
Operational	'AI-powered robots to automate sorting recyclable materials'	p. 20	Fly
Operational	'AI machine learning to determine the safest and most efficient packaging'	p. 22	Fly
Operational	'Detecting water leaks' via AI	p. 24	Fly
Operational	'Deep learning-based algorithm provides real-time best-fit recommendations'	p. 36	Fly
Institutional	'Review of the Company's approach to responsible AI development and AI governance'	p. 47	Run
Institutional	'ISO/IEC 42001 certification... establishes requirements for responsible AI'	p. 49	Fly
Global	'Joined the Frontier Model Forum to advance AI safety and security'	p. 49	Fly
Strategic	'Accelerated its investments in generative AI'	p. 4	Fly
Strategic	'Architecture that will simultaneously support next-generation AI capabilities'	p. 10	Fly

Otto Group Layer	Evidence	Page	Maturity Level
Operational	'AI-powered forecasting tools, including demand forecasting and return rate prediction'	p. 81	Run
Operational	'AI Forecasting solution since 2019'	p. 81	Run
Operational	'Sorting for Circularity' project harnesses artificial intelligence'	p. 77	Run
Institutional	'Explanatory learning path on how to use our internal AI chat function (ogGPT) to around 17 000 white-collar employees'	p. 80	Walk
Global	No explicit AI-specific global guidelines found	N/A	Crawl
Strategic	'Responsible use of artificial intelligence ... will remain priorities'	p. 79	Walk

Zalando Layer	Evidence	Page	Maturity Level
Operational	No explicit AI/ML/Algorithm mentions for due diligence	N/A	Crawl
Institutional	No AI-specific governance structures found	N/A	Crawl
Global	No AI-specific cross-border coordination found	N/A	Crawl
Strategic	No AI positioning in sustainability strategy	N/A	Crawl

B.4 Pattern matching results – Table B.4

Proposition	Amazon	Otto Group	Zalando
P1 (Tech-Ethics)	Consistent	Inconsistent	Inconsistent
P2 (Ethics-Culture)	Consistent	Consistent	Consistent
P3 (Tech-Culture)	Consistent	Consistent	Consistent

Source: own study.

B.5 Limitations

Assessments relied exclusively on public disclosures. Sustainability reports may underrepresent AI capabilities reported in other corporate communications. The conservative coding approach may understate actual AI deployment, particularly for Zalando, which uses advanced tools but does not explicitly label them as AI-driven.

Authors

The contribution share of authors was equal and amounted to 50% each. MW – conceptualisation, literature review, framework development, illustrative analysis, and writing; ŁS – methodology design, theoretical supervision, and critical revision.

Marcel Welsen (corresponding author)

PhD Student at the Department of Management and Quality Studies, WSB University (Poland) and lecturer at WSB campus Krakow. His research interests include International Business, AI-driven supply chain management, due diligence, and sociotechnical systems.

Correspondence to: Marcel Welsen, Management and Quality Studies, WSB University, ul. Zygmunta Ciepłaka 1c, 41-300 Dąbrowa Górnicza, Poland; e-mail: Marcel.Welsen@wsb.edu.pl

ORCID  <https://orcid.org/0000-0001-9456-1930>

Łukasz Sułkowski

Professor at the Institute of Public Affairs, Jagiellonian University (Poland). His research interests include organisational culture, management of higher education institutions, and digital transformation.

Correspondence to: Łukasz Sułkowski, Institute of Public Affairs, Jagiellonian University, ul. Gołębia 24, 31-007 Kraków, Poland; e-mail: lukasz.sulkowski@uj.edu.pl

ORCID  <https://orcid.org/0000-0002-1248-2743>

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Use of Artificial Intelligence

Artificial intelligence tools, specifically Google Gemini Pro and Anthropic Claude 3.5, were used during the preparation of this manuscript exclusively for language editing, proofreading, and text condensation to meet submission length requirements. These tools assisted with a grammar check, sentence refinement, and structural organisation. They were not used to generate original scientific concepts, data, or findings. The authors reviewed and edited all AI-assisted output and take full responsibility for the integrity and content of the final publication.

Conflict of Interest

The corresponding author is employed by Zalando SE, one of the firms included in the illustrative analysis. This employment informed the selection of e-commerce as the illustrative context but did not influence the maturity assessment, which was based solely on publicly available sustainability reports. No other potential conflicts of interest are declared.

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The impact of enterprises' internationalisation on their innovation activity

Marcin Salamaga

ABSTRACT

Objective: The objective of the article is to verify the impact of internationalisation processes on the innovativeness of companies in the Małopolska and Silesian Voivodeships.

Research Design & Methods: In the study of the impact of different ways of internationalisation of companies on their innovation activity, I used structural equation modelling (SEM), which I estimated using the partial least squares method (PLS). I obtained data for the study from a survey conducted in 2024.

Findings: The greatest innovation activity is demonstrated by companies that expand into foreign markets through export. Companies oriented towards export or import are more prone to innovation than companies oriented towards foreign direct investment (FDI). The moderating variable representing market conditions significantly increased the strength of the influence of internationalisation through export on innovation, while in the case of companies oriented towards FDI there was no such strengthening.

Implications & Recommendations: The article indicates which paths of internationalisation of enterprises activate innovation activity to the greatest extent. Innovation advantage was most often gained by companies that engage in foreign trade, and especially undertake export activity. This information may be useful for managers planning expansion into foreign markets.

Contribution & Value Added: The article presents an original analysis of the impact of various internationalisation methods on enterprise innovation. What is new is the broad research perspective adopted, which considers various forms of internationalisation and types of innovation, allowing for the examination of multidirectional relationships between these categories. The use of SEM is also unique in this approach. The study was conducted on a sample of companies from Southern Poland, a region with a high density of technology parks and economic activity zones. The studied region can serve as a reference point for comparative analyses of other regions of Central and Eastern Europe with similar economic profiles.

Article type: research article

Keywords: internationalisation; innovation; export; foreign direct investment; structural equation modelling; partial least squares

JEL codes: C39, F10, F21, F23

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INTRODUCTION

Economic progress would not be possible without innovation. Innovation drives every economy. The literature emphasises that enterprise innovation is one of the key mechanisms that increase enterprises' efficiency, flexibility, and adaptability to a changing market environment. Implementing innovations generally improves product quality, streamlines internal processes, reduces operating costs, and enables better tailoring of offerings to customer needs in various markets (Genc *et al.*, 2019). Consequently, innovative enterprises increase their productivity and resource efficiency, which improves international competitiveness (Genc *et al.*, 2019; Hilmersson *et al.*, 2023). Furthermore, we may view innovations as strategic resources and competencies that create an advantage difficult for

foreign competitors to replicate (Vuorio *et al.*, 2020). Poland's membership in the EU creates vast opportunities for Polish companies to expand into European foreign markets. Internationalisation of enterprises gives them access to new technologies, markets, and resources outside their home country. Through internationalisation, companies achieve a competitive advantage, among other things, by optimising costs and maximising revenues.

How internationalisation links to companies' innovativeness depends on the forms of expansion into external markets. According to Salomon and Jin (2010), the expansion of companies into foreign markets provides an opportunity to reach customers with diverse needs, which puts pressure on companies to intensify their innovative activity in the product and process areas. Cooperation with foreign companies that share knowledge also increases companies' capacity to innovate (Frenz & Ietto-Gillies, 2009). However, the development of companies' innovative activity may face limitations despite their participation in the internationalisation process.

These include, among other things, reduced efficiency of know-how transfer due to cultural and language barriers, possible flow of technological knowledge to competitors, as well as the need to limit investment in research and development activities, *e.g.*, when funds shift to operations to manage activities across many countries. Consequently, not every method of internationalisation leads to the expected increase in the innovativeness of companies in a specific industry.

Since the consequences of companies' internationalisation for their innovative activity are not always obvious and depend on various conditions, the relationships between these categories require continuous research for specific economies or industries. In Polish scientific literature, this type of research is not common. I aimed to examine the impact of internationalisation processes on innovation, using the example of companies in the Małopolska and Silesian Voivodeships. I selected companies from this region because it represents one of the most dynamic areas of economic development in Poland, with a diverse industry structure and a high share of innovative companies. The results of such research have broader implications than just local ones, as the mechanisms of the relationship between innovation and internationalisation are largely universal across the post-transition economies of Central and Eastern Europe. This article examines various forms of company internationalisation and various types of innovation activity, providing a new research perspective not only for the Polish economy. I used structural equation models to achieve this goal.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

According to the literature, internationalisation is a state, *e.g.*, the current level of internationalisation, or a process, *i.e.*, moving through successive levels of internationalisation (Johanson & Vahlne, 1977; Zweig, 2002). Here, we can consider the evolutionary internationalisation of business activities, starting from non-capital forms (direct and indirect export sales, selling licenses abroad, franchising, management contracts) to capital forms (creating subsidiaries and joint ventures). This approach is consistent with the Uppsala model (Welch & Luostarinen, 1988). Knowledge and innovation are currently the main factors motivating companies to operate internationally, but the company's involvement in internationalisation processes can also encourage it to innovate. Innovations determine a company's competitive position in international markets, which in turn often determines further innovation activity. A key component of this relationship is the companies' desire to improve their efficiency. Increased efficiency resulting from the implementation of technological, organisational, and process innovations is widely recognised as one of the main predictors of their international activity (Genc *et al.*, 2019). Higher efficiency fosters various forms of internationalisation, from exports, through strategic alliances, to direct investments, which in turn stimulate the further development of their innovation potential. This is because international activity provides access to new sources of knowledge, technologies, and organisational experience, which can strengthen companies' ability to generate further innovations (Vuorio *et al.*, 2020). Thus, a feedback loop exists between innovation, efficiency, and internationalisation: innovation increases efficiency, which in turn fosters internationalisation, which can then stimulate further innovation processes.

Numerous trends and theories in management and economics attempt to explain the relationship between internationalisation and innovation. Based on the literature review, Du *et al.* (2023) found that current research in this area focuses on the following trends: organisational learning theory (Piperopoulos *et al.*, 2018), institution theory/institution-based view (Xie & Li, 2018), network theory (including embeddedness perspective) (Isaac *et al.*, 2019), knowledge-based view (Hsieh *et al.*, 2018), and resource-based view (Michailova & Zhan, 2015). Most of these approaches predict a beneficial effect of internationalisation on enterprise innovation (*e.g.*, Piperopoulos *et al.*, 2018; Xie & Li, 2018). However, there are views in the literature pointing to negative outcomes of internationalisation mainly due to potentially high costs resulting from increased uncertainty and complexity (Kafourous & Buckley, 2008).

The mutual relationships between companies' internationalisation and innovation have also long been the subject of empirical scientific research. Based on a meta-analysis of 99 studies, Ding *et al.* (2021) showed that the effects of internationalisation on innovation are varied but generally positive. Their meta-regressions indicate that some differences in the assessment of the impact of internationalisation on the innovative activity of companies may stem from the type of internationalisation considered, the type of data used in the studies (panel data vs. cross-sectional data), the level of technological advancement of the industry (high-tech manufacturing vs. industries not specified). Interestingly, they did not observe significant differences in the effects they examined when taking into account many other criteria, such as model specifications (non-linear model vs. linear model), countries (developed countries vs. developing countries), firm size (Ding *et al.*, 2021). Many authors discuss the impact of innovation on the internationalisation of enterprises (Hilmersson *et al.*, 2023; Ji & Mou, 2023; Gómez-Bolaños *et al.*, 2022), but although it is part of the feedback mechanism between these categories, I will not discuss it in detail here as it lies outside this article's main research stream.

Haddoud *et al.* (2023) studied bidirectional cause-and-effect relationships between internationalisation and innovation of Moroccan companies. Their research shows that innovations stimulate export intensity and that foreign technology licenses and R&D expenditure improve the innovation activity of companies. The literature offers studies examining the impact of specific internationalisation activities of companies on their innovative solutions in product or organisational areas, and sometimes on their entire business models. However, a more general perspective that considers the simultaneous impact of different forms of internationalisation on different types of innovation activity is lacking. Therefore, the question of which form of internationalisation contributes most to corporate innovation remains open. This requires more in-depth research that considers various forms of internationalisation and innovation.

When examining the causal relationships between internationalisation and innovation, researchers use various tools from the field of multivariate statistical analysis. These are primarily linear single- and multi-equation econometric models, usually estimated using OLS estimators (McCarthy & Aalbers, 2016), GMM (Tse *et al.*, 2017), 2SLS (Hashai, 2018), GLS (Xie & Li, 2018). Some researchers also use structural equation modelling (SEM) (Efrat *et al.*, 2018; Ding *et al.*, 2021). Other econometric tools are used much less frequently (Ding *et al.*, 2021).

Polish scientific literature on entrepreneurship also devotes considerable attention to the innovativeness of companies and their internationalisation. Unfortunately, few scientific works examine the cause-effect relationships between these categories using the example of Polish companies. Among them, we can point to the scientific monograph written by Mińska-Struzik (2014), who showed that export is a key factor supporting product innovations for Polish companies from the industrial processing sector. However, narrowing the study to a group of high-tech companies, Mińska-Struzik showed that the impact of export on the product and process innovativeness of companies is moderate at best. Szymura-Tyc (2015) also considers these issues in the context of the networking of companies in Poland.

Based on Mińska-Struzik's results, we may state that the relationship between the internationalisation and innovativeness of an enterprise is positive but weak. In turn, the networking of Polish companies is also weakly and positively related to their internationalisation and innovative activity. Other works also discuss the internationalisation and innovativeness of Polish enterprises (Głodowska *et al.*,

2019; Grzegorzewska & Stasiak-Betlejewska, 2022). When the scope of internationalisation of enterprises is territorially limited to the EU, we can talk about the Europeanisation of enterprises. A comprehensive study of the Europeanisation of enterprises based on a sample of over 300 companies in the Małopolska province was conducted by Wach (2012). Although he obtained many new and valuable results, he did not directly examine the impact of Europeanisation on innovativeness.

Therefore, there is a gap in the area of research on the innovation-internationalisation relationship of Polish enterprises. This article attempts to fill this research gap. I aimed to examine the impact of the internationalisation process on the innovative activity of enterprises operating in the Małopolska and Silesian voivodeships. I chose these voivodeships because both regions offer excellent conditions for the development of entrepreneurship; they have large scientific, research, and educational potential with many universities, modern technology parks, and innovation centres, and prestigious scientific institutes. The excellent communication infrastructure of both regions is also significant.

In this study, I considered the most common forms of internationalisation and types of innovation, allowing for the examination of multidirectional relationships between these categories. This approach is novel not only in research conducted for the Polish economy.

The analysis of the research sample indicates that companies expanding into external markets through foreign trade dominate. The literature review suggests that this form of internationalisation may stimulate innovation more than others (Aghion *et al.*, 2018; Cumming *et al.*, 2022). However, this requires verifying appropriate research hypotheses. Therefore, to achieve the main objective of the study, I put forward the following hypotheses:

H1: Export-oriented companies are more prone to innovation than FDI-oriented companies.

H2: Introducing the moderating variable *market conditions* will strengthen the interaction between different forms of internationalisation of companies and their innovativeness.

The structural equation modelling I used enabled the verification of both hypotheses.

RESEARCH METHODOLOGY

I analysed the impact of internationalisation of enterprises on their innovativeness using structural equation models estimated with partial least squares (PLS). Thus far, SEM has been used to study these categories for enterprises, among others, in China (Efrat *et al.*, 2018), Greece (Makri *et al.*, 2017), or in the study of various groups of countries (Ding *et al.*, 2021). The method optimises the variance of latent variables. Due to the two types of relationships occurring in the SEM, I distinguished a structural model (1) and a measurement (external) model (2).

$$Y_{[Px1]} = B^T Y_{[Px1]} + \zeta_{[Px1]} \quad (1)$$

$$X_{[Jx1]} = C^T Y_{[Px1]} + \varepsilon_{[Jx1]} \quad (2)$$

in which:

Y - vector containing P latent variables;

X - vector containing J indicator variables;

C - matrix of dimensions $P \times J$ containing loadings;

B - matrix of dimensions $P \times P$ containing path coefficients;

ε - vector of residual indicator variables;

ζ - vector of residuals of latent variables.

The Y and X matrices in PLS models are related via the matrix of component weights $W_{[JxP]}$:

$$Y_{[Px1]} = W^T X_{[Jx1]} \quad (3)$$

Latent variables in this study represent the internationalisation of enterprises or their innovativeness. Enterprises expand into foreign markets mainly through export, import, and foreign direct investment (Wach, 2012; Róžański & Voytovych, 2023). This is evidenced by numerous theories of internationalisation, as well as concepts and models of international entrepreneurship (*e.g.*, Dunning's OLI paradigm (Dunning, 1988), the Uppsala model (Johanson & Vahlne, 1977), resource-based view (Bar-

ney, 1991). Hence, including latent variables related to foreign trade and FDI was fully justified. Theoretical constructs representing export appear in many SEM works on internationalisation, such as Papadopoulos and Martín (2010), while the construct containing FDI was used in structural models by, for example, Grandinetti and Mason (2012).

Other forms of internationalisation include outsourcing, foreign franchising, and licensing. I include these variables in the article as separate constructs.

Notably, we may consider enterprise innovation at the product, process, marketing, or organisational level. The ecological and sustainable development aspects also merit consideration. Enterprises increasingly consider this aspect when planning their innovation activities (Figueroa-García *et al.*, 2018). Currently, it is difficult for enterprises to compete in the global economy if they do not implement digital innovations (Del Giudice *et al.*, 2021). Therefore, the proposed construct with the latent variable INN refers to the above-mentioned types and dimensions of innovation. Considering such diverse areas of innovation is consistent with different ways of measuring innovation from the perspective of inputs, outputs, and efficiency (Nasir & Zhang, 2024).

Notably, the innovation activity of companies and their relationship with internationalisation are largely determined by external market conditions and such a latent variable is also used in SEM (García-Machado *et al.*, 2023). In this study, I introduced it to the model as a moderating variable. Below, I list the latent variables and their indicators, adopted in the initial form of the theoretical model.

Table 1. Constructs and observable variables in measurement models

Indicator	Description	Scale	
		High	Low
Export (EX)			
EX1	Export is an important tool for entering foreign markets in your company's operations.	7	1
EX2	What is the intensity of your export activity? a) continuous b) cyclical c) sporadic d) none	4	1
EX3	The share of exports in the total production of goods/services of your company should be higher	7	1
Import (IM)			
IM1	Import is an important tool for engaging your company in foreign markets	7	1
IM2	What is the intensity of your import activity a) continuous b) cyclical c) sporadic d) none	4	1
IM3	Your company intends to increase the scale of import of goods/services	7	1
Foreign trade (TR)			
TR1	Participation in foreign trade in the case of your company is a fundamental form of its activity on foreign markets	7	1
TR2	Engagement in foreign trade has increased the competitiveness of your company	7	1
Foreign direct investment (FDI)			
FDI1	FDI is an important form of your company's activity on foreign markets	7	1
FDI2	Greenfield investments are an important tool for entering foreign markets in your company's operations.	7	1
FDI3	Brownfield investments are an important tool for entering foreign markets in your company's operations.	7	1
FDI4	Creating a joint venture is an important tool for entering foreign markets in your company's operations.	7	1
FDI5	The creation of subsidiaries is an important tool for entering foreign markets in your company's activities.	7	1
FDI6	Establishing foreign branches is an important tool for entering foreign markets in your company's operations.	7	1
FDI7	Mergers and acquisitions are an important tool for entering foreign markets in my company's operations	7	1
FDI8	Thanks to FDI, the competitiveness of your company has increased significantly	7	1
Other forms of company internationalisation (OT)			
OT1	Franchising is an important tool for entering foreign markets in your company's operations.	7	1
OT2	Licensing is an important tool for entering foreign markets in your company's operations.	7	1
OT3	Using other internationalisation tools (e.g., outsourcing, R&D contracts) allows your company to expand its operations in foreign markets	7	1

Indica- tor	Description	Scale	
		High	Low
Innovation (INN)			
INN1	The introduction of product innovations is important for your company and significantly in- creases its competitiveness	7	1
INN2	Introducing innovations in the area of production methods or service provision is important for your company and significantly increases its competitiveness	7	1
INN3	Introducing innovations in the area of marketing is important for your company and signifi- cantly increases its competitiveness	7	1
INN4	The introduction of innovations in the area of organisational methods in the functioning of the enterprise and its structure is important for your company and significantly increases its competitiveness	7	1
INN5	In recent years, your company has been introducing product innovations a) very often b) from time to time c) very rarely d) not at all	4	1
INN6	In recent years, your company has been introducing process innovations a) very often b) from time to time c) very rarely d) not at all	4	1
INN7	In recent years, your company has been introducing marketing innovations a) very often b) from time to time c) very rarely d) not at all	4	1
INN8	In recent years, your company has been introducing organisational innovations a) very of- ten b) from time to time c) very rarely d) not at all	4	1
INN9	In recent years, your company has been introducing digital innovations a) very often b) from time to time c) very rarely d) not at all	4	1
INN10	In recent years, your company has been introducing pro-ecological innovations: a) very often, b) from time to time, e) very rarely, d) not at all	4	1
Market conditions (MC)			
MC1	The markets in which your company operates are characterised by political and legal stability	7	1
MC2	Your company operates in an environment of increasing international competition	7	1

Source: own study.

In the created construct, I defined exports (EX) as the value of sales of goods or services produced in the enterprise's home country to foreign markets (both exports to European Union countries (intra-EU) and exports outside the EU (extra-EU). In turn, imports (IM) were the value of goods or services purchased from abroad by a domestic enterprise. Foreign trade (TR) was a broader concept encompassing the value of the total flow of goods and services between the enterprise's home country and abroad.

The path diagram below illustrates the relationship between latent variables and their indicator variables.

Research Sample Description

I conducted the study on a random sample of over 600 companies operating in the Małopolska and Silesian Voivodeships. Southern Poland constitutes a particularly attractive research area, reflecting the characteristics of many post-industrial European regions undergoing transformation towards a knowledge-based economy. I selected enterprises from the Małopolska and Silesian Voivodeships for the study due to their particular importance for innovation processes and internationalisation in Poland. They are characterised by a relatively high density of thriving technology parks and economic activity zones, which facilitate the opening of new businesses. They form a region that can serve as a benchmark for comparative analyses of other regions of Central and Eastern Europe with similar economic profiles. The strong innovative position of companies from these voivodeships is evident, among other things, in their high share of R&D expenditures, and their strong internationalisation activity is reflected in numerous reports and statistical analyses. Therefore, enterprises operating in the Małopolska and Silesian Voivodeships constituted an adequate sample to achieve the research objective. I drew the representatives of the research sample from the REGON database maintained by the Central Statistical Office, with the sample including only companies that pursued at least one possible form of internationalisation. I used simple random sampling, which gave each unit of the finite population an equal chance of inclusion. This is one of the key criteria for sample representativeness.

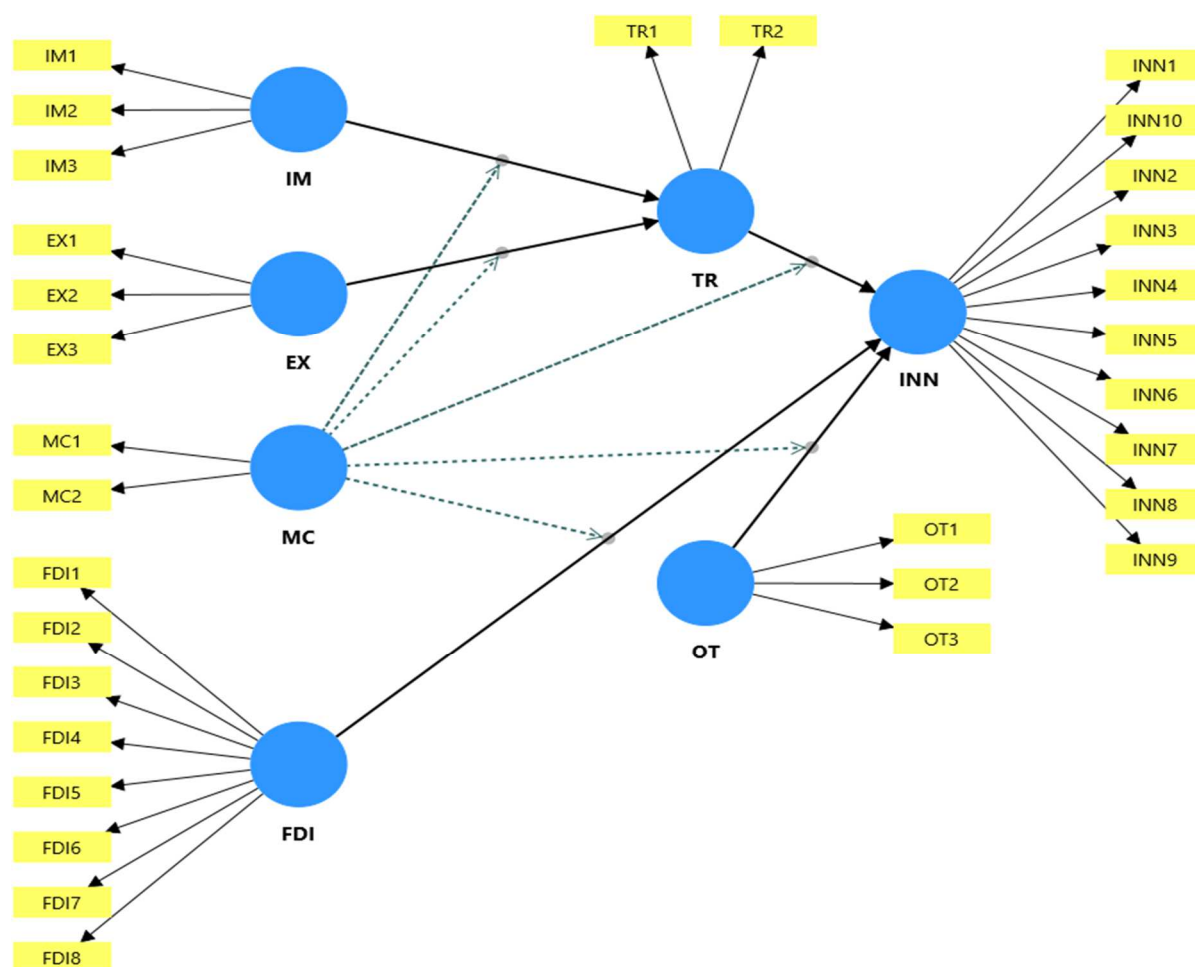


Figure 1. Scheme of relationships between variables in the SEM

Source: own elaboration.

I conducted the study in the last quarter of 2024. Individuals knowledgeable about the company's operations, strategy, and situation completed the surveys: owners or co-owners (in the case of small enterprises), and in medium-sized and large enterprises, by individuals in management positions or authorised to provide information on behalf of the enterprise. The survey return rate was 56%. After verifying completed surveys and rejecting incomplete ones, I qualified 342 companies representing various industries for further analysis. A sample of this size is sufficient if statistical inference is conducted with a maximum error of 5.3% at a standard confidence coefficient of 0.95.

Companies from the communications and IT sectors made up the largest share of the sample (95 companies), followed by companies from the industrial processing sector (65). Moreover, there were 60 companies from the financial and insurance services sector, and 48 companies from the retail sector. The remaining sectors were more fragmented in the sample. The sectoral structure of the sample indicates a clear representation of knowledge-intensive industries and internationalised industries, or industries with high innovation activity. The relatively high share of communications and IT enterprises in the sample reflects that these industries are among the most dynamically developing sectors of the economy and have a strong position in the economic structure of the surveyed regions. Nearly 50% of the surveyed companies were microenterprises employing up to nine employees. Companies with 10-49 employees constituted approximately 21.6% of the sample, while the share of companies employing 50-249 people was approximately 17%. The smallest group consisted of companies employing over 250 employees (14%).

RESULTS AND DISCUSSION

I estimated the measurement and structural models using the SmartPLS package. Figure 2 presents the path model containing estimates of path coefficients between latent variables, factor loadings for individual constructs, and coefficients of determination for endogenous variables. Almost all constructs had a majority of outer loadings with values above 0.7 (for the FDI construct, half of all outer loadings), and the average variance extracted (AVE) values exceeded 0.5 (except for the FDI construct), which indicated satisfactory convergent validity (Hair *et al.*, 2014). Simultaneously, the coefficients of determination of 0.816 for the TR variable and 0.753 for the INN variable indicated a high explanation of the variance of latent variables by their observable variables.

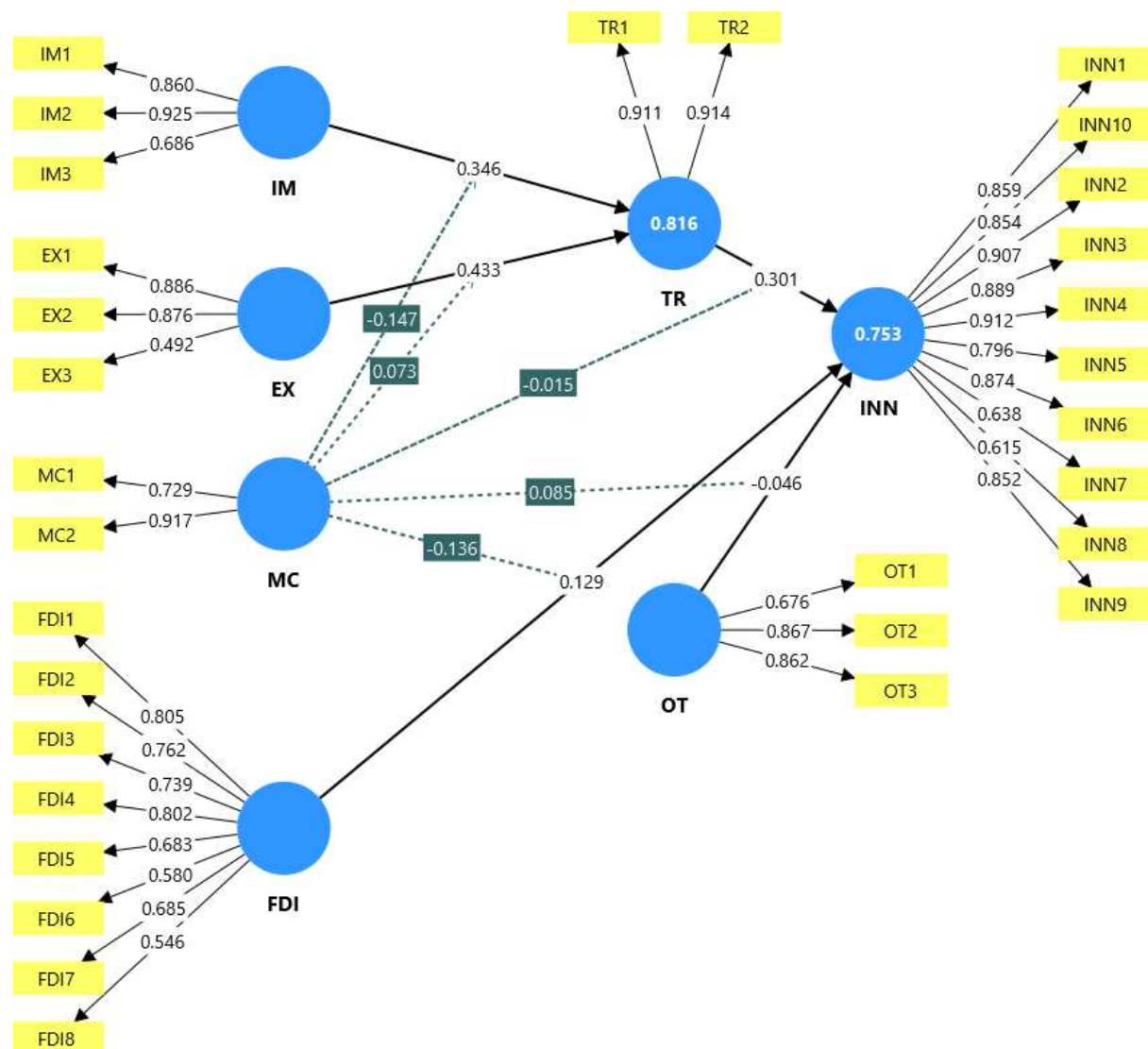


Figure 2. Debugged explanatory PLS-SEM model

Source: own elaboration.

I assessed the reliability and validity of the measurement model using Cronbach's Alpha, composite reliability, the results of which, together with the average variance extracted (AVE), are presented in Table 2. Cronbach's alpha values exceeded the reference value of 0.7 for all latent variables except for the constructs EX and MC. Similarly, the composite reliability indicators exceeded the threshold of 0.7 except for the latent variable EX, which generally indicates high reliability and credibility of the constructs.

Table 2. Construct validity and reliability

Latent variable	Constructs	Outer loadings	Cronbach's alpha	Composite reliability (rho_a)	Average variance extracted (AVE)
Import (IM)	IM1 <- IM	0.860	0.774	0.840	0.688
	IM2 <- IM	0.925			
	IM3 <- IM	0.686			
Foreign direct investment (FDI)	FDI1 <- FDI	0.805	0.853	0.866	0.498
	FDI2 <- FDI	0.762			
	FDI3 <- FDI	0.739			
	FDI4 <- FDI	0.802			
	FDI5 <- FDI	0.683			
	FDI6 <- FDI	0.580			
	FDI7 <- FDI	0.685			
	FDI8 <- FDI	0.546			
Export (EX)	EX1 <- EX	0.886	0.658	0.771	0.598
	EX2 <- EX	0.876			
	EX3 <- EX	0.492			
Innovation (INN)	INN1 <- INN	0.859	0.946	0.955	0.682
	INN10 <- INN	0.854			
	INN2 <- INN	0.907			
	INN3 <- INN	0.889			
	INN4 <- INN	0.912			
	INN5 <- INN	0.796			
	INN6 <- INN	0.874			
	INN7 <- INN	0.638			
	INN8 <- INN	0.615			
	INN9 <- INN	0.852			
Market conditions (MC)	MC1 <- MC	0.729	0.568	0.678	0.687
	MC2 <- MC	0.917			
Other forms of company internationalisation (OT)	OT1 <- OT	0.676	0.733	0.779	0.650
	OT2 <- OT	0.867			
	OT3 <- OT	0.862			
Foreign trade (TR)	TR1 <- TR	0.911	0.799	0.800	0.833
	TR2 <- TR	0.914			

Source: own study.

Regarding the heterotrait-monotrait ratio (HTMT) index, in four cases out of 21 pairs of constructs, the index values exceeded 0.8, which may indicate potential problems with discriminant validity (Gold *et al.*, 2001; Henseler *et al.*, 2015). These are the following pairs of latent variables: EX <-> IM, EX <-> FDI, TR <-> IM, TR <-> EX. For over 80% of construct pairs, the index results were satisfactory.

In summary, the obtained SEM model was characterised by a satisfactory level of convergent validity, coherence, reliability and discriminant validity. It could therefore serve as the basis for further statistical inference based on bootstrap analysis conducted using 5 000 runs (bootstrapping with 5 000 samples in SmartPLS). This allowed me to assess the statistical significance of the obtained results and verify the research hypotheses. Table 3 presents the results of the estimation of total effects (including the assessment of path coefficients). The results show that companies that were oriented towards foreign trade showed greater innovative activity ($\beta = 0.301$, $p < 0.01$) than companies that internationalised through foreign direct investment ($\beta = 0.129$, $p < 0.05$). For standardised loadings, this means that an increase in the level of internationalisation of a company through foreign trade by one standard deviation caused an increase in its innovativeness by about 0.301 standard deviations on average, *ceteris paribus*, while a unit increase in internationalisation through FDI contributed to an increase in the innovativeness of a company by about 0.129 standard deviations on average. In turn, the expansion of companies into foreign markets through foreign trade was most strongly influenced by the export ac-

tivity of companies ($\beta=0.433$, $p<0.01$). The interaction of MC and FDI variables significantly weakened the innovativeness of enterprises (a decrease in the level of innovation by 0.136 standard deviations *ceteris paribus* with a unit increase in the MC×FDI variable). The moderating variable also reversed the direction of the influence of internationalisation through import on innovation from positive to negative (direct effect coefficient -0.044; $p<0.05$), while the interaction of market conditions and export did not significantly affect innovation. Noteworthy, the interaction of market conditions and internationalisation in a way other than foreign trade and FDI strengthened the impact on innovation: an increase in the MC×OT variable by one standard deviation caused a significant increase in the level of innovation by about 0.085 *ceteris paribus*, while the influence of the OT variable on innovation was negative.

Table 3. Results of the total effects estimation in bootstrap analysis

Relationships between latent variables	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
IM -> INN	0.104	0.103	0.030	3.446	0.001
IM -> TR	0.346	0.347	0.053	6.538	0.000
FDI -> INN	0.129	0.132	0.063	2.039	0.041
EX -> INN	0.130	0.128	0.033	3.945	0.000
EX -> TR	0.433	0.433	0.053	8.206	0.000
MC -> INN	0.604	0.607	0.044	13.740	0.000
MC -> TR	0.209	0.208	0.033	6.415	0.000
MC x IM -> INN	-0.044	-0.042	0.019	2.303	0.021
MC x IM -> TR	-0.147	-0.144	0.056	2.611	0.009
MC x FDI -> INN	-0.136	-0.135	0.060	2.274	0.023
MC x EX -> INN	0.022	0.021	0.018	1.252	0.211
MC x EX -> TR	0.073	0.072	0.055	1.320	0.187
MC x OT -> INN	0.085	0.081	0.041	2.096	0.036
MC x TR -> INN	-0.015	-0.013	0.055	0.277	0.782
OT -> INN	-0.046	-0.046	0.037	1.252	0.211
TR -> INN	0.301	0.296	0.069	4.350	0.000

Source: own study.

Table 4 presents the constructed path model, which also included a moderating variable, and the results of conditional effects considering its impact on the relationships between latent variables.

Table 4. Results of conditional effects assessments including the moderating variable

Relationships between latent variables	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
FDI -> INN MC at zero	0.129	0.132	0.063	2.039	0.041
FDI -> INN MC at one	-0.007	-0.004	0.054	0.128	0.898
OT -> INN MC at zero	-0.046	-0.046	0.037	1.252	0.211
OT -> INN MC at one	0.039	0.036	0.041	0.949	0.342
TR -> INN MC at zero	0.301	0.296	0.069	4.350	0.000
TR -> INN MC at one	0.286	0.283	0.074	3.851	0.000
IM -> TR MC at zero	0.346	0.347	0.053	6.538	0.000
IM -> TR MC at one	0.199	0.203	0.083	2.399	0.016
EX -> TR MC at zero	0.433	0.433	0.053	8.206	0.000
EX -> TR MC at one	0.506	0.505	0.085	5.929	0.000
IM -> TR -> INN MC at zero	0.104	0.103	0.030	3.446	0.001
IM -> TR -> INN MC at one	0.057	0.059	0.031	1.820	0.069
EX -> TR -> INN MC at zero	0.130	0.128	0.033	3.945	0.000
EX -> TR -> INN MC at one	0.145	0.142	0.042	3.438	0.001
MC -> TR -> INN MC at zero	0.063	0.062	0.018	3.477	0.001
MC -> TR -> INN MC at one	0.060	0.059	0.019	3.114	0.002

Source: own study.

The influence of market conditions as a moderating variable (MC) on the relationship between internationalisation of the enterprise through foreign trade and innovation was statistically significant, but weakened the strength of the relationship. With the moderating variable active, a one-standard-deviation increase in internationalisation through foreign trade raised innovation by 0.286 standard deviations *ceteris paribus* (i.e., by 0.015 less than without the moderating variable). On the other hand, the influence of market conditions on the relationship between FDI and innovation was negative and statistically insignificant. The moderating variable also had no significant influence on the relationship between other ways of internationalisation (OT) and enterprise innovation.

The active moderating variable also strengthened internationalisation through foreign trade among export-oriented firms and reduced internationalisation among import-oriented firms. The results of moderation of these two relationships were statistically significant at the 0.05 significance level. Including the mediating variable TR in the indirect effects, the moderating variable (MC) strengthened the effect of internationalisation through export on innovation: with market conditions active, a one-standard-deviation increase in internationalisation through export raised innovation by 0.145 standard deviations, *ceteris paribus* (in the absence of the moderating variable, this increase was 0.13). The moderating variable did not significantly affect the indirect relationship between internationalisation through import and innovation.

To detail how individual components of the internationalisation constructs affect elements of the innovativeness construct, I calculated a matrix of Spearman's rank correlation coefficients.

Table 5. Spearman's rank correlation coefficients for indicators creating constructs representing internationalisation and innovation of companies

Indicator	INN1	INN2	INN3	INN4	INN5	INN6	INN7	INN8	INN9	INN10
IM1	0.618	0.514	0.397	0.405	0.496	0.503	0.541	0.373	0.579	0.592
IM2	0.590	0.517	0.472	0.452	0.503	0.561	0.587	0.412	0.616	0.644
IM3	0.324	0.251	0.272	0.205	0.272	0.303	0.324	0.243	0.354	0.389
EX1	0.540	0.473	0.345	0.382	0.428	0.471	0.526	0.335	0.539	0.528
EX2	0.557	0.430	0.390	0.357	0.421	0.509	0.525	0.376	0.525	0.546
EX3	0.317	0.236	0.216	0.265	0.265	0.271	0.287	0.119	0.324	0.357
TR1	0.674	0.625	0.475	0.480	0.510	0.560	0.585	0.386	0.635	0.629
TR2	0.561	0.544	0.467	0.494	0.538	0.578	0.620	0.400	0.668	0.694
FDI1	0.490	0.479	0.437	0.420	0.464	0.497	0.531	0.321	0.566	0.588
FDI2	0.512	0.445	0.336	0.358	0.416	0.438	0.466	0.248	0.497	0.485
FDI3	0.371	0.277	0.196	0.330	0.405	0.370	0.385	0.274	0.389	0.384
FDI4	0.478	0.381	0.296	0.325	0.379	0.418	0.411	0.246	0.477	0.493
FDI5	0.576	0.499	0.372	0.402	0.452	0.476	0.521	0.355	0.522	0.542
FDI6	0.430	0.333	0.253	0.242	0.306	0.362	0.292	0.147	0.382	0.479
FDI7	0.417	0.380	0.324	0.322	0.352	0.383	0.415	0.264	0.442	0.480
FDI8	0.220	0.228	0.150	0.219	0.258	0.271	0.225	0.187	0.277	0.348
OT1	0.411	0.352	0.263	0.289	0.325	0.357	0.437	0.248	0.430	0.461
OT2	0.423	0.380	0.305	0.333	0.330	0.416	0.484	0.322	0.471	0.446
OT3	0.398	0.355	0.293	0.304	0.308	0.386	0.431	0.309	0.433	0.468

Source: own study.

All correlation coefficients presented in Table 5 were statistically significant at the 0.01 significance level. A detailed analysis of Table 5 shows that companies' greater involvement in foreign trade had a particularly strong impact on digital and ecological innovations, and supported organisational innovations to the least extent. Although imports and exports had a similar impact on innovation overall, imports tended to show slightly higher Spearman coefficients than exports. This stems from the fact that companies that import advanced products, components, or technologies learn from foreign suppliers: they acquire new production processes, quality standards, design, technological innovations, and can effectively translate this knowledge into their own innovations, for example, by improving

products, processes, or introducing new functionalities. Among FDI-oriented companies, greenfield investors and companies with subsidiaries had a particularly strong impact on most types of innovation. In contrast, companies pursuing FDI through their foreign branches generally had the least impact on innovation. Among forms of internationalisation other than foreign trade and FDI, foreign licensing had the strongest impact on innovation activity.

CONCLUSIONS

The research shows that foreign trade, and export in particular, is the form of internationalisation that most strongly supports the innovation activities of the surveyed enterprises. Enterprises oriented towards foreign trade are more prone to innovation than those oriented towards FDI. Including market conditions as a moderating variable does not increase the strength of the influence of latent variables on innovation, except for export. Export-oriented enterprises must cope with international competition, and one of the tools for effective competition is innovative goods, services, or entire business models.

Thus, hypothesis H1 was supported in the light of the present research results, *i.e.*, export-oriented companies are more prone to innovation than FDI-oriented companies. Meanwhile, hypothesis H2 was only partially confirmed, because the moderating variable of market conditions significantly strengthened only one relationship: export->foreign trade->innovation. The obtained conclusions did not contradict the results obtained by conclusions align with the results of other researchers (Wach, 2012; Róžański & Voytovych, 2023), who indicate export as the basic form of internationalisation of Polish companies. Greater innovativeness of companies that internationalise through foreign trade results, among other things, from their greater flexibility, speed of adjustment to changing market conditions, diversity of these markets and constant pressure from competitors. Empirical studies of firms' learning by exporting support these results. For example, using panel data of US manufacturing firms, Salomon and Shaver (2005) demonstrated that participation in export markets increases firms' innovative activity. Liang *et al.* (2024) also confirmed the learning-by-exporting effect, implying a positive impact of exports on the innovation performance of Chinese firms. They demonstrated that the learning effect remains significant and consistent, even with the spread of FDI. Silva *et al.* (2012) obtained less conclusive results. They combined the results of numerous empirical studies from developing and developed countries. Their analysis showed that simply entering foreign markets does not always result in a sustained increase in innovation and productivity. Differences are caused by factors such as industry and the level of competition. Mińska-Struzik (2014) reached a similar conclusion for Polish companies, showing that the strength of the impact of internationalisation of companies on innovation depends on the industry.

Moreover, foreign trade requires a company to constantly adapt its products and services to the requirements of many different markets, which puts pressure on their innovation activity. For this reason, the moderating variable considering the impact of international market competition significantly strengthened the impact of the internationalisation of such companies on their innovation. Notably, FDI-oriented companies invest a significant part of their financial resources in infrastructure; their decision-making usually takes longer, and their operational rigidity is greater, which may limit the possibilities of investing in innovation in the short term. Such operational inertia of FDI-oriented companies means that their response to changing market conditions is weaker and slower.

Hence, hypothesis H2 was not supported for such companies. Greater flexibility of export-oriented companies and greater inertia of FDI-oriented companies seem to be key factors explaining the result of the verification of the research hypotheses. The obtained conclusions are consistent with the results of much research (Filipescu *et al.*, 2013; Aghion *et al.*, 2018; Cumming *et al.*, 2022). The presented results and research method have their limitations. The SEM model proposed in this article cannot determine which types and levels of innovation are most supported by different forms of internationalisation. This requires further detailed studies based on SEM models or other econometric tools. In this article, I partially addressed this limitation by conducting a correlation analysis between the components of the relevant constructs. Furthermore, the adopted constructs of latent variables may not contain all the important indicator variables. In future studies based on structural modelling, one can try to expand the list of these indicators. Further, broader survey studies will also be necessary. Despite

many advantages of the PLS estimation method of structural and measurement models, its serious limitation is the required linearity of relations between variables, which does not always hold and limits the possibility of modelling more complex, nonlinear dependencies. The study covers an economically vibrant region with numerous companies engaged in international and innovative activities. Therefore, the results can serve as a benchmark for other similar economic activity zones, particularly in Central and Eastern European countries.

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Author**Marcin Salamaga**

Professor at the Department of Statistics at the Krakow University of Economics, Poland, and a member of the Section of Classification and Data Analysis of the Polish Statistical Society. He holds a PhD in economics and the title of professor in the scientific discipline of economics and finance. His research interests include the application of statistical methods in economic research.

Correspondence to: Prof. dr hab. Marcin Salamaga, Krakow University of Economics, Department of Statistics, ul. Rakowicka 27, 31-510 Krakow, Poland, e-mail: salamaga@uek.krakow.pl

ORCID  <https://orcid.org/0000-0003-0225-66511>

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Use of Artificial Intelligence

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Conflict of Interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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