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Adaptive Firm Performance under Uncertainty: Innovation, Finance, and Risk

Edited by

Piotr Łasak

Ewa Kopeć

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Adaptive firm performance under uncertainty: Integrating operational efficiency, risk, digital capabilities, innovation, and entrepreneurial finance

***Ewa Kopeć*[1], *Piotr Łasak*[2]**

Abstract

PURPOSE: *The paper develops an integrative explanation of how firms, entrepreneurial ventures, employees, and investors sustain performance when uncertainty arises from market crises, technological change, cyber threats, fragmented institutions, financing constraints, and bounded rationality.* ***METHODOLOGY:*** *We conduct an integrative narrative synthesis of the six articles in this Issue and map their theoretical lenses, levels of analysis, methods, and findings into a cross-level framework, and future research directions.* ***FINDINGS:*** *We identify four interdependent domains of adaptive performance: resources and financing, human and behavioral capabilities, governance and risk architecture, and institutional and ecosystem embeddedness. Across the studies, access to finance and technology is enabling but not sufficient. Outcomes depend on how resources are converted through learning, managerial discipline, institutional connectivity, and context-appropriate risk measurement. Digitalization is simultaneously a source of efficiency and a source of cyber and organizational exposure. The studies also show that average effects conceal meaningful heterogeneity across regions, sectors, firm sizes, lifecycle stages, employee groups, and crisis types.* ***IMPLICATIONS:*** *Research should move from isolated determinants toward multilevel, longitudinal, and configurational designs. Managers and policymakers should align resources, capabilities, governance, and institutional support rather than optimize any single factor.* ***ORIGINALITY & VALUE:*** *The paper integrates employee readiness, entrepreneurial decision-making, innovation, startup financing, cybersecurity, and downside portfolio risk into a single adaptive-performance architecture and derives a focused research agenda.*

Keywords: *adaptive performance, operational efficiency, uncertainty, risk management, digital capabilities, cybersecurity, innovation, entrepreneurial finance, institutions, resilience*

INTRODUCTION

Uncertainty is not simply an external variable that impacts organizations. Instead, there are many types of uncertainty that exist, including sudden market downturns, geopolitical and economic instability, cyberattacks, technological obsolescence, financing issues, organizational fragmentation, and cognitive biases. Each type of uncertainty has different origins and levels of analysis. They all have the same effect: undermine the ability of organizations to rely upon previously existing data to transform available resources into desired results. Thus, under conditions of high levels of uncertainty, performance cannot be measured solely by a single financial metric, nor can operational efficiency be viewed as the only factor that determines whether an organization will be able to sustain operations. Operational efficiency is vital for all organizations,

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particularly for small and medium-sized enterprises (SMEs), since it directly influences liquidity, expense management, customer satisfaction, and the long-term viability of the organization.

The authors in this Issue examine other measures of organizational success such as employee readiness for digital work, product/process innovation, startup funding patterns, cybersecurity performance, perceived entrepreneurial investment success, and asset resilience during times of market downturn. Consequently, financial performance and organizational value should be viewed as protected outcomes within a broader adaptive system. Historically, the literature related to organizational adaptation and innovation has been developed independently. The resource-based view (Barney, 2001; Conner & Prahalad, 1996; Wernerfelt, 1984) and dynamic-capabilities (Teece, 2007; Teece et al., 1997) describe how firms utilize and adapt their resources. Behavioral finance (Kahneman & Tversky, 1979; Ritter, 2003; Thaler, 1985) describes deviations from rational decision-making. Competence theory (Prahalad & Hamel, 1990) describes learning and readiness. Then institutional theory (DiMaggio & Powell, 1983) and entrepreneurship ecosystems (Stam, 2015) describe external support/constraints. Finally, risk-management theory describes methods for identifying/containing risk and was grounded first by Knight (1921).

Each of these theories provides a partial explanation for organizational performance under uncertainty. They together demonstrate that performance under uncertainty depends on complementary relationships between organizational assets/resources, employee/behavioral capabilities, governance/risk-management structures, and institutional/ecosystem characteristics. Consequently, effective organizational functioning requires an integrated approach that simultaneously develops adaptive capabilities, strengthens resilience, and enables the efficient use of available resources in a dynamic and constantly changing environment.

Therefore, this article attempts to address the following question: How do resources/funding, human/behavioral capabilities, governance/risk-management structures, and institutional/ecosystem characteristics combine to determine organizational adaptation, innovation, resilience, and performance under uncertainty? To answer this question, we present a narrative synthesis of six studies addressing accounting employees in Poland, innovation-active service SMEs in Colombia, European equity markets, ethnic entrepreneurs in Quebec, ICT startups in Albania, and corporations in the United States, Europe, and China. We are not treating these studies as tests of a single causal model. Rather, we are using the results from these studies to identify common mechanisms, complementarities, boundaries, and methodological implications.

ADAPTIVE PERFORMANCE UNDER UNCERTAINTY: AN INTEGRATIVE FRAMEWORK

We define "adaptive performance" as the capability of maintaining, protecting, or improving desired results using information about changes, utilizing resources, coordinating efforts, and recovering from disruptions. Thus, the idea of adaptive performance allows for the consideration of operational efficiency within a larger context. Operational efficiency relates to converting inputs to outputs, while adaptive performance relates to revising objectives, reconfiguring resources, preserving value, and reacting differently to various types of uncertainty.

The first area of focus is resources and financing. This includes internal and external sources of capital, leverage, tangible and intangible investments, digital infrastructure, and the size of available organizational resources. The resource-based view and dynamic-capabilities perspective distinguish between possessing resources and deploying/reconfiguring those resources for productive purposes (Barney, 2001; Teece et al., 1997). The distinction is important because financing enables action; however, it does not automatically lead to innovation, resilience, or performance.

The second area of focus is human and behavioral capabilities. Human and behavioral capabilities include professional competence, informal learning, digital readiness, founder experience, and the cognitive/emotional processes through which individuals interpret information. Competence is context-specific and develops through interactions with the work/learning environment (Billett, 2001; Salo et al., 2024; Sandberg, 2000). At the same time, judgments made under conditions of uncertainty are susceptible to heuristic-based biases, framing effects, and loss-related biases (Kahneman & Tversky, 1979). Therefore, human capability includes both the capacity to learn and the self-discipline to recognize limitations in judgment.

The third area of focus is governance and risk architecture. It includes monitoring systems, incentive alignment mechanisms, project governance processes, cybersecurity practices, and methods for assessing adverse-state exposure. Agency theory and transaction cost economics argue that resources and decisions must be supported by appropriate structures for control and coordination (Jensen & Meckling, 1976; Williamson, 1985). The articles presented in this

Issue extend that argument by illustrating how governance influences whether behavioral tendencies are translated into disciplined execution and whether operational/financial exposures are visible prior to causing losses.

The fourth area of focus is institutional/ecosystem embeddedness. Formal rules, sector-specific regulations, regional institutions, universities, governmental agencies, intermediary organizations, and entrepreneurial networks provide access to knowledge, legitimacy, capital, and protection. Institutional arrangements influence organizational choice and performance (Williamson, 2000), while entrepreneurial-ecosystem research suggests that support is relational and unevenly distributed among even geographically proximate ventures (Stam, 2015). Table 1 presents those four domains through the prism of principal theoretical lenses, core mechanisms, and illustrative evidence.

Table 1. Four domains of adaptive performance under uncertainty

Domain	Principal theoretical lenses	Core mechanism	Illustrative evidence in this Issue
Resources and financing	Resource-based view, dynamic capabilities, entrepreneurial finance	Accessing, allocating, and reconfiguring financial, tangible, and intangible resources	Funding and innovation investment, startup financing portfolios, leverage and financial flexibility
Human and behavioral capabilities	Competence theory, behavioral finance, bounded rationality	Learning, interpreting information, making decisions, and adapting behavior	Digital readiness and informal learning, cognitive biases, founder experience
Governance and risk architecture	Agency and transaction-cost perspectives, project and risk management	Coordinating execution, aligning incentives, monitoring exposure, and protecting value	PM^2 methodology, cybersecurity performance, drawdown-sensitive risk measures
Institutional and ecosystem embeddedness	Institutional theory, triple/quadruple helix, entrepreneurial ecosystems	Providing or constraining legitimacy, knowledge, finance, regulation, and intermediation	Regional and sectoral cybersecurity differences, institutional support for innovation, startup ecosystem typologies

We propose the four major conceptualizations. First, complementarity of resources (e.g., financial) is more significant than the individual existence of a particular resource. When firms do not have absorptive capacity, implementation capability, or institutional linkages to the market, financial access adds very little value. Similarly, when employees do not have the readiness or support to use digital infrastructure, it adds very little value. When risk management tools are used without being integrated into governance and decision-making processes, they add very little value.

Second, digitalization has a dual nature. On one hand, it reduces processing time and increases information availability. It also facilitates process innovations and expands the scope of organizations. On the other hand, it increases the interdependency of systems, creates cyber vulnerabilities and increases the demand for ongoing education/training and investment in security. Therefore, digital transformation should be assessed based upon its net-value proposition rather than as an unambiguous productivity enhancement.

Third, heterogeneity is substantive and not simply noise. Articles demonstrate differences between regions, industries, firm sizes, organizational lifecycles, employee groups, ecosystems, and crisis types. Therefore, averaging results may mask configurations, where the same resource/practice yields differing results. This is especially true for SMEs and startups that exhibit substantial variation in resource constraints, founder attributes and ecosystem access within the same national environment.

Fourth, performance measurements should be consistent with the current state of the world and the level of analysis. A typical market beta may mask behaviors exhibited during drawdown periods. Employee self-assessment of digital readiness is not equivalent to empirically verified competence. Perception of entrepreneurial success is not equivalent to independently audited financial performance, and innovation occurrence does not represent innovation scale. Inferential strength depends upon clarity regarding whether a study evaluates preparedness, behavior, resilience, efficiency, financial outcomes, or protection of value.

Figure 1 interprets the relationships between the main idea of uncertainty and adaptive-performance architecture.

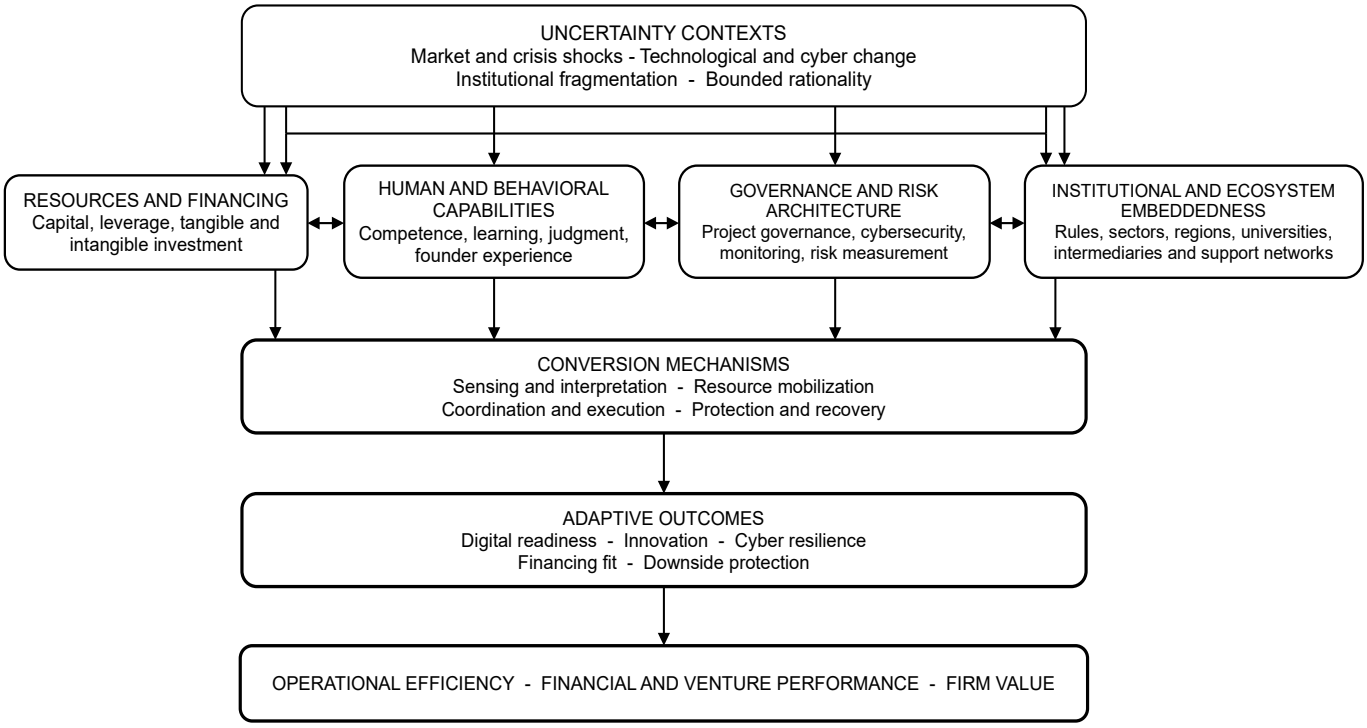

Figure 1. An adaptive-performance architecture

Methodologically, this Issue illustrates how important it is to match analytical design to this phenomenon: 1) Binary logistic regression identifies those variables that correlate with categorical cybersecurity performance and perceived digital readiness, 2) Partial least squares structural equation modeling examines composite innovation paths and behavioral-governance relationships, 3) Cluster analysis illustrates within-ecosystem heterogeneity, 4) Drawdown-based measures illustrate market behavior during adverse states. This multiplicity is an advantage, but it also creates a common disadvantage: most relationships are observational, several outcomes are self-reported or categorical and therefore, causal interpretation should be limited.

CONTRIBUTORS

Bąk et al. (2026) perceive the digital transformation to occur at the employee-organization interface. Based on survey data collected from 332 accounting department employees in Poland and using logistic regression, confirmatory factor analysis and structural equation modeling, they assess employee perceptions of their readiness for working in a digitized environment. Employee perceptions of readiness vary by gender, enterprise size, and foreign-capital participation; however, are positively correlated with workplace digitization, contact with IT specialists, and the level of informal online learning. The authors consider digital competence to be contextually dependent and not solely an individual trait: the combination of organizational infrastructure, technical support, and learning opportunities will determine whether employees feel ready to participate. Formal training as the presence of internal training could indicate existing capability gaps or a lack of alignment between employee needs and training offered.

Romero-Alvarez et al. (2026) investigate distinct routes toward innovation using micro-level data on 2,782 SMEs service sector firms that have been active in innovation in Colombia. They used two PLS-SEM models to differentiate between product innovation and process innovation. Institutional support had the largest positive association with product innovation (β = 0.416), while investment in innovation, specifically in intangible assets including training, software, and intellectual property, had the largest positive association with process innovation (β = 0.371). Both sources of funding were positively associated with both types of innovation; however, these associations had significantly lower coefficient values. Thus, this research indicates that financial assistance is an important facilitating factor, but its impact

is dependent upon how well firms convert their available funds into building-blocks to increase their capabilities through investment, and upon their ability to access institutions that provide them with knowledge, legitimacy and marketing/commercialization assistance. As the sample used in this research was comprised of firms that reported having engaged in innovation activities and the data collected was cross-sectional, the results of this research represent associations among the participating firms and do not provide evidence of causal relationships for all SMEs.

Feder-Sempach et al. (2026) transition the focus of their analysis from the operational aspects of organizations to their capacity for maintaining stability in times of turmoil in capital markets. They utilized data collected from 2004 to 2024 for 428 surviving components of the STOXX Europe 600 index and compared the traditional beta to two new betas – Expected Regret of Drawdown (ERoD) beta and Conditional Drawdown at Risk (CDaR) beta. Drawdown measures allow for the identification of those securities whose performance changes significantly during periods of turmoil in markets and identify securities with negative exposure during periods of turmoil that may be indicative of hedging or safe haven behavior. During the COVID-19 pandemic, many healthcare and technology stocks as well as firms located in certain countries demonstrated such behaviors. Conversely, the traditional beta continued to be positive and offered little insight into crisis specific behaviors. The authors, however, did not discover a clear connection between market capitalization and resilience during periods of drawdown. Additionally, this analysis recognized survivorship bias as only firms that remained within the index sample were included in the study.

Salehi et al. (2026) expand upon previous work in behavioral finance by exploring the role of heuristics-driven biases and framing biases in the context of ethnic entrepreneurial ventures. Based on survey data collected from 183 ethnic entrepreneurs in Quebec, the authors find that heuristics-driven biases and framing biases are significantly related to entrepreneurs' perceptions of their own success as ethnic entrepreneurs. In contrast, they find that contextual factors do not exhibit a significant relationship. They also find that the use of PM^2 methodology is significantly related to entrepreneurs' perceptions of their own success and that PM^2 acts as both an intervening variable and a moderating variable that links entrepreneurs' behavioral tendencies to their ability to execute projects successfully. The authors' main contribution is to demonstrate that entrepreneurs' individual judgments can be influenced by formal organizational processes such as structured planning, monitoring and governance, and that these processes may affect how entrepreneurs' intuitive decisions translate into actual outcomes for their ventures. However, since the authors evaluate entrepreneurs' perceptions of success rather than independent measures of venture success (e.g., financial performance, survival), caution is warranted when interpreting the results.

Kruja & Irimia-Diéguez (2026) investigate heterogeneity among startups operating within a single emerging economy entrepreneurial ecosystem. Using survey data collected from 111 Albanian ICT startups and k-means clustering, the authors identify three distinct profiles of startups: financially constrained, ecosystem-enabled, and ecosystem-disconnected. Ecosystem-enabled startups report having greater access to financing and achieving higher levels of performance than either financially constrained or ecosystem-disconnected start-ups. In addition, financially constrained and ecosystem-disconnected startups differ in terms of the types of financing sources they utilize (e.g., bootstrapping, crowdfunding), they do not differ in the total number of financing sources utilized. This distinction between the types of financing sources utilized and the number of financing sources utilized is theoretically valuable. They also show that prior experience in startups, firm size, and lifecycle stage can help predict which profile a particular startup will fall into. Ultimately, this research suggests that ecosystem supports are neither uniform nor automatically available to all startups and that a "one-size-fits-all" approach to supporting startups may fail to recognize the structural differences between different types of startups within the same environment.

Doś et al. (2026) examine institutional and organizational correlates of cybersecurity performance using binary logistic regression analysis on data collected from 1,211 corporations located in the United States, Europe, and China in 2022. The researchers find that corporations in China and Southern and Northern Europe are significantly less likely than corporations in the United States to achieve advanced cybersecurity performance. Corporations in Western Europe achieve comparable levels of cybersecurity performance to those achieved by corporations in the United States. Additionally, financial services and healthcare corporations perform better in terms of cybersecurity performance than corporations in other industries, and higher levels of leverage are consistently associated with lower levels of cybersecurity performance. The authors also observe a non-linear relationship between profitability and cybersecurity performance. Specifically, find that corporations with moderately profitable operations tend to make larger investments in cybersecurity than corporations with extremely profitable operations. Finally, firm size is negatively associated with cybersecurity performance in their full model. However, when the researchers examine their sectoral analyses separately, they find that

firm size is not consistently negatively associated with cybersecurity performance across all sectors. Ultimately, the authors' main contribution is to position cyber risk within an institutional and organizational risk management framework.

The studies in this Issue reinforce the editors' initial premise: operational efficiency is a key mechanism for converting inputs into outputs; however, operational efficiency cannot be considered a universal explanation for success. Input resources and financing must be converted through competence, judgment, governance, and institutional linkages. Risks must be quantified in a manner consistent with their potential impacts, and performance must be evaluated at the level where it occurs. The focus moves away from the identification of isolated determinants of success towards the development of an adaptive-performance architecture, where complementary elements and contextual factors determine whether organizations maintain or enhance value under uncertain conditions.

FUTURE RESEARCH AGENDA

The research agenda suggested by these contributions is much more specific and, thus, much more amenable to empirical testing than simply calling for "more research." In addition, there are six primary areas of focus that should be considered as part of this agenda (Table 2).

Table 2. Future research agenda for adaptive performance under uncertainty

Priority	Core research question	Recommended designs and evidence
Cross-level causal mechanisms	In what way do institutions and ecosystems influence the governance of an organization, the behavior of employees/founders, and the resulting performance?	Longitudinal multilevel models, natural experiments, regulatory changes, matched employer-employee or firm-ecosystem data
Complementarities and configurations	What are the combinations of funding mechanisms, capabilities, governing structures, and institutional supports that will be required or sufficient to create resilience/innovation?	Configurational methods, finite-mixture or latent-class models, longitudinal typologies, interaction and complementarity tests
Perceived versus objective capability and performance	At what times do self-assessments align with demonstrated competencies, audited performances, survival, and/or actual innovation value?	Linked surveys and administrative records, digital-skill tests, objective cyber ratings, accounting and financing records
Dynamic and crisis-specific resilience	How do preventive actions, absorptive capacities, recovery efforts, and adaptive responses vary among different types of shock events (e.g., financial, cyber-related, geopolitical, technology-related)?	Event studies, panel and survival models, repeated drawdown analysis, recovery-time and persistence measures
Interdependent risk portfolios	Under what conditions do cyber-related, operational, funding, and market-related risk factors cluster together, enhance each other, and/or transfer across organizations/networks?	Network models, stress testing, copulas and tail-dependence methods, supply-chain and portfolio-level data
Net value of digitalization	At what time do the advantages of productivity and innovation outweigh the costs of implementation, training, security, and organizational restructuring?	Quasi-experimental adoption studies, cost-benefit analysis, mediation models, longitudinal productivity and security data

These priorities will also need more clearly defined boundaries. Comparisons of emerging vs. developed economies, micro and small businesses vs. larger corporations, early stage vs. growth stage ventures, and industries with varying levels of regulatory intensity and data sensitivity are all examples of how comparative studies should be differentiated. Researchers should consider factors such as gender, immigration status, language, previous entrepreneurial experience, and international capital involvement as theoretically relevant sources of access, learning and confidence for entrepreneurs and employees instead of just as control variables. Another priority is to study the transitions employees, startups, companies and assets make over time rather than just looking at their current position. An employee could transition from a low level of digital readiness to a high level of digital readiness. A startup could transition between being constrained by its environment, enabled by it, and disconnected from it. A company could transition from having strong cybersecurity

measures to weaker ones or *vice versa*. And assets that protect against a crisis today could increase loss in the event of a different crisis tomorrow. Therefore, researchers studying adaptive performance should not only look at the state an individual/organization is in but also at the transition between states.

CONCLUSION

The main finding of this Issue is that operational efficiency is not the only factor determining financial performance. Adaptive performance under uncertain circumstances is based on the integration of four areas: (1) Resource and financing, (2) Human/behavioral capabilities, (3) Governance/risk architecture, and (4) Institutional/Ecosystem embeddedness. Some combination of all four areas will be necessary in certain situations but no single area will ever be enough. Resources that are available but cannot be used effectively are wasted. Capabilities without an effective governance system may not translate into disciplined action. A governance system that does not fit well within the broader institutional structure of the organization/sector/ecosystem can lead to constraints or costs. Digitalization without learning/cybersecurity can create greater fragility. The studies also illustrate that performance is dependent upon the context of the situation and the dimensions of interest. An individual, employee, venture, etc., may seem to perform well during stable times only to respond differently to changes in the environment.

Therefore, for managers, investors, and policy makers, the key question is not which of the five domains (finance, technology, people, governance, or institutional support) should receive top priority. Rather, it is how each domain should be configured and integrated together for a given organization/sector/ecosystem/type of uncertainty. The transition – from isolated factors to integrated configurations – represents the largest shared contribution of this Issue and provides the best starting point for further investigation.

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Determinants of the perceived readiness of accounting department employees to work in a digitalized environment

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Abstract

PURPOSE: *Digitalization of accounting processes has become integral to contemporary professional practice. Accountants are now required to possess digital competencies. This study addresses a research problem concerning the self-assessment of accounting department employees' perceived readiness to work in a digitalized environment. The aim is to identify and assess the impact of selected demographic factors, organizational characteristics, work environment factors, and informal online education in modern information technologies on perceived readiness to work in a digitalized environment.* ***METHODOLOGY:*** *This study surveyed employees of the accounting department in Poland. The questionnaire included questions on the digitalization of accounting and education in information technology. The analysis used Mulder's competence model to examine demographic, organizational, work environment, and educational determinants. Statistical analyses included logistic regression, odds ratios, confirmatory factor analysis, structural equation modeling, and visualization methods.* ***FINDINGS:*** *The results extend knowledge on the determinants shaping the perceptions of accounting department employees in Poland regarding their perceived readiness. The perceived readiness of the surveyed employees varied by demographic factors, enterprise organizational characteristics, work environment factors, and educational determinants. Respondents' gender, enterprise size, and the presence of foreign capital significantly influenced their perceived readiness. The highest level of declared readiness was observed among men employed in other enterprises (including large enterprises) with foreign capital. The intensity of using informal online education in modern information technologies plays an important role in the relationship between gender and work environment factors supporting the digitalization process, particularly the degree of workplace digitalization, the frequency of contact with IT specialists, and perceived readiness. More frequent use of online knowledge sources was associated with higher perceived readiness, while the partial attenuation of the gender effect indicated differentiated learning patterns among women and men.* ***IMPLICATIONS:*** *From a business management perspective, the findings indicate that effectively increasing employees' readiness to work in a digitalized environment requires strengthening the digitalized work environment, ensuring continuous IT support, and consciously integrating informal online education into human resource development strategies. Practical implications also include revising the format of internal training programs and implementing communication and educational initiatives to reduce*

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employees' concerns about digitalization, thereby fostering the perception of technology as a tool that supports work performance.
ORIGINALITY & VALUE: *This study contributes to the literature by providing empirical evidence of the factors influencing the perceived readiness of accounting department employees to work in a digitalized environment. The added value of this study lies in incorporating informal online education as a variable in the relationships between gender, work environment factors, and perceived readiness to function under conditions of digitalization. The findings confirm the contextual nature of digital competencies, which are shaped by interactions with technology, organizational settings, and educational processes, in line with Mulder's competence model.*
Keywords: *accounting digitalization, digital competencies, perceived digital readiness, accounting professionals, informal online learning, workplace digitalization, technology acceptance, IT support, lifelong learning, future of accounting*

INTRODUCTION

The process of introducing information technologies in accounting proceeds in stages associated with successive generations of hardware and evolving technologies that enable access to new sources of information (Hogianto, 2023; Imene & Imhanzenobe, 2020; Arnaboldi et al., 2017). Implementing these solutions poses new challenges for enterprises and accounting department employees (Hogianto, 2023; Chan et al., 2012). Digitalization is a key area of this process and poses a particular challenge for the accounting profession.

Digitalization affects accounting and the work of accountants, both technically and socially (Knudsen, 2020; Hogianto, 2023). It enhances accounting practice, inter alia, by blurring the boundaries of accounting, creating new relationships within organizations and with their external environment, and generating the information necessary for decision-making (Knudsen, 2020; Hogianto, 2023).

Accountants constitute a professional group that is particularly affected by this process (Hall, 2008; Biyikli & Çetin, 2023). They operate within a changing accounting system, adapting to an increasingly digitalized environment that demands appropriate competencies and technological skills (Hall, 2008; Taib et al., 2022). Solutions such as Big Data, cloud computing, and artificial intelligence are fundamentally transforming the "world of accountants" (Hogianto, 2023).

Competence theories hold that development involves becoming aware of knowledge gaps and addressing them through education (Mulder, 2017; Kravetz, 2008; Boyatzis, 1982; Argyle, 1991). Competences have both an individual dimension and a dimension aligned with the expectations of the work environment (Willis & Todorov, 2006). In the case of accountants, these two dimensions converge, as competence assessment also encompasses the ability to function in a digitalized environment, which corresponds to employers' expectations (Cordoș & Tiron-Tudor, 2023).

Research indicates that despite progressing digitalization, accountants' technological knowledge and qualifications do not increase proportionately, which limits their professional competencies and affects their working conditions, task scope, and relationships with managers and other employees (Taib et al., 2022).

This raises the question of which factors influence the professional preparedness of accounting department employees to work in a digitalized environment. According to the authors, it is particularly important to consider this issue from the perspective of accountants themselves – whether, as a professional group, they feel prepared for the changes brought about by the digitalization of accounting. These changes are consistent with the concept of lifelong learning, which is a characteristic of the accounting profession (Taib et al., 2022). Simultaneously, the pace and scope of these changes raise doubts about whether accountants, without adequate support, can independently update their knowledge and competencies, and whether they are aware of the importance of these competencies in the new work environment. In this context, the authors formulated the following research question (RQ):

RQ: Which demographic factors, organizational characteristics of enterprises, work environment factors, and educational factors related to modern information technologies shape the perceived readiness of accounting department employees to work in a digitalized environment?

To operationalize the main research question and enable empirical verification, research hypotheses were formulated and subjected to statistical analysis. In addition, the study included descriptive auxiliary questions (Q1-Q2) that allowed for a better understanding of the research context and complemented the interpretation of the results obtained in the hypothesis testing process:

RQ1: Do accounting department employees in Poland accept the digitalization of their work environment, and what potential benefits and threats do they perceive in this process?
RQ2: How do accounting department employees in Poland assess their readiness to work in a digitalized environment in the context of formal and informal online education?

The answers to the auxiliary questions provide interpretive context for the results of the empirical analysis and enable more in-depth inferences regarding the determinants of perceived readiness to work in a digitalized environment. RQ2 provided a descriptive assessment of respondents' educational preparedness, including formal education, which was not subject to statistical verification but served as interpretive context for the empirical analysis.

About the theoretical foundations of the studied issue, reference to competence theories is particularly important, especially Mulder's concept, which emphasizes educational, professional, and adaptive competencies. This perspective enables a multidimensional analysis of the respondents' competence resources and the identification of conditions shaping their readiness to function in an environment characterized by the intensive use of modern technologies.

The enterprise information system, of which the accounting system is a component, constitutes a key area of digitalization (Hasin et al., 2022). The effective implementation of this process requires appropriate employee attitudes, awareness of the need to use digital technologies, and acceptance of continuous skill development in this area. Accountants' attitudes and their self-assessment of readiness to work in a digitalized environment remain a relatively underexplored area of empirical research. As noted by Grosu et al. (2023), the literature still lacks sufficient studies on accountants' perceptions of digitalization. According to available sources, studies that simultaneously consider determinants of accountants' perceptions of the work environment (e.g., gender, age, professional experience, workplace, or degree of workplace digitalization) and refer to competence concepts, particularly Mulder's approach, have not yet been conducted on a broader scale in Poland.

Despite the growing number of studies on the digitalization of accounting and accountants' skills, the literature still lacks comprehensive empirical research on the extent to which accounting department employees feel prepared to work in a digital environment. In particular, the determinants of this readiness – encompassing demographic, organizational, work environment, and educational factors, including the role of informal online education – remain insufficiently explored. This research gap is especially evident in studies conducted in the Polish context and in approaches drawing on competence theories, particularly Mulder's concept of competence.

This study contributes to the literature by empirically addressing a research gap by identifying and assessing the determinants of accounting department employees' perceived readiness to work in a digitalized environment. The study aims to identify and evaluate the impact of selected demographic factors, enterprise organizational characteristics, work environment factors, and informal online education in modern information technologies on employees' perceived readiness. The analysis enables a comprehensive examination of both individual employee resources and organizational and educational conditions that shape readiness for work in a digital environment. The article adopts a classification of determinants of perceived readiness, which is further developed in the literature review. These determinants comprise four groups of factors:

1) Demographic factors (gender, age, level, and field of education).
2) Organizational characteristics of enterprises (workplace, enterprise size, and presence of foreign capital).
3) Work environment factors include:
   a) structural conditions of work performance (job position, professional experience, work system);
   b) supporting the digitalization process (degree of workplace digitalization, organization of internal IT-related training, access to ongoing IT support, and frequency of contact with IT specialists).
4) Educational factors related to modern information technologies include formal education and informal online education.

Professional experience was classified as a work environment characteristic, as it influences the scope of assigned tasks, organization of work, and level of employee autonomy in using information technologies at the workplace. The selection of determinants was based on an original survey questionnaire designed as a research tool with a broader scope of application. For this study, only questions directly related to the adopted research objective and formulated research questions were used. In particular, the analysis included questions from Section A (Respondent characteristics: A1–A10), questions C1 and C3–C5 from Section C (Digitalization of the accounting profession), and question B7 from Section B

(Accountants' knowledge). Other elements of the questionnaire were excluded from the analysis because they fell outside the publication's thematic scope. The identified determinants relate to digital competencies, professional development, and employees' functioning in the context of advancing digitalization. The adopted approach enables a coherent and focused examination of selected aspects of readiness to work in a digital environment, considering both individual resources and organizational and educational conditions.

The statistical analysis of the survey data employed logistic regression models (GLM), odds ratios, confirmatory factor analysis (CFA), structural equation modeling (SEM), and visualization. The results of this study extend the knowledge of the determinants shaping accountants' perceptions of their readiness to work in a digitalized environment. They highlight the complexity of the factors influencing this perception and emphasize the importance of the idea of lifelong learning in the context of the digitalization of the accounting profession.

This article consists of six sections. The Introduction introduces the topic of digitalization in accounting and its impact on accountants' work, presents the main research objective and questions, and classifies the determinants. The Literature review comprises four elements: the relationship between digitalization and accountants' competences; the theoretical framework of digital competences (Mulder's model); the presentation of determinants and perceived readiness to work in a digitalized environment; and the formulation of hypotheses and the components of digital competences. The Research Methods section describes the data used in the study and the analytical methods applied. The Results section presents the findings along with their interpretation, while the Discussion relates them to the existing literature, focusing on the determinants that significantly differentiate perceived readiness. The Conclusions section presents the main conclusions, practical implications, and recommendations, and outlines the limitations of the study.

LITERATURE REVIEW

Digitalization and accountants' competences

Digitalization is perceived as a key factor shaping the methods through which economic entities create value and gain competitive advantage (Kotarba, 2018). In the development strategies of accounting professionals, the implementation of modern digital technologies plays a particularly important role (Melnyk et al., 2020), as it enables greater efficiency while simultaneously reducing workload and errors. New technologies influence how accountants work and think, introducing significant changes in the profession's performance (Janvrin & Watson, 2017; Gulin et al., 2019). In response to these requirements, specialists in accounting departments are obliged to continuously upgrade their skills in digitalization and increasingly use advanced information technologies in their daily work (Borrego et al., 2020). This is largely made possible by automating internal corporate business and operational processes (Ribeiro et al., 2021).

Research on digitalization in the context of the accounting profession and accounting systems focuses on three main areas. The first area concerns the mechanisms of implementing new digital technologies in organizations and their impact on accountants' work (Granlund & Mouritsen, 2003; Lutfi et al., 2022). Vitali and Giuliani (2024) indicate that technologies such as Robotic Process Automation (RPA) and artificial intelligence (AI) are changing the daily operations of audit firms, generating new requirements for IT and analytical competencies, which younger employees most often possess. Simultaneously, these technologies deepen the competitive advantage of large firms over smaller entities. Studies on the digitalization of accounting systems analyze its impact on the organization and functioning of accounting within organizations (Bhimani & Willcocks, 2014; Hiebl & Mayrleitner, 2019; Zhang et al., 2020) and forecast future changes in the accounting profession (Herbert et al., 2016; Kokina & Davenport, 2017; Sheldon, 2018; Melnyk et al., 2020). The implementation of digitalization in financial and accounting systems has radically transformed accountants' work and continues to evolve, becoming increasingly dependent on modern technology (Awang et al., 2022).

The second area addresses perceptions of the opportunities and threats associated with the digitalization of the accounting profession, as well as the factors influencing these perceptions among current and future accountants (Awang et al., 2022). The work of accountants requires creativity, interpersonal interaction, and continuous professional development; therefore, it is unlikely to be fully automated in the near future. However, repetitive tasks that do not require high qualifications or interpersonal communication can be easily automated by AI. Awang et al. (2022) applied the Technology Acceptance Model (TAM), demonstrating that users' willingness to adopt new systems increases their engagement in learning and technological adaptation. In the TAM framework, two key factors determine technology acceptance: perceived ease of use and perceived usefulness. These findings confirm that accountants' attitudes toward

new technologies significantly influence the development of their digital competencies and their self-assessed readiness to work in a digitalized environment. Accounting information systems focus on processing, storing, and disseminating data and supporting managerial decision-making through modern hardware and software (Ratmono & Zuhrohtun, 2023; Laudon & Laudon, 2020; Sarwar et al., 2021). Empirical studies on accountants' digital competencies consider technological conditions, training needs, implementation challenges, and benefits such as automation and efficiency gains (Hasin et al., 2022). The literature also examines the impact of demographic variables on perceptions of digitalization and job satisfaction (Biyikli & Çetin, 2023; Grosu et al., 2023), levels of acceptance of new technologies (Awang et al., 2022; Steens et al., 2024), and preparedness to work in a digitalized environment (Santonastaso & Macchioni, 2022).

The third area focuses on identifying and assessing factors influencing accountants' behavioral intentions regarding technology acceptance, including expected performance, perceived ease of use, social influence, innovativeness, and discomfort (Mohd Faizal et al., 2022). Technological progress has transformed the role of accountants, generating new competence requirements, while the global digital revolution has reshaped the labor market (Al-Htaybat et al., 2018; Jackson et al., 2022, 2023). In this context, accountants' attitudes toward digitalization processes and their self-assessment of their readiness to work in a digitalized environment become particularly important.

Theoretical framework in the context of digital competences: Mulder's model

In light of these changes, not only accountants' acceptance of technology but also their level of digital competence, which determines their readiness to work in a digitalized environment, becomes crucial. To capture the competence dimension, it is appropriate to refer to Mulder's (2017) competence model, which describes the integrated nature of professional competences.

Competence theories have been developed since the 1970s (McClelland, 1973; Boyatzis, 1982; Spencer & Spencer, 1993) and subsequently evolved toward integrated and contextual approaches, leading to the contemporary understanding of competencies proposed by Mulder (2017). In this approach, competencies are holistic in nature and strongly embedded in professional and educational contexts (Eraut, 1994; Cheetham & Chivers, 1996). They encompass not only knowledge and skills but also attitudes, values, the ability to critically reflect, self-regulation, and lifelong learning (Mulder, 2016, 2017, 2019).

A key element of Mulder's approach is the assumption that competences develop through interaction between individual characteristics and the work and educational environment, and that their level and structure are determined by the requirements of a specific professional context (Mulder 2001, 2017). About professional competencies, including digital competencies, this implies the need to consider components such as contextuality, self-regulation, self-assessment, organizational frameworks, and the integrated nature of knowledge, skills, and attitudes (Mulder, 2016, 2017, 2019).

Mulder (2017) distinguishes three generations of competencies. Competences 1.0 are rooted in a behaviorist approach and focus on observable skills and task-specific activities. Competences 2.0 are integrated and include interconnected elements of knowledge, skills, and attitudes embedded in a specific professional context. Competences 3.0 refers to future-oriented forms of action, such as creativity, innovativeness, and the ability to cope with new and unpredictable tasks. This study adopts the Competences 2.0 perspective, which enables the analysis of digital competencies as an integrated potential of individuals functioning in a specific work environment.

From the perspective of the accounting profession, this concept is supported by Boritz and Carnaghan (2017), who analyze the education and professional certification of accountants in Canada and the United States. They argue that contemporary competence frameworks in accounting integrate expert knowledge, practical skills, and attitudes necessary to perform the profession in a changing work environment. Although they do not explicitly refer to Mulder's model, their approach to professional competencies is consistent with the integrated Competences 2.0 paradigm and may serve as a starting point for analyzing digital competencies.

Georgieva (2019), analyzing accountants' digital competences in the context of the Fourth Industrial Revolution, emphasizes that they cannot be limited solely to technical skills related to the operation of IT tools. Digital competencies simultaneously encompass specialized knowledge, practical skills in using information technologies, and attitudes that enable adaptation to a dynamically changing professional environment. The digitalization of accounting processes shifts the focus from routine tasks to activities that require the analysis, interpretation, and critical evaluation of data, underscoring the contextual and dynamic nature of digital competencies. Georgieva (2019) also highlights the contextual nature of digital competencies, noting that their scope and level vary across professional roles within accounting. Chief accountants are expected to have different digital competencies than operational accountants or employees responsible for document

recording. This differentiation supports the validity of conceptualizing digital competencies as a category embedded in a specific work context.

Van der Klink and Boon (2003) indicate that Mulder's model is useful for assessing workplace competences, particularly in the context of lifelong learning and adaptation to a changing technological environment. In the case of digital competencies, this model enables the capture of how technical knowledge, practical skills, and employee attitudes interact with work environment conditions, enabling the effective use of digital tools and continuous competence development in response to dynamic technological changes.

Adopting Mulder's Competences 2.0 model as the theoretical framework enables a comprehensive analysis of accountants' digital competencies, encompassing knowledge, skills, attitudes, and professional context. The model provides a foundation for diagnosing accountants' level of preparedness to work in a digitalized environment and the determinants influencing this preparedness.

Determinants and perceived readiness to work in a digitalized environment

Age

A review of the literature indicates that the development of digital competences within the population is uneven and strongly conditioned by demographic factors. Age is one of the most important predictors of differences in digital competences, which in turn shape perceived readiness to work in a digitalized environment.

Younger individuals typically demonstrate higher levels of technological proficiency and more frequently use online forms of learning (Helsper & Eynon, 2010; van Deursen & van Dijk, 2011). However, Helsper and Eynon (2010) question the universality of the "digital natives" hypothesis, according to which younger generations automatically possess higher digital competences. Research shows that age or generational affiliation constitutes only one of many factors influencing technological proficiency, while experience, frequency of internet use, level of education, and gender play a key role. The authors distinguish between "being" a digital native and "doing" digital activities, emphasizing that digital competences result more from activity and practice than from age alone. This suggests that intergenerational differences can be reduced within educational environments.

Research by Steens et al. (2024) among senior controllers in the Netherlands found that older professionals often possess technological competencies below those required at work. Although respondents were aware of the need to learn, they did not always accurately anticipate future competence requirements. Moreover, the greater their existing knowledge, the more strongly they expressed the need to further develop digital skills. In turn, Novelidhawaty et al. (2023) emphasize that developing technical skills among older employees requires support in digital tools, data security, and analytical competencies, while barriers to implementing new technologies may stem from resistance to change and organizational culture. These findings clearly indicate that older users require both education and practical support to fully exploit the potential of digitalization.

Van Deursen and van Dijk (2011) highlight that age is a significant predictor of digital competences, influencing both access to technology (the first digital divide) and levels of operational, informational, and strategic skills, which are often constrained by lack of experience and adaptive difficulties. This differentiation deepens the second digital divide, related to the quality, effectiveness, and efficiency of internet use, underscoring the important role of age not only in access but also in the quality of digital interactions.

Gender

Gender is an important predictor of digital competences, particularly influencing self-assessment of technological skills and confidence in using modern tools (Cooper, 2006). Women more often report lower self-assessments of their technological abilities and are less likely to engage in advanced digital activities, mainly due to socio-cultural factors such as stereotypes and prior experiences rather than biological predispositions. Education, practice, and support in learning how to use digital tools can effectively reduce these differences, increasing digital competencies regardless of gender. Gender may indirectly influence self-assessed digital competences and perceived readiness to work in a digitalized environment, although these differences can be mitigated through appropriate educational support and practical experience.

Awang et al. (2021) examined gender differences among students in terms of technological knowledge and readiness for the accounting profession in a digitalized environment. Their findings indicate that future accountants (Generation Z) exhibit similar levels of technological knowledge and readiness for digitalization regardless of gender, suggesting a gradual equalization of digital competencies among younger cohorts. Furthermore, Awang et al. (2022) investigated how "future accountants" perceive the digitalization of the profession as a developmental opportunity or as a risk. Their survey of accounting students and interns showed that respondents recognized both benefits (task automation, increased efficiency) and challenges (longer working hours, pressure of constant availability). Importantly, no statistically significant gender differences were observed in the assessment of benefits and threats, suggesting that gender does not determine young professionals' attitudes toward digitalization.

Studies by Santonastaso and Macchioni (2022) revealed gender- and region-based differences in Italian accountants' assessments of professional preparedness in the digital era. Men reported digital competences more frequently in their professional profiles than women, which may reflect women's lower self-assessment (Gorbacheva et al., 2016). Accountants from northern Italy were more likely to report digital competencies than those from central and southern regions, which may be linked to significant economic and technological disparities across Italian regions.

Lenard et al. (2010) examined self-assessed computer skills among participants (women and men) in an Accounting Information Systems (AIS) course. Among women, a significant increase in self-assessed skills was observed after completing the course, while no significant change was found among men. Women achieved higher average scores than men, and a strong correlation was identified between confidence in computer skills and self-assessed competence. The AIS course effectively built confidence and computer competencies, particularly among women, which may influence their career decisions. Positive self-perception and awareness of one's skills may encourage women to further develop careers in accounting and information systems.

Demographic differences in perceptions of digitalization are also confirmed by Biyikli and Çetin (2023). Age, gender, tenure, and professional title significantly influence assessments of the effects of digital transformation in the accounting profession. Age emerged as a particularly strong predictor, with similar trends observed for tenure – longer experience was associated with lower acceptance of digitalization. Gender differences were also noted, with women reporting higher levels of dissatisfaction with digitalization and technological tools than men. Professional title, partially reflecting education level and hierarchical position, was another important differentiating factor.

Education and professional experience

Level of education and professional experience are further determinants influencing digital competences, which condition readiness to work in a digitalized environment.

Research shows that individuals with higher education levels are more likely to engage in online self-learning and possess more advanced information-processing skills (Hargittai & Shafer, 2006). These authors demonstrate that actual internet skills are largely determined by education level and experience using computers at work. Individuals with higher education and regular exposure to technology performed better in tasks related to online navigation and information retrieval. At the same time, gender remains a significant predictor of perceived digital competences, as women tend to rate their skills lower than men, even when actual competence levels are comparable.

Professional experience in technology-intensive environments promotes competence development and positively affects self-assessed readiness to work in a digitalized environment (van Laar et al., 2017; Park, 2012). Fitria and Sari (2023) showed that employees' technical skills and professional experience significantly enhance the effectiveness of accounting information systems, whereas formal education does not moderate these relationships. These findings highlight the importance of practical training and professional experience as key determinants of preparedness for digital work. In contrast, Hinterhuber and Pavone (2020) identified a positive correlation between education level and digital maturity among accounting professionals, suggesting that educational predispositions strengthen readiness to adopt digital tools.

Job position

Job position is an important factor differentiating levels of digital competences within the accounting profession. Stoica and Ionescu-Feleagă (2021) note that the nature of one's role determines both the range of IT tools used and the degree of involvement in digitalization processes. Similar conclusions are drawn by Pargmann et al. (2023), who indicate

that as the level of professional responsibility increases, so does the demand for more advanced technological skills, particularly in highly digitalized organizations. Taib et al. (2023) further demonstrate that managers and higher-level employees exhibit significantly higher digital competencies than operational staff, due to both the nature of their tasks and access to specialized training. These results clearly indicate that job role constitutes an important determinant of variation in accountants' digital competences.

Workplace and organizational size

Workplace characteristics and organizational size are important determinants of accountants' digital competences, reflecting readiness to work in a digitalized environment. Stoica and Ionescu-Feleagă (2021) demonstrated that organizational size significantly differentiates the range of technologies used. Micro and small enterprises are typically limited to basic applications, whereas large organizations and capital groups implement advanced systems with high levels of automation. Pargmann et al. (2023) confirm that the degree of organizational digitalization directly affects the scope of required competences and the nature of the tasks performed. Competence differences arise primarily from the level of digitalization and the role performed within the organization.

Taib et al. (2023) observed that accounting firms and large enterprises have the highest expectations for employees' technological skills, making the work environment one of the most important factors in determining accountants' digital preparedness. Kotowska and Sikorska (2023) analyzed the impact of workplace characteristics on the development of accountants' digital competences, studying employees and owners of accounting firms. They found that organizational specificity – particularly in accounting firms intensively implementing technologies – significantly shapes both the scope of digital tool use and awareness of the need to enhance technological competencies. At the same time, competence gaps often become apparent precisely in the workplace, confirming its crucial role as a determinant of digital skill development.

Mohd Faizal et al. (2022) further indicate that willingness to engage in further digital training is largely determined by workplace expectations and beliefs about the importance of digital competences for effective job performance.

Foreign capital participation

The presence of foreign capital in an enterprise is an important factor influencing accountants' competencies and can be considered from the perspective of organizational training practices. Bloom et al. (2012) found that enterprises with foreign capital participation are more likely to implement advanced management practices, including activities that support employee competence development, particularly in the areas of information and digital technologies. This results from higher management standards and international requirements, which foster an organizational environment that actively promotes the development of digital competence. In the context of this study, this observation justifies including foreign capital participation as a factor differentiating the level of accounting employees' preparedness to work in a digitalized environment.

Training and perceived readiness to work in a digitalized environment

Research by Quraishi et al. (2025) indicates that the work environment and the level of organizational digitalization constitute an important context shaping the digital competences of accounting department employees. The authors also emphasize the importance of education and IT-related training, confirming the need to develop both formal and informal learning forms to effectively prepare employees for work in a digitalized environment. At the same time, the study identifies financial, technical, and competence-related barriers that may limit the effectiveness of digitalization, justifying the inclusion of determinants such as professional experience, organizational support, and training availability in the research model.

Pargmann et al. (2023) emphasize that the development of analytical and technological competences in the accounting profession is strongly linked to access to workplace training. Taib et al. (2023) show that managers and higher-level employees who participate in regular technology-related training achieve higher levels of digital competencies than operational staff, highlighting the important role of informal education and organizational support in adapting to digitalization. Hasin et al. (2022) stress that providing adequate training support is a key condition for the effective functioning of accountants in a digitalized environment. Access to modern digital tools must be complemented by training aimed at developing

technological competencies. In their view, developed frameworks of accountants' digital competences should serve as a basis for designing training programs and development activities aligned with digitalization requirements. Digitalization offers numerous opportunities to improve work processes, but simultaneously requires accountants to continuously upgrade their qualifications through technology-oriented training.

Degree of workplace digitalization and IT support as determinants of perceived readiness to work in a digitalized environment

The degree of workplace digitalization and access to IT support are key determinants of employees' perceived readiness to function in a digitalized environment. This readiness is understood as a set of predispositions enabling effective use of digital technologies and adaptation of new tools in the workplace, encompassing technological competences, attitudes toward technology, and the level of organizational support in the implementation for digital innovations (Abdul Hamid, 2022).

The degree of workplace digitalization, access to technical support, and opportunities for training and development of digital competence create a context that either facilitates or hinders technology adoption. An OECD report (2019) emphasizes that access to training and opportunities to develop digital competences directly influence perceived readiness to work in a digitalized environment.

Limited access to digital infrastructure, insufficient technical support, or inadequate training can significantly reduce the effectiveness of digital tools and negatively affect perceived readiness to use them. In contrast, regular contact with IT specialists fosters greater trust in technology and a greater willingness to use it in everyday work (Tarafdar et al., 2015). In this context, IT support functions as a factor reducing uncertainty and technological strain, thereby strengthening subjective readiness to function in a digitalized environment.

Safi et al. (2024) likewise confirm that a high degree of workplace digitalization and easy access to IT support foster greater comfort in using technology, enhance self-confidence, and increase readiness to undertake tasks in a digitalized environment. The development of employees' digital competences is a crucial factor in shaping digital work readiness, and possessing these skills is associated with higher perceived readiness to work in a digitalized environment (Suhada et al., 2026). Both individual competences and attitudes toward technology, as well as organizational conditions – including access to infrastructure, technical support, and training – constitute key determinants of perceived readiness to work in a digitalized environment.

Hypotheses and the structure of digital competence components indicating readiness to work in a digitalized environment

The literature review indicates that the development of digital competences largely depends on individuals' personal characteristics, their professional and educational experiences, and organizational conditions. Accordingly, the analysis focused on determinants of perceived readiness to work in a digitalized environment, encompassing demographic factors, enterprise organizational characteristics, work environment factors, and educational factors.

Research hypotheses were formulated to examine the effects of selected demographic factors, organizational characteristics of enterprises, work environment factors, and educational factors on the perceived readiness of accounting department employees to work in a digitalized environment:

H1: Respondents' gender and organizational characteristics of enterprises (enterprise size and the presence of foreign capital) are significantly associated with the level of perceived readiness to work in a digitalized environment.
H2: The intensity of using informal online education sources related to modern information technologies is significantly associated with the level of perceived readiness to work in a digitalized environment, while accounting for respondents.
H3: Respondents' gender and work environment factors supporting the digitalization process (degree of workplace digitalization and frequency of contact with IT specialists) are significantly associated with perceived readiness to work in a digitalized environment.

The formulated hypotheses assume the existence of relationships between selected factors and the level of perceived readiness to work in a digitalized environment. Hypothesis H1 addresses the direct impact of selected demographic and organizational enterprise characteristics on self-assessed readiness. Hypothesis H2 incorporates an educational factor in the form of informal online education in modern information technologies, analyzed as an additional explanatory construct associated with perceived readiness to work in a digitalized environment, while accounting for respondents'

gender and work environment factors supporting the digitalization process. Hypothesis H3 focuses on the direct impact of gender and work environment factors supporting digitalization on perceived readiness to work in a digitalized environment. In this hypothesis, the role of informal online education is considered an accompanying factor that reflects individual engagement in acquiring digital knowledge and skills.

Although the same work environment factors supporting digitalization are included in both hypotheses H2 and H3, these hypotheses refer to different analytical perspectives. Hypothesis H2 emphasizes the role of informal online education in explaining perceived readiness to work in a digitalized environment, whereas Hypothesis H3 concentrates on the direct relationships between work environment factors and perceived readiness. Including these variables in both hypotheses enables a more comprehensive interpretation of the relationships between individual characteristics, workplace conditions, and readiness to function in a digitalized work environment.

Different sets of determinants are included in hypotheses H1–H3 because each hypothesis focuses on a distinct aspect of digital competences influencing perceived readiness to work in a digitalized environment. Within the hypotheses, three complementary components of digital competences are analyzed:

1) Technical component – encompassing practical skills in using modern information technologies in professional work. It is operationalized through self-assessed readiness to work in a digitalized environment and constitutes the component analyzed in all hypotheses H1–H3.
2) Educational component – encompassing modes of acquiring technological knowledge through informal online education (Hypothesis H2).
3) Organizational component – related to enterprise characteristics (Hypothesis H1) and work environment conditions supporting the digitalization process (Hypotheses H2 and H3).

The digital competence components distinguished in the study are consistent with the competence framework proposed in Mulder's model, which conceptualizes competences as an integrated set of skills, knowledge, and organizational and contextual conditions manifested in professional practice. The components adopted in this study constitute a selective operationalization of this model, focusing on technical, educational, and organizational aspects that are particularly relevant to work in a digitalized environment.

This triad of components enables a comprehensive assessment of technical skills, modes of developing technological knowledge, and organizational conditions influencing the use of technology. Such an approach allows for simultaneous examination of the effects of informal online education in modern information technologies and the work environment on accountants' self-assessed readiness to work, representing a significant and novel contribution to the analysis of digital competences among accounting department employees operating in a digitalized environment.

RESEARCH METHODS

Empirical data were collected using an original survey questionnaire (Appendix B). The questionnaires were addressed to accountants (members) of the Association of Accountants in Poland from regional branches in Kraków, Katowice, and Wrocław, as well as to participants and graduates of Executive MBA programs at the Wrocław University of Economics, the University of Warsaw, SGH Warsaw School of Economics, Gdańsk University of Technology, and the Poznań University of Economics and Business. The survey was conducted in two stages: October 2023 and March 2024.

The questionnaire entitled "Sustainable development of accountants in the areas of knowledge – digitalization – ethics" consists of the following sections: (A) respondent characteristics, (B) knowledge of the accountant/manager, (C) digitalization of the accounting/managerial profession, and (D) ethics of the accounting/managerial profession. Section D of the questionnaire was excluded from the analysis because the ethics topic falls outside the scope of this article.

A non-random, non-representative research sample was selected through accidental (convenience) sampling (Szreder, 2004), and the conclusions drawn from the study apply only to the surveyed respondents. Empirical data were collected using an online questionnaire administered via a web-based form. A total of 333 questionnaires were collected, of which 332 were included in further analysis. Some of the questionnaires contained missing data. Missing responses to selected questions were addressed using statistical data imputation.

Multivariate imputation by chained equations (MICE) was applied. This method is an iterative algorithm based on a chain (sequence) of regression equations, in which each step corresponds to a subsequent variable (van Buuren, 2018).

The MICE algorithm predicts missing values (estimates their probabilities) based on observed values of multiple variables using a range of regression models. To assess the quality of the multiple imputation performed in the study, the following measures were used: RIV – Relative Increase in Variance (values close to 0 indicate a small impact of missing data on estimation uncertainty), FMI – Fraction of Missing Information (values below 0.20 indicate very good imputation quality), and RE – Relative Efficiency (values above 0.95 indicate efficient imputation) (Rubin, 1987; van Buuren, 2018). The values of all measures indicate very good quality in missing-data imputation across all four sections of the questionnaire. For sections A and C, from which the questions used in this article were drawn, the values were as follows: A – RIV = 0.03, FMI = 0.03, RE = 0.99; C – RIV = 0.17, FMI = 0.14, RE = 0.97.

The statistical analysis of the survey data employed logistic regression models (GLM), odds ratios (OR), confirmatory factor analysis (CFA), structural equation modeling (SEM), and visualization methods. All analyses were conducted using the R software environment and the following packages: epade, DescTools, lmtest, caret, questionr, finalfit, MASS, sjPlot, vcd, vreg, lavaan, and psych (R Development Core Team, 2026; Aitkin et al., 2009; Fox, 2002; Rosseel, 2012).

Logistic regression was used to analyze binomial data (Agresti, 2002; Long, 1997; Cameron & Trivedi, 2005). Such data often include binary variables when the dependent variable takes one of two values (e.g., yes/no responses in a questionnaire). The logistic regression model takes the form $f(x) = \frac{e^x}{1+e^x}$.

This model allows estimating the probability p_i of selecting one of the two options (yes/no) depending on the value of the explanatory variable x (or explanatory variables), based on the formula:

$$p_i = \frac{exp(\beta_0+\beta_1 x_i)}{1+exp(\beta_0+\beta_1 x_i)}, \text{ where } 0 < p_i < 1$$

To estimate the parameters β of the logistic regression model, the concept of Generalized Linear Models (GLM), proposed in the article by Nelder & Wedderburn (1972) and developed in the monograph by McCullagh & Nelder (1989), was applied. Generalized linear models, in which the dependent variable follows a distribution other than normal (e.g., binomial), are estimated using maximum likelihood and iterative optimization algorithms (appropriate R functions are available for these purposes).

When interpreting the logistic regression model, the sign of the parameter $(+\beta \text{ or } -\beta)$ indicates the direction of influence of the explanatory variable on the dependent variable in terms of probability. The assessment of the impact of explanatory variables is also performed using odds ratios. The expression $\Omega = \frac{\pi}{1-\pi}$ describes the odds of an event occurring with π probability (how many times an event occurs relative to not occurring). The odds ratio (OR = Θ) compares two odds: $\Theta = \frac{\Omega_1}{\Omega_2} = \frac{\pi_1/(1-\pi_1)}{\pi_2/(1-\pi_2)}$ (Agresti, 2002, p. 44). The values of the odds ratios are computed based on the exponential expression e^{β}, where β is the estimated parameter. If the value of an explanatory variable increases by one unit, the odds of the dependent variable taking the value of 1 change (increase or decrease) by the factor of . The interpretation is as follows:

- if $e^{\beta} > 1$, the influence on choosing "yes" is positive (an increase in odds);
- if $e^{\beta} < 1$, the influence is negative (a decrease in odds);
- if $e^{\beta} = 1$, the influence is neutral (odds unchanged).

The dependencies between variables in the logistic regression model are more easily interpreted using advanced visualization techniques. In this article, the visreg() function from the visreg package was used (Breheny & Burchett, 2017).

Structural Equation Modeling (SEM) is an advanced statistical method used to analyze the relationships between observed and latent variables, as well as the dependencies among latent variables (Bollen, 1989; Hair et al., 2019; Jöreskog et al., 2016). SEM consists of two components: the measurement model and the structural model. A common preliminary step before estimating SEM models is conducting the Exploratory Factor Analysis (EFA). Its aim is to uncover the underlying structure of factors without imposing theoretical assumptions. EFA allows for dimensionality reduction and the identification of the groups of variables that measure common constructs. The measurement model in EFA can be expressed as: x=Λf+ϵ, where denotes the vector of observed variables (indicators), Λ – the matrix of factor loadings, f – the vector of latent factors, and – error terms. Based on EFA results, Confirmatory Factor Analysis (CFA) is conducted to test whether the adopted factor structure (e.g., based on EFA) fits the empirical data. In CFA, the number of factors and the assignment of indicators to factors are predetermined. The CFA measurement model is expressed as: x=Λη+ϵ, where η denotes the latent factor vector. Structural Equation Modeling (SEM) extends CFA by incorporating a structural model

that describes the dependencies among latent variables and predictors (both latent and observed). The structural model is expressed as: $\eta=B\eta+\Gamma\xi+\zeta$ where η represents the latent dependent variables, ξ – latent (or observed) explanatory variables, B – the matrix of relations among latent variables, Γ– the matrix of predictor effects, and ζ – error terms. SEM enables simultaneous modeling of measurement errors, relationships among constructs, and the influence of predictors on latent constructs.

RESULTS

The survey data analysis included 332 respondents, whose characteristics are presented in Table A1 (Appendix A) and the codebook of variables used in the analysis is presented in Table A2 (Appendix A). Women predominate in the sample, accounting for 254 respondents (77%). The respondents represent a diverse age structure, classified into four age groups corresponding to the generations to which they belong: Baby Boomers (up to 1964), Generation X (1965–1980), Generation Y – Millennials (1981–1994), and Generation Z (after 1995). The most numerous groups in the study are Generation Y (41%) and Generation X (35%), which are characterized, inter alia, by a high level of knowledge, experience, and professional competencies, as well as an awareness of the need for continuous learning in the accounting profession.

As many as 96% of respondents hold a higher education degree, including 75% with a master's degree, 12% with a bachelor's degree, and 6% with a doctoral degree or higher. The results concerning generational affiliation and type of education are consistent with the characteristic features of these generations – for example, master's degrees are predominantly represented among Generations X and Y, while bachelor's degrees are more typical of Generation Z. The vast majority of respondents (78%) identified their field of education as economics.

The most frequently held job positions among respondents are accountant (62%) and financial/accounting (controlling) manager (19%). Accountants constitute the dominant professional group in the sample; therefore, subsequent conclusions and analyses focus primarily on this group. Respondents were also asked about their workplace. The largest share (44%) are employees of enterprises, while 27% work in accounting firms. Professional experience varied across respondents: 40% reported 0-10 years, 29% reported 11–20 years, and 21% reported 21–30 years.

The COVID-19 pandemic led to the introduction of remote work arrangements, which continue to be applied in various forms of employment. As their preferred work system, 51% of respondents indicated a hybrid model combining on-site and remote work, while 41% preferred exclusively on-site work. The sizes of the enterprises in which respondents are employed are diverse. A substantial group is represented by other entities (medium-sized and large enterprises), accounting for 34%, while micro and small enterprises together account for 42%. A total of 67% of respondents declared that they work in enterprises without foreign capital participation.

Given the size and sampling method of the study, the results should be interpreted solely as about the surveyed group and should not be generalized to the entire population of accounting department employees in Poland. At the same time, the sample's structure, consisting of individuals actively engaged in the profession, provides valuable insights into practitioners' perceptions and attitudes toward the digitalization of the work environment and the use of formal and informal education in digital competencies.

The respondents are individuals employed in financial and accounting departments who perform professions that require lifelong learning and preparedness to work in a digitalized environment. Some of them have used several forms of education which, at different stages of their professional development, contributed to increasing their knowledge and skills, i.e., their intellectual capital. Among the most popular forms of formal education, respondents indicated courses and training organized by the Association of Accountants in Poland (220 responses), courses and training provided by commercial entities (188 responses), postgraduate studies in accounting (119 responses), and ACCA (Association of Chartered Certified Accountants) programs (68 responses). MBA (Master of Business Administration), CIMA (Chartered Institute of Management Accountants), and IMA (Institute of Management Accountants) programs were selected much less frequently, which may be explained by the high proportion of accountants among the respondents.

The main reasons (multiple responses were allowed) that motivated respondents to undertake formal education in the indicated forms were: expanding and supplementing theoretical and practical knowledge (281 responses), increasing knowledge, skills, and competences (so-called intellectual capital) (274 responses), and efforts to achieve professional advancement (106 responses). Less frequently, respondents indicated the following motivations: the need to learn modern methods, tools, and software applicable to professional practice (96 responses), achieving prestige and recognition in the professional community (72 responses), and mandatory training requirements (30 responses).

In response to question B3 – "Did the education undertaken in the selected form meet your expectations to a satisfactory degree?" – as many as 87% of respondents answered "yes," positively evaluating their experience with the selected form of formal education. Respondents stated that their expectations had been met to a satisfactory extent. Moreover, 82.2% of respondents declared that they are well prepared to work in a digitalized environment, which may result from their engagement in lifelong learning, for example, through courses and training. It is also worth emphasizing that 79.5% of respondents confirmed the need to upgrade qualifications in modern technologies, while simultaneously stating that education related to their application should be mandatory.

Responses to question B4 – "Does the educational offer you use include topics related to the application of modern information technologies?" – were almost evenly distributed (48.5% "yes" and 51.5% "no"), which reflects respondents' use of various forms of education with curricula differing in thematic scope. It can be inferred that formal education offerings (e.g., courses and external training) related to modern information technologies prepare slightly less than half of respondents (48.5%) to work in a digitalized environment.

Education in modern information technologies was included in the survey questionnaire as a factor shaping respondents' digital competences, encompassing both formal education and informal online education. Formal education was subjected only to descriptive analysis, as it did not show statistical significance in preliminary analyses, whereas informal online education was included in further modeling and subjected to statistical verification.

To identify factors differentiating perceived readiness to work in a digitalized environment (dependent variable C2, responses: yes/no), a logistic regression model was estimated using the generalized linear model (GLM) framework with a logit link function. The model allows for assessing the impact of selected demographic and organizational characteristics (predictors) on the probability of providing a positive ("yes") response to question C2.

The dependent variable C2 – "Are you well prepared to work in a digitalized environment?" – is a dichotomous variable (1 – yes, 0 – no). Given the binary nature of the dependent variable, a binomial distribution was used. Three explanatory variables were included in the model (one demographic variable and two organizational variables related to the enterprise):

- A1 – Gender of the respondent. Dichotomous demographic variable (1–reference category: women; 2–comparison category: men);
- A9 – Enterprise size. Polytomous organizational variable (reference category: 1–micro-enterprises; comparison categories: 2–small enterprises, 3–other enterprises, 4–capital groups);
- A10 – Foreign capital participation. Dichotomous organizational variable (reference category: 1 – yes; comparison category: 2–no).

Other demographic variables (age, education) and organizational enterprise variables (workplace) were not included in the GLM modeling because they were not statistically significant. Reference levels were selected so that the regression coefficients could be interpreted as differences relative to the most typical response options. Table 1 presents the results of the logistic regression model estimation, while Figures 1 and 2 illustrate the odds ratios and regression relationships between variable C2 and variables A1, A9, and A10.

The analysis of the model estimation results indicates that the explanatory variables (A1, A9, A10) are statistically significant and differentiate the probability of a positive response to question C2. For variable A9 (due to having three degrees of freedom), a Wald test was conducted ($F = 5.93$, $p = 0.003$), confirming the statistical significance of this categorical variable.

The model as a whole significantly improves the fit to the data compared with the null model, as confirmed by goodness-of-fit tests and information criteria (AIC).

Table 1. Logistic regression model and odds ratios (C2 – explained variable)

Variable	Coefficient	Std. error	z-value	p-value	Odds ratio
(Intercept)	3.015	0.566	5.327	0	–
A1 [2]	1.038	0.435	2.387	0.017	2.823
A9 [2]	–1.257	0.470	–2.675	0.007	0.285
A9 [3]	–0.834	0.461	–1.808	0.071	0.434
A9 [4]	–1.276	0.575	–2.218	0.027	0.279
A10 [2]	–1.090	0.425	–2.567	0.010	0.336

Note: Model fit assessment: McFadden pseudo-$R^2 = 0.06$ (moderately good fit of the logistic regression model), likelihood ratio chi-square $G^2 = 20.06$ with df = 5 and $p < 0.001$ (the model with predictors is significantly better than the null model), AIC = 302.62.

Variable A1 (gender) is statistically significant. Gender differentiates the probability of a positive self-assessment of readiness to work in a digitalized environment. Compared with women, men are significantly more likely to declare readiness to work in a digitalized environment (OR ≈ 2.8, $p < 0.05$).

Variable A9 (enterprise size) shows significant differences across categories of enterprise size (micro, small, other, capital group). Enterprise size significantly differentiates readiness to work in a digitalized environment. In particular, employees of small enterprises (OR ≈ 0.28, $p < 0.05$) and capital groups (OR ≈ 0.28, $p < 0.05$) are significantly less likely to declare such readiness than employees of large enterprises. The effect of the "other enterprises" category is also negative with respect to responses to question C2, but the effect is weaker and at the margin of statistical significance (OR ≈ 0.43, $p \approx 0.07$).

Variable A10 (foreign capital participation) is statistically significant. The presence of foreign capital is associated with a significantly different level of declared readiness to work in a digitalized environment. Respondents employed in enterprises without foreign capital participation (OR ≈ 0.34, $p < 0.05$) report lower readiness to work in a digitalized environment than those employed in enterprises with foreign capital participation.

Figure 1 presents the odds ratios with 95% confidence intervals estimated from the logistic regression model predicting readiness to work in a digitalized environment (C2). Odds ratios greater than one indicate an increase in the probability of a positive self-assessment relative to the reference category, whereas odds ratios below one indicate a decrease in this probability. The vertical reference line at OR = 1 indicates no effect.

Regarding variable A1, men have approximately 2.8 times the odds of declaring readiness to work in a digitalized environment than women. The analysis of variable A9 indicates that, compared with the reference category (micro-enterprises), the odds of a positive self-assessment of readiness to work in a digitalized environment are lower for small and other enterprises as well as for capital groups. For variable A10, the absence of foreign capital reduces the odds of a positive response to question C2 compared with enterprises with foreign capital participation (the reference category).

Figure 2 presents the predicted probability of a positive response to the question assessing readiness to work in a digitalized environment (C2), estimated using the logistic regression model. The panels illustrate the effects of gender (A1), enterprise size (A9), and foreign capital participation (A10), with predicted values shown on the probability scale. The left panel shows that male respondents have a higher predicted probability of being ready to work in a digitalized environment than female respondents. This pattern is consistent with the positive and statistically significant gender coefficient observed in the logistic regression model. The middle panel shows substantial variation in predicted probabilities across different enterprise size categories. Compared with the reference category, employees in small and other enterprises (including large enterprises) and in capital groups display lower predicted probabilities of a positive self-assessment, indicating that enterprise size is an important contextual factor influencing perceived digital readiness. Not all enterprise size categories differ significantly from the reference level, suggesting a non-linear relationship between enterprise size and perceived readiness. The right panel shows that respondents employed in enterprises without foreign capital participation exhibit a lower predicted probability of being ready to work in a digitalized environment than those employed in enterprises with foreign capital participation.

Figures 1 and 2 are complementary from an interpretative perspective. The odds ratios (Figure 1) indicate how many times the odds of a positive response to question C2 change relative to the reference levels of predictors A1, A9, and A10, whereas the predicted probability plots (Figure 2) show the magnitude of change in the predicted probability of a positive self-assessment of readiness to work in a digitalized environment across the predictor categories.

The results of the logistic regression model estimation (Table 1) and the visualizations (Figures 1 and 2) support Hypothesis H1, as they indicate that gender, enterprise size, and foreign capital participation significantly differentiate the level of perceived readiness to work in a digitalized environment. The highest probability of a positive self-assessment is observed among men employed in other enterprises (including large enterprises) with foreign capital participation, which may reflect greater access to technological resources, training, and a more advanced digital environment.

The specific nature of respondents' professions requires familiarity with current legal regulations and the appropriate use of instruments. To meet these requirements, respondents engage in lifelong learning and, in addition to organized forms of education, use other sources to acquire up-to-date, practical knowledge in preparation for work in a digitalized environment. These sources are selected individually based on their capabilities and needs. Respondents answered question B7 – "For the purpose of acquiring up-to-date knowledge (including practical knowledge), which forms do you use?" – using a four-point Likert scale (forced-choice scale) (Table 2). The results confirm that respondents very often or often use online publications and online training.

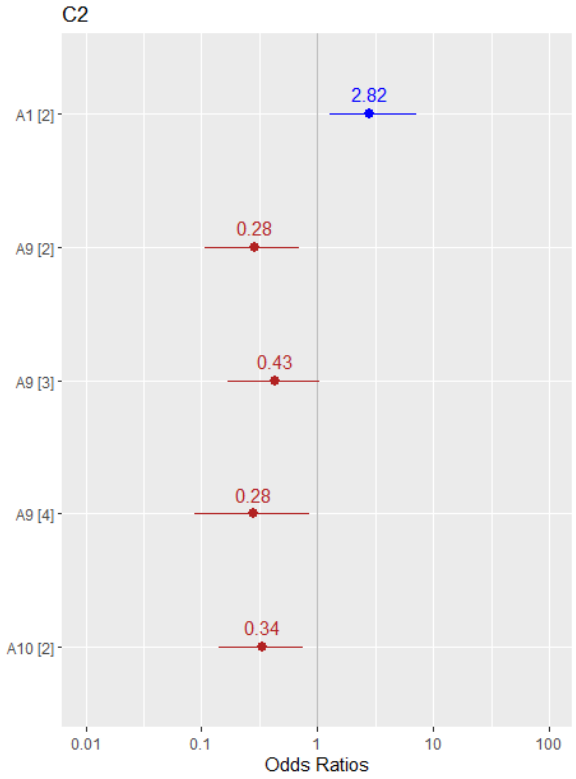


Figure 1. Odds ratios for predictors A1, A9, A10 of perceived readiness to work in a digitalized environment (C2)

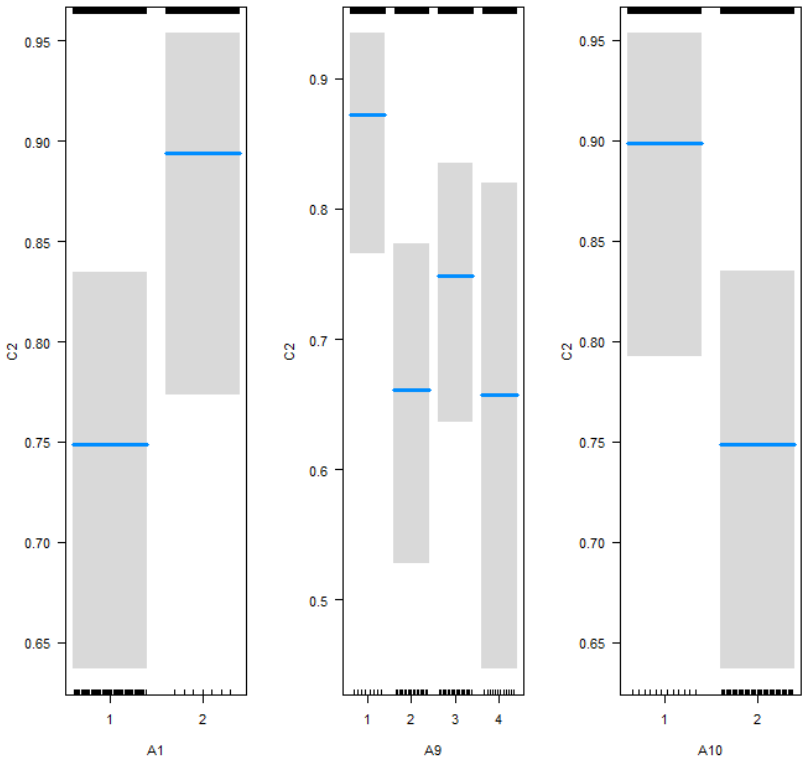


Figure 2. Predicted probabilities of a positive self-assessment of readiness to work in a digitalized environment (C2) by gender (A1), firm size (A9), and foreign capital participation (A10)

Table 2. Responses to Question B7

Options in question B7	Online forms of acquiring up-to-date (practical) knowledge	Very often	Often	Rarely	Never
B7_1	Social media, including: WhatsApp, Messenger, Facebook, LinkedIn	74	103	88	67
B7_2	Online publications	148	161	21	2
B7_3	Webinars	105	112	93	22
B7_4	E-learning	66	105	112	49
B7_5	Online training	115	138	65	14
B7_6	Media broadcasts	32	120	121	59
B7_7	Emails and chats with acquaintances	48	90	129	65
B7_8	Audio or audio/video communication tools (e.g., Skype, ClickMeeting, Zoom, Microsoft Teams)	69	114	102	47
B7_9	File-sharing platforms (e.g., Google Drive, OneDrive)	34	70	130	98
B7_10	Virtual whiteboard	3	19	90	220

To simultaneously account for relationships between observed variables and the latent variable describing the intensity of using informal online education in modern information technologies, structural equation modeling (SEM) was applied. This method enables the concurrent estimation of a measurement model, specifying the relationships between scale indicators and the latent construct, and a structural model, describing the effects of demographic and work environment variables on perceived readiness to work in a digitalized environment.

In this study, the latent variable (B7K) was operationalized using Likert-scale items measuring the frequency of use of informal online educational forms (Table 2, items B7_1–B7_10) and subsequently used as a predictor in the structural model. Estimation was conducted using the WLSMV estimator, which is appropriate for dichotomous and ordinal data, allowing for reliable parameter estimates and model fit indices. The model was estimated based on polychoric correlations (for Likert-scale items) and tetrachoric correlations (for binary variables).

In the first stage of the analysis, the measurement model was estimated using confirmatory factor analysis (CFA) to verify the unidimensionality of the latent variable describing the intensity of informal online education in modern information technologies (B7K). The latent construct was initially operationalized using ten four-point Likert-scale items (B7_1–B7_10). An analysis of standardized factor loadings (Table 3) indicated that item B7_1 exhibited a low loading (Std.all < 0.40), suggesting a weak association with the underlying construct (B7K). Consequently, this item was removed from further analyses, and the final measurement model included nine items (B7_2–B7_10).

In the subsequent stage, the structural model (SEM) was estimated, in which the latent variable B7K was included as a predictor of perceived readiness to work in a digitalized environment (C2), alongside selected demographic and work environment variables: gender (A1), degree of workplace digitalization (C1), and frequency of contact with IT specialists (C5). Other demographic variables (age, education) and work environment variables (job position, professional experience, work system, organization of internal training, and access to ongoing IT support) were not included in the SEM modeling because they were not statistically significant. The results of the structural model estimation after removing indicator B7_1 from the measurement model are presented in Table 4 and Figure 3.

Table 3. Standardized factor loadings and indicator evaluation for the latent variable B7K in the measurement model (CFA)

Indicator (options in question B7)	Estimate	Std. Err	z-value	p-value	Standardized loading (Std. all)	Evaluation
B7_1	1.000	–	–	–	0.240	weak – excluded
B7_2	1.737	0.432	4.020	0.000	0.436	acceptable
B7_3	2.932	0.699	4.191	0.000	0.736	very good
B7_4	3.074	0.731	4.206	0.000	0.772	very good
B7_5	2.868	0.711	4.035	0.000	0.720	very good
B7_6	2.487	0.614	4.051	0.000	0.624	good
B7_7	2.149	0.485	4.426	0.000	0.539	acceptable
B7_8	2.641	0.633	4.171	0.000	0.663	good

Indicator (options in question B7)	Estimate	Std. Err	z-value	p-value	Standardized loading (Std. all)	Evaluation
B7_9	2.518	0.585	4.303	0.000	0.632	good
B7_10	2.571	0.629	4.085	0.000	0.645	good

Note: Standardized factor loadings (Std.all) are reported. Loadings ≥ .70 were interpreted as very good, 0.50–0.69 as good, 0.40–0.49 as acceptable, and < .40 as weak. Indicator B7_1 was excluded from further analyses due to a weak loading.

Table 4. Predictors of perceived readiness to work in a digitalized environment (C2) – structural model (SEM)

Predictor	Estimate	Std. Error	z-value	p-value	Std. all
B7K (latent variable)	0.456	0.195	0.019	0.019	0.174
A1 (gender)	0.431	0.215	2.003	0.045	0.163
C1 (digitalized workplace)	–1.815	0.324	–5.607	0.000	–0.375
C5 (contact with IT specialist)	0.523	0.215	2.433	0.015	0.219

Note: Estimates after excluding indicator B7_1.

The overall model fit was assessed using standard fit indices (CFI, TLI, RMSEA, SRMR), the values of which are reported in Table 5. The obtained indices indicate an acceptable fit of the model to the data, and the model meets the criteria recommended for SEM analyses with ordinal data estimated using the WLSMV method.

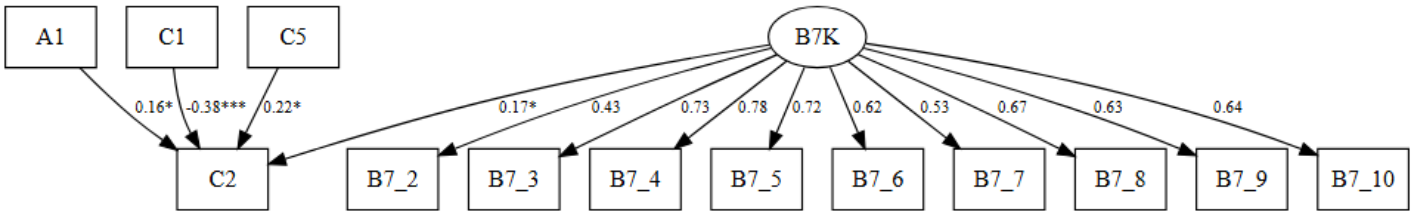
Table 5. Assessment of SEM model fit

Indicator	Indicator value	Criterion	Assessment
χ^2 (df)	χ^2 (62) = 218.57, p < .001	p > 0.05 (rare with large N)	acceptable
CFI	0.944	≥ 0.95 very good; ≥ 0.90 acceptable	good
TLI	0.959	≥ 0.95 very good; ≥ 0.90 acceptable	very good
RMSEA	0.087	≤ 0.05 very good; ≤ 0.08 good	acceptable
SRMR	0.084	≤ 0.05 very good; ≤ 0.08 good	acceptable

The obtained fit indices indicate an acceptable fit of the model to the data. Despite the statistically significant chi-square test, which is typical of models estimated from large samples, the CFI and TLI values were good. The RMSEA and SRMR indices are at the threshold of acceptability, suggesting a moderate yet permissible model fit. Overall, the results confirm the correctness of both the measurement and structural model specifications.

The results of the structural model estimation indicate that self-assessed preparedness to work in a digitalized environment (C2) is shaped primarily by work environment factors, such as the degree of workplace digitalization (C1) and the frequency of contact with IT specialists (C5). The intensity of informal online education (B7K) plays a significant supportive role, while gender (A1) differentiates the level of declared readiness to a moderate extent. Taken together, these findings confirm that the development of readiness to work in a digitalized environment is a multidimensional process that combines work environment conditions with individual learning strategies.

Figure 3 presents the structural equation model, including the measurement model for the latent variable B7K and the structural paths predicting perceived readiness to work in a digitalized environment (C2). Standardized SEM regression coefficients are reported. The model illustrates the direct effects of selected work environment variables (C1 and C5), the demographic variable (A1), and the latent construct representing informal knowledge acquisition (B7K) on perceived readiness to work in a digitalized environment (C2). Although the initial conceptual framework assumed a mediating role of informal online education (B7K), the estimated indirect effects were not statistically significant, and their confidence intervals included zero. Therefore, the mediating mechanism was not empirically supported.



Note: Standardized estimates are shown after excluding indicator B7_1. Asterisks denote statistically significant regression paths ($p < 0.05$).

Figure 3. Structural equation model of perceived readiness to work in a digitalized environment

The latent variable B7K, reflecting the intensity of informal online education in the field of information technologies, shows a statistically significant, positive effect on self-assessed preparedness to work in a digitalized environment (C2). This means that individuals who more frequently use various online knowledge sources – such as online publications, webinars, e-learning, online training, media content, emails and chats, online communication tools, file-sharing platforms, and virtual whiteboards – are more likely to report a higher level of readiness to function in a digitalized environment. Although this effect is moderate, it remains statistically significant after controlling for work environment factors supporting the digitalization process and demographic characteristics, indicating that self-directed and informal learning play a genuine supporting role in the development of digital competences. Among online knowledge sources, respondents most frequently use e-learning (0.78), webinars (0.73), and online training (0.72).

Respondent gender (A1) differentiates the level of declared readiness to work in a digitalized environment. The positive regression coefficient indicates that one gender group (according to the adopted coding, men) more frequently declares a higher level of preparedness. This effect is moderate in magnitude but remains significant even after accounting for work environment factors supporting the digitalization process and the use of informal online education. This result may reflect differences in professional experience, the scope of tasks performed, or exposure to information technologies, without implying actual differences in competencies. However, the effect of gender on perceived readiness to work in a digitalized environment is attenuated after including informal knowledge acquisition (B7K – intensity of using online knowledge sources) and work environment factors supporting digitalization in the model. This indicates that part of the differences between women and men in declared readiness results from differences in the use of online knowledge resources and work environment conditions, rather than from gender alone.

The variable describing the "degree of workplace digitalization" (C1) exhibits the strongest effect among all analyzed predictors. The direction and magnitude of the effect indicate that everyday work contact with information technologies significantly shapes the sense of readiness to work in a digital environment. In practical terms, this means that respondents employed in positions that intensively use IT tools are more likely to report a high level of self-assessed preparedness, regardless of gender or type of further education. This finding confirms the key importance of "learning by doing" in the development of digital competences.

The "frequency of contact with IT specialists" (C5) has a significant and positive effect on perceived readiness to work in a digitalized environment. This suggests that ongoing technical support and the possibility of consulting with IT experts increase the sense of security and competence in using information technologies. This effect highlights the role of technological support as a factor strengthening the subjective assessment of preparedness to work in a digitalized environment, complementing the effect of the degree of workplace digitalization itself.

To analyze relationships among demographic factors, enterprise organizational characteristics, work environment factors, and educational factors, and perceived readiness to work in a digitalized environment, two complementary models were applied: logistic regression (GLM) and structural equation modeling (SEM). The logistic regression model (GLM) was used to test the direct relationships between selected respondent characteristics (A1, A9, A10) and the binary dependent variable (C2), reflecting respondents' self-assessment of their preparedness to work in a digitalized environment. Structural equation modeling (SEM) was employed to test theoretical assumptions. In the SEM framework, the latent variable B7K represents the intensity of using informal online sources to acquire up-to-date knowledge, while variables A1, C1, and C5 represent demographic and work environment factors that support the digitalization process and influence responses to question C2.

The logistic regression model (GLM) and structural equation modeling (SEM) applied in this study do not compete with one another but rather address different levels of hypothesis verification. The GLM identifies direct differences in

the probability of declaring readiness to work in a digitalized environment, answering the question of which respondent groups are more likely to report a positive self-assessment of preparedness. In contrast, the SEM explains the structure of these relationships by reconstructing the links between demographic and work environment factors supporting digitalization and perceived readiness to work in a digitalized environment, while accounting for the latent variable B7K, which represents the intensity of use of informal online sources of up-to-date knowledge. Thus, the results of both approaches are complementary: logistic regression indicates that "who" is more frequently the one who declares readiness to work in a digitalized environment, whereas structural equation modeling explains "why" and in what organizational and cognitive contexts this readiness develops, highlighting the role of the intensity of use of online knowledge sources.

Below, the results of the verification of hypotheses H1–H3 regarding the determinants of perceived readiness to work in a digitalized environment are presented using GLM and SEM models. Both the direct effects of demographic, organizational, and work environment factors and the indirect effects of informal online education were analyzed. A detailed summary of the results of hypothesis testing for H1–H3 is provided in Table 6.

Table 6. Verification of hypotheses H1–H3 using GLM and SEM models (C2 – dependent variable)

Hypothesis	Model	Predictor	Effect direction	Effect size	p-value	Conclusion
H1	GLM	A1 (gender)	positive	OR=2.82	< 0.05	supported
H1	GLM	A9 (firm size)	negative	OR=0.28–0.43	< 0.05	supported
H1	GLM	A10 (foreign capital)	negative	OR=0.34	< 0.05	supported
H2	SEM	B7K (latent variable)	positive	β=0.17	< 0.05	supported
H3	SEM	A1 (gender)	positive	β=0.16	0.045	supported
H3	SEM	C1 (digitalized workplace)	negative	β=−0.38	< 0.001	supported
H3	SEM	C5 (contact with IT)	positive	β=0.22	< 0.05	supported

Note: GLM = Generalized Linear Model (logistic regression). SEM – Structural Equation Modeling. OR – odds ratio. β – standardized regression coefficient. Statistical significance was evaluated at $p < 0.05$. Predictor B7K represents a latent construct measured by Likert-scale indicators capturing the intensity of internet-based knowledge acquisition.

Hypothesis H1 posits relationships among selected demographic factors, enterprise organizational characteristics, and the level of perceived readiness to work in a digitalized environment. The verification of Hypothesis H1 was conducted using a logistic regression model (GLM). The results indicate that respondents' gender (A1), enterprise size (A9), and foreign capital participation (A10) significantly differentiate the probability of providing a positive response to question C2, which asks about self-assessment of being well prepared to work in a digitalized environment. The obtained findings confirm Hypothesis H1 and demonstrate that perceived readiness to work in a digitalized environment is not solely an individual employee characteristic but is, to a significant extent, conditioned by the enterprise's organizational context.

Hypothesis H2 assumes that the intensity of using informal online education in modern information technologies is associated with respondents' perceived readiness to work in a digitalized environment, while accounting for demographic characteristics, particularly gender, and work environment factors supporting the digitalization process (degree of workplace digitalization and frequency of contact with IT specialists).

The verification of Hypothesis H2 was supported by structural equation modeling (SEM) results, as logistic regression does not allow for modeling relationships involving latent variables. The SEM results indicate a significant positive relationship between the latent variable B7K, representing the intensity of informal online education use, and perceived readiness to work in a digitalized environment (C2). This means that more frequent use of online knowledge sources is associated with higher perceived readiness for work in digitally transformed workplaces. At the same time, the effect of gender (A1) on C2 becomes weaker after B7K and work environment factors are included in the model. This result suggests that differences in perceived readiness to work in a digitalized environment may partly reflect different patterns of informal knowledge acquisition from various online sources.

Overall, the obtained results support Hypothesis H2 and highlight the important role of informal learning and access to online knowledge sources in shaping employees' readiness to work in a digitalized environment.

Hypothesis H3 assumes significant relationships between respondents' gender and work environment factors supporting the digitalization process, including the degree of workplace digitalization, the frequency of contact with IT specialists, and perceived readiness to work in a digitalized environment. Hypothesis H3 was verified primarily based on the results of the structural equation model (SEM), which enabled the simultaneous assessment of the effects of gender

(A1) and work environment characteristics – particularly the level of workplace digitalization (C1) and more frequent contact with IT specialists (C5) – on perceived readiness to work in a digitalized environment (C2), while accounting for the intensity of using online knowledge sources (B7K). The logistic regression model provides only complementary information on direct differences between groups and does not test the underlying mechanisms of these relationships. The results confirm Hypothesis H3 and indicate that the readiness of accounting department employees to work in a digitalized environment is shaped by both gender and the degree of workplace digitalization, as well as the frequency of contact with IT specialists.

Table 7 presents the distribution of respondents' answers to question C17 on a five-point Likert scale: "What opportunities and threats for accountants/managers arise from the development of the digital economy?" Among the most important opportunities, respondents indicated, inter alia, the elimination or minimization of routine and repetitive accounting tasks, improved work organization and information flow within enterprises, and increased attention to data security and compliance with principles of data processing, analysis, and storage. A key challenge for respondents is undoubtedly continuous training in the use of new information technologies. The main threat identified by respondents was the potential loss of employment, cited by 42.5%.

Table 7. Responses to Question C17

Options in Question C17	Opportunities and threats for the respondents resulting from the development of the digital economy	Strongly YES				Strongly NO
		5	4	3	2	1
C17_1	The development of new technologies has a positive impact on the work of an accountant/manager	134	136	50	9	3
C17_2	Greater attention to data security and compliance with rules for data processing, analysis, and storage	118	146	57	10	1
C17_3	Improved organization of work and information flow within the enterprise	150	123	48	8	3
C17_4	The use of IT technologies has reduced errors and distortions in accounting information	118	130	54	22	8
C17_5	Elimination or minimization of routine and repetitive accounting activities	153	111	51	10	7
C17_6	Possibility of placing greater emphasis on soft skills, e.g., building interpersonal relationships within the enterprise	83	95	97	36	21
C17_7	Improved efficiency of the accountant's/manager's work	119	135	66	7	5
C17_8	Greater creativity in task execution, as well as financial and business decision-making	74	127	96	19	16
C17_9	Greater possibilities of intentional influence on information presented in financial statements	73	118	97	32	12
C17_10	Continuous education in the use of modern information technologies	115	137	60	16	4
C17_11	Greater attention to data security and compliance with the rules for data processing, analysis, and storage	142	123	50	12	5
C17_12	Reduction of the costs of maintaining finance and accounting departments in enterprises	74	102	92	33	31
C17_13	Possibility of job loss	80	61	100	51	40

Modern information technologies, which underpin the digital economy, significantly influence changes in respondents' work. While working in a digitalized environment that requires appropriate competences and skills in the use of information technologies, respondents are aware of the need to continuously expand their knowledge in this area through ongoing learning, the use of support from IT specialists, and access to appropriate information technology tools.

DISCUSSION

Develi et al. (2022) divided the determinants of job satisfaction into individual factors (age, gender, position, professional experience, education) and organizational factors (job description, remuneration, employee rights, work environment, motivation). In the literature on the digitalization of the accounting profession, both categories have been examined to varying extents. Our study indicates that both individual and organizational factors significantly influence the perceived readiness of accounting employees to work in a digitalized environment. The findings of Grosu et al. (2023), in turn,

indicate that readiness to develop digital competences depends on perceived necessity, benefits, and awareness of the effort required to acquire such skills, as well as on situational factors such as organizational culture and regulatory policies. This implies that employees' decisions to enhance their digital competences are motivated not only by personal predispositions but also by the organizational context and access to appropriate educational resources.

The discussion focuses on selected determinants that significantly influenced perceived readiness to work in a digitalized environment. The analysis considered factors that demonstrated statistically significant and differentiated effects on perceived readiness, in particular, gender, enterprise size, foreign capital participation, degree of workplace digitalization, frequency of contact with IT specialists, and informal online education in modern information technologies.

The analysis revealed significant differences in perceived readiness depending on respondents' gender. According to the results, men declared approximately 2.8 times higher odds of a positive self-assessment of perceived readiness compared with women. This finding is consistent with previous observations concerning gender differences in self-assessed digital competences (Santonastaso & Macchioni, 2022; Gorbacheva et al., 2016). The literature emphasizes that lower self-assessments of digital competences among women stem mainly from socio-cultural factors, such as stereotypes regarding women's technological abilities or limited access to earlier technological experiences, rather than from biological predispositions (Lenard et al., 2010; Awang et al., 2021).

At the same time, the results indicate that part of the differences in declared readiness to work in a digitalized environment between women and men is explained by the use of informal online knowledge sources. The intensity of self-directed learning in modern technologies increased the level of self-assessed professional preparedness, and its inclusion in the model attenuated the direct effect of gender. This suggests that differences in perceived readiness are not determined solely by gender but also depend substantially on how technological knowledge and experience are acquired. In this sense, the present study confirms the observations of Lenard et al. (2010), according to which education and digital practice effectively increase women's confidence in computer-related competences, and at the same time highlights the role of informal online education in shaping digital readiness.

The results also confirm that women more frequently use online forms of education, consistent with studies indicating their greater propensity to engage in developmental activities in the area of digital competences (Awang et al., 2021). At the same time, men more often declare high readiness to work in a digitalized environment, which, according to the literature, does not necessarily reflect actual levels of digital skills (Cooper, 2006; Santonastaso & Macchioni, 2022). Studies by Biyikli and Çetin (2023) further show that women more frequently report difficulties and lower satisfaction with the technologies used. These findings suggest that observed differences in readiness to work in a digitalized environment may primarily result from differing patterns of self-assessment of technological competences.

The organizational context of the enterprise also plays a significant role in shaping readiness to work in a digitalized environment among the surveyed employees. Both enterprise size and foreign capital participation significantly differentiate the probability of declared readiness. Employees of small enterprises and capital groups exhibited lower readiness than employees of other enterprises (including large ones), while micro-enterprises had the highest predicted probability of a positive self-assessment in this regard. In microenterprises, greater employee autonomy and the need to use digital tools independently may foster higher self-assessed technological competencies. In small enterprises, digitalization is often fragmented, and limited organizational support may reduce the subjective sense of readiness. In capital groups, lower declared readiness may result from a high degree of formalization, complexity of IT processes, and limited employee autonomy. These interpretations are explanatory in nature and require further in-depth research. Higher readiness in enterprises with foreign capital participation may, in turn, reflect a more developed digital environment and broader use of advanced information systems. These findings are consistent with the conclusions of Stoica and Ionescu-Feleagă (2021), who demonstrated that enterprise size differentiates the scope of technologies used, as well as with observations by Taib et al. (2023) and Kotowska and Sikorska (2023), which emphasize the role of organizational specificity in shaping awareness of the need to develop technological competences.

Among all analyzed predictors, the degree of workplace digitalization exerted the strongest influence on perceived readiness to work in a digitalized environment. This result confirms the importance of everyday, direct contact with information technologies for building a sense of preparedness to function in a digital environment. Respondents employed in positions that intensively use IT tools more often declared high self-assessed readiness, regardless of gender or forms of further education. This observation confirms the importance of learning by doing and highlights the contextual nature of digital readiness, shaped through interactions between individual competences and organizational and technological conditions (Abdul Hamid, 2022; Tarafdar et al., 2015).

The frequency of contact with IT specialists also emerged as a significant and positive predictor of readiness. Access to ongoing technical support and the possibility of consulting IT experts reduces uncertainty and technological strain, strengthening the sense of competence and security in using technologies (Tarafdar et al., 2015). This result is consistent with the findings of Safi et al. (2024) and Suhada et al. (2026), who emphasize the importance of IT support as a key organizational factor facilitating technological adaptation.

The study also confirms the significant role of informal online education in shaping readiness to work in a digitalized environment. At the same time, the level of formal education did not prove to be a significant predictor of this readiness. Although the literature suggests that higher education fosters the development of information-processing skills and the use of online resources (Hargittai & Shafer, 2006; Hinterhuber & Pavone, 2020), the results indicate that, in a professional context, current and practical sources of knowledge, as well as direct support from IT experts, are of key importance. The intensive use of online knowledge sources was associated with higher perceived readiness to work in a digitalized environment and helped explain some gender-related differences in self-assessed preparedness, suggesting that formal education alone is limited in enhancing the subjective sense of preparedness for work.

The limited role of internal training as a factor differentiating readiness to work in a digitalized environment is one of the study's more complex findings. Although the literature emphasizes the importance of training in developing the digital competences of accounting employees (Pargmann et al., 2023; Hasin et al., 2022), the results revealed an effect that was the opposite of expectations. The organization of internal training was associated with lower declared readiness to work in a digitalized environment. This phenomenon may result from the general or incidental nature of such training, its misalignment with rapidly changing competence needs, or the fact that training increases awareness of competence gaps and the complexity of IT tools, leading respondents to make more critical self-assessments. It should also be noted that training may be organized in response to previously identified knowledge and skill deficits, meaning that its frequent implementation does not necessarily stimulate development but rather signals existing problems in technological preparedness. These results do not undermine the importance of training as a competence development tool but instead point to the complex and contextual nature of its impact on digital readiness assessment, which depends on both the quality of training programs and their implementation within enterprises.

The lack of a significant effect of age on perceived readiness to work in a digitalized environment may be attributed to the specificity of the studied sample. Respondents were professionally active employees in the financial and accounting sector, operating in environments with high demands for continuous learning and adaptation to technological change. Under such conditions, intergenerational differences may be flattened, as workplace pressure forces the development of digital competencies regardless of age. These results are consistent with those of Steens et al. (2024), indicating that as technological awareness increases, so does the reported need for further learning.

In summary, the readiness of the surveyed accounting department employees to work in a digitalized environment is shaped by complex interactions among demographic, organizational, work environment, and educational factors. The study results indicate that effective support for digital readiness requires not only technological investments but also the creation of an environment conducive to informal learning and the provision of easy access to IT support.

CONCLUSION

The study aimed to identify and assess the impact of selected demographic factors, enterprise-related organizational factors, work environment characteristics, and informal online education in modern information technologies on the perceived readiness of accounting department employees to work in a digitalized environment.

Regarding the main research question (Q), it was found that the perceived readiness of the surveyed accounting department employees to work in a digitalized environment is shaped by a variety of demographic, enterprise-related organizational factors, work environment–related factors, and informal online education factors. The significant determinants include respondents' gender, enterprise size, participation in foreign capital, degree of workplace digitalization, frequency of contact with IT specialists, and informal online education in modern technologies.

Most respondents accept the digitalization of their work environment and perceive it as an inevitable element of contemporary professional practice (question Q1). They demonstrate a high awareness of the need to develop digital competences, reflected in the perceived necessity of upgrading qualifications in modern technologies. At the same time, digitalization is evaluated both as a source of benefits and as a source of challenges, mainly related to the requirement for continuous education. Respondents perceive numerous benefits of digitalization, such as the automation of routine tasks,

improved work organization, and increased data security. The main threat identified by respondents is the risk of job loss as a result of the automation of accounting processes.

Most respondents positively assess their preparation for working in a digitalized environment (question Q2), although the sources of this preparation are diverse. A high proportion of respondents declaring satisfaction with formal education indicates that it meets their subjective expectations; however, the lack of statistical significance of this factor suggests its limited impact on the actual development of digital competences. At the same time, 82.2% of respondents considered themselves well prepared to work in a computerized environment, which may be linked to lifelong learning activities and the use of various knowledge sources, including online resources. This confirms the importance of informal online education, which was included in the statistical modeling as a latent construct representing the intensity of using online knowledge sources.

The nearly even distribution of responses regarding the presence of technological topics in formal education offerings (48.5% affirmative responses) points to the diversity of educational programs and a competence gap largely filled through informal online education.

Selected demographic and enterprise-related organizational factors significantly differentiate the probability of declaring readiness to work in a digitalized environment (Hypothesis H1). Respondents' gender, enterprise size, and foreign capital participation were statistically significant, with the highest level of declared readiness observed among men employed in other (including large) enterprises with foreign capital participation. These results indicate that an organizational environment conducive to the use of advanced information technologies and access to modern digital solutions strengthens the sense of competence and readiness to work under conditions of ongoing digitalization.

The results confirm that the intensity of using informal online education in modern information technologies is positively associated with perceived readiness to work in a digitalized environment, while accounting for gender and work environment factors supporting the digitalization process, such as the degree of workplace digitalization and the frequency of contact with IT specialists (Hypothesis H2).

More frequent use of online knowledge sources is associated with higher self-assessed readiness to work in a digitalized environment, while the partial attenuation of the gender effect suggests that men and women differ in the extent to which they use informal online education. This finding confirms that digital competences develop not only within formal educational pathways but largely through self-directed, flexible, and continuous learning, which is consistent with the assumptions of the Mulder competence model emphasizing lifelong learning and the adaptive nature of competences.

The study results also confirm that respondents' perceived readiness to work in a digitalized environment is significantly shaped by both gender and work environment factors supporting the digitalization process (hypothesis H3). A higher degree of workplace digitalization and more frequent contact with IT specialists foster a higher self-assessment of readiness to function in a digital environment. These results indicate that, in addition to individual characteristics, organizational and technical working conditions play a key role, as they may either strengthen or constrain employees' ability to adapt during the digitalization process.

In summary, the conducted study addresses the research gap identified in the introduction and confirms that respondents' perceived readiness to work in a digitalized environment is shaped by both individual characteristics – particularly gender – and by enterprise-related organizational factors, work environment conditions, and informal online education. The findings align with the stream of research emphasizing the contextual nature of competences, which develop through interactions with technology, organization, and learning opportunities, in accordance with the assumptions of the Mulder model.

The theoretical implications of the study concern confirming the contextual character of digital competences, which develop through interactions among technology, organization, and educational processes. An important contribution is also the empirical demonstration of the role of informal online education in the relationships between gender, the work environment, and perceived readiness to work in a digitalized environment.

From a managerial practice perspective, the results suggest that practical implications include supporting the readiness of accounting department employees to work in a digitalized environment and creating a work environment conducive to the development of digital competencies. In particular, the following are recommended: strengthening the digitalized work environment; ensuring ongoing IT support; promoting informal online education (supporting e-learning, webinars, and online training, co-financing access to educational platforms, and recognizing the outcomes of informal education in employee evaluation systems); integrating informal education with everyday work (enabling learning during work, for example through access to online educational materials); revising the formula of internal training programs (the lack

of a significant effect of internal training on perceived readiness suggests the need for better alignment with employees' actual needs); and managing employees' concerns related to digitalization (e.g., fears of job loss indicate the need for communication and educational initiatives emphasizing technology as a tool that supports work).

The study is subject to certain limitations. The results apply only to the surveyed group of respondents and cannot be generalized to the entire population of accounting department employees in Poland. The study is based on declarative self-assessments of readiness to work in a digitalized environment, which may involve the risk of subjectivity.

Future research should include longitudinal studies enabling the analysis of the development of digital competences and changes in perceived readiness over time. It would also be valuable to incorporate objective measures of digital competences and in-depth qualitative analyses to better understand learning strategies and barriers to technological adaptation in the accounting profession.

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Appendix A. Additional tables

Table A1. Characteristics of the analyzed sample – respondents' profile (Part A of the questionnaire)

Respondents' particulars	**Categories (options)**	**All respondents (N = 332; 100%)**	
		n	%
A1. Gender	☐ female	254	77
	☐ male	78	23
A2. Age (generational ranges)	☐ up to 1964	33	10
	☐ 1965-1980	116	35
	☐ 1981-1994	136	41
	☐ after 1995	47	14

Respondents' particulars	Categories (options)	All respondents (N = 332; 100%)	
		n	%
A3. Education	☐ vocational education	0	0
	☐ secondary education	23	7
	☐ higher education – bachelor/engineer	41	12
	☐ higher education – master	250	75
	☐ phd or higher	18	6
A4. Education profile	☐ economics	256	77
	☐ law	16	5
	☐ technical	28	8
	☐ other	32	10
A5. Work position	☐ manager	63	19
	☐ accountant	204	62
	☐ financial analyst	21	6
	☐ other	44	13
A6. Workplace (if accountant)	☐ employee in an enterprise	146	44
	☐ employee in an accounting office	89	27
	☐ employee of an outsourcing corporation	50	15
	☐ employee of a public sector institution	47	14
A7. Professional experience in years	☐ up to 10	133	40
	☐ from 11 to 20	96	29
	☐ from 21 to 30	72	21
	☐ from 31 to 40	25	8
	☐ 41 and more	6	2
A8. Work system	☐ on-site work	137	41
	☐ remote work	26	8
	☐ hybrid (on-site and remote work)	169	51
A9. Size of the enterprise in which the respondent works	☐ micro	69	21
	☐ small	71	21
	☐ other	114	34
	☐ capital group	78	24
A10. Foreign capital participation in the enterprise	☐ yes	111	33
	☐ no	221	67

Table A2. Codebook of variables used in the analysis

Variable	Questionnaire item	Coding	Type	Role in analysis
C2	Are you well prepared to work in a digitalized environment?	1 = Yes 2 = No	Binary	Dependent variable (GLM, SEM)
A1	Gender	1 = Female; 2 = Male	Categorical	Predictor
A9	Size of the enterprise	1 = Micro enterprise 2 = Small enterprise 3 = Other enterprises 4 = Capital group	Categorical	Predictor (GLM)
A10	Presence of foreign capital in the enterprise	1 = Yes; 2 = No	Binary	Predictor (GLM)
C1	Is your workplace digitalized?	1 = Yes 2 = No	Binary	Predictor (SEM)
C5	Has the development of the digital economy increased the frequency of contacts with IT specialists in your workplace?	1 = Yes 2 = No	Binary	Predictor (SEM)
B7_2–B7_10	Frequency of using specific online sources of knowledge in the field of modern information technologies	1 = Never 2 = Rarely 3 = Often 4 = Very often	Ordinal (Likert)	Indicators of latent variable
B7K	Intensity of using informal online knowledge sources	Latent construct estimated from indicators B7_2–B7_10	Latent variable	Predictor (SEM)

Note: The table presents the variables used in the empirical analysis together with their questionnaire items, coding schemes, data types, and roles in the statistical models (GLM and SEM).

Appendix B. Survey questionnaire

SURVEY QUESTIONNAIRE

on the sustainable development of the accounting profession in the areas of:
knowledge – digitalization – ethics

Dear Sir or Madam,

We kindly ask you to complete this survey questionnaire. The purpose of the study is to diagnose the sustainable development of the accounting profession across three areas: knowledge, digitalization, and ethics. Researchers from the Cracow University of Economics, the University of Economics in Katowice, and the Wroclaw University of Economics and Business conduct the study. The survey is anonymous and the collected data will be used solely for statistical analysis.

PART A. RESPONDENT CHARACTERISTICS

1	Gender	☐ Female ☐ Male
2	Age (generational ranges)	☐ Up to 1964 ☐ 1965–1980 ☐ 1981–1994 ☐ From 1995
3	Education	☐ Vocational education ☐ Secondary education ☐ Higher education – Bachelor/Engineer ☐ Higher education – Master ☐ PhD or higher
4	Education profile	☐ Economics ☐ Law ☐ Technical ☐ Other: …….
5	Work position	☐ Manager ☐ Accountant ☐ Financial analyst ☐ Other: …….
6	Workplace (if accountant)	☐ Employee in enterprise ☐ Employee in accounting office ☐ Employee in outsourcing corporation ☐ Employee in public sector institution
7	Professional experience in years	Years of work: ……..
8	Work system	☐ On-site work ☐ Remote work ☐ Hybrid (on-site and remote work)
9	Size of enterprise	☐ Micro ☐ Small ☐ Other ☐ Capital group
10	Foreign capital participation in the enterprise	☐ Yes ☐ No

PART B. KNOWLEDGE OF THE ACCOUNTANT/MANAGER

1. Which educational forms do you use? (multiple answers possible)
   ☐ Courses and training at the Accountants Association in Poland
   ☐ Courses organized by commercial entities
   ☐ Postgraduate studies in accounting

☐ MBA (Master of Business Administration)
☐ CIMA (Chartered Institute of Management Accountants)
☐ ACCA (Association of Chartered Certified Accountants)
☐ IMA (Institute of Management Accountants)
☐ Other: _____

2. What motivated you to undertake education? (multiple answers possible)
☐ Expansion of theoretical and practical knowledge
☐ Learning modern methods and software
☐ Career advancement
☐ Prestige and recognition
☐ Increase of competences (intellectual capital)
☐ Mandatory training
☐ Other: _____

3. Did the undertaken education meet your expectations satisfactorily?
☐ Yes
☐ No

4. Does the educational offer include modern IT technologies?
☐ Yes
☐ No

5. Which thematic area is particularly important? (multiple answers possible)
☐ Accounting in a digital environment
☐ Management in a digital environment
☐ Corporate finance
☐ Strategic management
☐ Human capital management
☐ Business management
☐ Taxes (PIT, CIT, VAT) / tax strategies
☐ Small business accounting
☐ Management accounting
☐ Cost accounting
☐ Controlling
☐ Reporting and analysis
☐ Ethics and social responsibility
☐ Other: _____

6. Should improving qualifications in modern technologies be obligatory?
☐ Yes
☐ No

7. To obtain up-to-date knowledge, how often do you use the following?

Specification	Very often	Often	Rarely	Never
Social media	☐	☐	☐	☐
Online publications	☐	☐	☐	☐
Webinars	☐	☐	☐	☐
E-learning	☐	☐	☐	☐
Online training	☐	☐	☐	☐

Specification	Very often	Often	Rarely	Never
Mass media	☐	☐	☐	☐
Emails and chats	☐	☐	☐	☐
Audio/video communication tools	☐	☐	☐	☐
File-sharing platforms	☐	☐	☐	☐
Virtual whiteboard	☐	☐	☐	☐

PART C. DIGITALIZATION OF THE ACCOUNTING/MANAGERIAL PROFESSION

1. Is your work environment computerized?
   ☐ Yes
   ☐ No

2. Are you well prepared to work in a computerized environment?
   ☐ Yes
   ☐ No

3. Does your enterprise organize internal IT training?
   ☐ Yes
   ☐ No

4. Does your enterprise provide ongoing IT support?
   ☐ Yes
   ☐ No

5. Has digital economy development increased contact with IT specialists?
   ☐ Yes
   ☐ No

6. How often do you use the following tools?

Specification	Very often	Often	Rarely	Never
Financial and accounting software	☐	☐	☐	☐
Cloud computing	☐	☐	☐	☐
Online accounting	☐	☐	☐	☐
Advanced Excel	☐	☐	☐	☐
Blockchain	☐	☐	☐	☐
Big Data	☐	☐	☐	☐
Data Science	☐	☐	☐	☐
Python	☐	☐	☐	☐
Databases (SQL Server, Oracle)	☐	☐	☐	☐
Microsoft Power BI	☐	☐	☐	☐
Artificial Intelligence	☐	☐	☐	☐

7. Are blockchain technologies an important factor in accounting development?
   ☐ Yes
   ☐ No

8. Do digital solutions significantly impact the accounting profession?
   ☐ Yes
   ☐ No

9. Do you use structured invoices?
- ☐ Yes
- ☐ No
- ☐ The company plans to implement them

10. Does your F-K system allow data export based on user-defined criteria?
- ☐ Yes
- ☐ No

11. Available export formats:
- ☐ XLSX
- ☐ XML
- ☐ CSV
- ☐ TXT
- ☐ PDF
- ☐ DBF
- ☐ XTML
- ☐ Other: _____

12. Application server used in F-K system:
- ☐ No application server
- ☐ Oracle WebLogic Server
- ☐ Microsoft IIS
- ☐ JBoss Application Server
- ☐ IBM Application Server
- ☐ Other: _____

13. Will artificial intelligence replace accountants?
- ☐ Yes
- ☐ No

14. If yes, in what time horizon?
- ☐ Within 10 years
- ☐ Within 20 years
- ☐ More than 20 years

15. Does the use of modern technologies support enterprise development?
- ☐ Yes
- ☐ No

16. What makes it difficult to use new technologies?

Specification	Strongly YES				Strongly NO
	5	4	3	2	1
Cost of software licenses	☐	☐	☐	☐	☐
Continuous software changes	☐	☐	☐	☐	☐
Lack of access to training	☐	☐	☐	☐	☐
Cost of training	☐	☐	☐	☐	☐
Lack of time for training	☐	☐	☐	☐	☐

17. What opportunities and threats result from digital economy development?

Specification	Strongly YES				Strongly NO
	5	4	3	2	1
Positive impact on work	☐	☐	☐	☐	☐
Redesign of accounting procedures	☐	☐	☐	☐	☐
Improved organization and information flow	☐	☐	☐	☐	☐
Reduction of errors	☐	☐	☐	☐	☐
Elimination of routine activities	☐	☐	☐	☐	☐
Greater focus on soft skills	☐	☐	☐	☐	☐
Improved efficiency	☐	☐	☐	☐	☐
Greater creativity	☐	☐	☐	☐	☐
Greater influence on financial information	☐	☐	☐	☐	☐
Continuous IT education	☐	☐	☐	☐	☐
Greater data security concern	☐	☐	☐	☐	☐
Lower maintenance costs	☐	☐	☐	☐	☐
Risk of job loss	☐	☐	☐	☐	☐

18. Will digitalization depreciate the accounting profession?
☐ Yes
☐ No

19. Does digitalization influence remuneration?
☐ Yes
☐ No

20. Will accounting change radically due to digitalization?
☐ Yes
☐ No

PART D. ETHICS OF THE ACCOUNTING/MANAGERIAL PROFESSION

1. Should the accountants' social and economic role be reflected in their responsibility?
☐ Yes
☐ No

2. Do you know and comply with business ethics principles?
☐ Yes
☐ No

3. Does ratification of ethical principles increase professional status?
☐ Yes
☐ No

4. Does digitalization influence ethical behavior?
☐ Yes
☐ No

5. Does advanced digitalization require changes in ethical principles?
☐ Yes
☐ No

6. Which factors may influence unethical behavior?

Specification	Strongly YES				Strongly NO
	5	4	3	2	1
Pursuit of promotion and higher remuneration	☐	☐	☐	☐	☐
Fear of financial/criminal sanctions	☐	☐	☐	☐	☐
Improved work organization	☐	☐	☐	☐	☐
Concealing lack of knowledge	☐	☐	☐	☐	☐
Pressure from superiors	☐	☐	☐	☐	☐
Personality traits	☐	☐	☐	☐	☐
Emotions and over-optimism	☐	☐	☐	☐	☐
Opportunity without control	☐	☐	☐	☐	☐
Financial benefits	☐	☐	☐	☐	☐
Non-financial benefits	☐	☐	☐	☐	☐
Work stress	☐	☐	☐	☐	☐
Professional burnout	☐	☐	☐	☐	☐

Thank you for your time devoted to completing the questionnaire.

Biographical notes

Melania Bąk, PhD, DSc, Associate Professor at the Wroclaw University of Economics and Business, Department of Finance and Accounting. She is the author and co-author of numerous scientific articles, monographs, and educational publications in the fields of financial accounting and financial and non-financial reporting. She has supervised numerous master's and bachelor's theses and reviewed doctoral dissertations. She has also served as a lecturer and examiner for postgraduate accounting programs. She has reviewed monographs and scientific articles. Her research interests include accounting policy, behavioral and creative aspects of accounting, social responsibility in accounting, narratives in reporting, non-financial reporting, issues of intangible assets disclosed and undisclosed (invisible) in accounting, invisible property of an enterprise from an accounting perspective, and digitalization of the accounting profession. She is a member of the Accountants Association in Poland and the Finance and Accounting Association for Sustainable Development.

Andrzej Bąk, Professor, Department of Econometrics and Computer Science at the Faculty of Economics and Finance, Wroclaw University of Economics and Business. He is the editor-in-chief and a member of the Scientific Council of the journal *Research Papers of Wroclaw University of Economics and Business* and a member of the Editorial Board of the journal *Argumenta Oeconomica*. He is a member of the Council for Innovation in Higher Education and Science of the Ministry of Science and Higher Education. He is the author and co-author of monographs and scientific articles, student textbooks, and computer software for economic data analysis. He has served as a supervisor for doctoral dissertations and a reviewer for doctoral, habilitation, and professorial proceedings. He has reviewed numerous monographs and scientific articles. His research areas include microeconomics, marketing research, preference research, data analysis; microeconometrics, multivariate comparative analysis, simulation methods, machine learning and computer software used in economic research.

Marzena Strojek-Filus, PhD, DSc – chartered accountant (certified accountant certificate issued pursuant to a resolution of the Main Board of the Accountants Association in Poland – AAP register number 780), academic lecturer, employee of the Department of Accounting at the University of Economics in Katowice, author and co-author of numerous articles, scientific monographs, and educational publications in the field of financial accounting, financial reporting, including capital groups, and ESG reporting. Member of the Scientific Council of the Accountants Association in Poland (term 2023-2026) and the European Accounting Association, member of the Scientific Committee of the Economics and Finance discipline at the University of Economics in Katowice. Supervisor of doctoral dissertations and numerous master's theses. Manager and participant of research grants and implementation projects. Research areas: ESG reporting, financial reporting, consolidated financial statements, valuation in accounting, digitalization in accounting system.

Katarzyna Świetla is an Associate Professor at the Department of Financial Accounting at the College of Economics and Finance at the University of Economics in Krakow. Her research interests include financial statement consolidation in Polish and international corporations. An important area of her research is the analysis of multidimensional cost accounting and financial and accounting outsourcing at the national and transnational levels. She has published numerous articles and monographs in this field and has presented her research findings at national and international conferences. She is a member of the Accountants Association in Poland (SKwP), the European Accounting Association (EAA) and the International Association for Accounting Education and Research (IAAER).

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Author contribution statement

Melania Bąk: Conceptualization; Data Curation; Writing – Original Draft Preparation; Writing – Review & Editing. **Andrzej Bąk**: Data Curation; Formal Analysis; Software; Validation; Visualization; Writing – Original Draft Preparation. **Marzena Strojek-Filus**: Conceptualization; Data Curation; Writing – Original Draft Preparation; Writing – Review & Editing. **Katarzyna Świetla**: Conceptualization; Data Curation. **Monika Turek-Radwan**: Conceptualization; Data Curation.

Conflicts of interest

The authors declare no conflicts of interest.

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Pathways to innovation in Colombian service SMEs: The role of funding, institutions, and intangible investments

***Yaneth P. Romero-Alvarez*[1], *Katherinne Salas-Navarro*[2], *Lisana B. Martinez*[3]**

Abstract

PURPOSE: *This study investigates the multidimensional factors associated with innovation outcomes among innovation-active small and medium-sized enterprises (SMEs) in the Colombian service sector, an emerging economy characterized by financial asymmetries and fragmented innovation support and knowledge-transfer frameworks. The objective is to examine how aggregate funding structures, institutional linkages, and innovation-oriented investments relate differentially to the incidence of product innovation (market-oriented) and process innovation (internally oriented). By disentangling these pathways among innovation-active firms, the study provides evidence on how resource configurations shape innovation trajectories in contexts with relatively low technological intensity.* ***METHODOLOGY:*** *The study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) using firm-level microdata from 2,782 innovation-active service-sector SMEs derived from Colombia's VIII Survey of Technological Development and Innovation (EDIT VIII 2020–2021). All constructs are first-order composites, measured formatively with non-redundant binary indicators that capture multidimensional resource configurations. Two independent structural models are estimated to represent distinct innovation pathways: one explaining the incidence of product and service innovations, and another capturing process-related innovations associated with operational and organizational improvements.* ***FINDINGS:*** *The results reveal a clear asymmetry in the patterns of association observed across innovation outcomes. Institutional support shows the strongest association with product innovation ($\beta = 0.416$), indicating that connectivity with the broader innovation ecosystem—universities, public agencies, and international partners—helps compensate for limited internal R&D capacity in SMEs. Conversely, innovation investment, particularly in intangible assets such as software, training, and intellectual property, shows the strongest association with process innovation ($\beta = 0.371$), highlighting the role of internal capability building for operational upgrading. Funding sources show a positive but comparatively modest association in both models ($\beta = 0.07$), suggesting that financial access operates primarily as an enabling condition when effectively translated into innovation investments and institutional collaboration.* ***IMPLICATIONS:*** *These findings highlight the importance of integrated innovation support mechanisms that extend beyond credit provision. For policymakers, strengthening institutional linkages and knowledge-transfer channels appears particularly effective for fostering market-oriented innovations. For firm managers, prioritizing investment in intangible assets and participating in collaborative networks may help mitigate structural resource constraints and enhance innovation outcomes.* ***ORIGINALITY & VALUE:*** *This study contributes to the literature on innovation in emerging economies by providing context-sensitive evidence on differentiated innovation pathways in service-sector SMEs.*

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Methodologically, it demonstrates the usefulness of composite-based modeling for analyzing national innovation survey data with dichotomous indicators and complements the analysis with an Importance–Performance Map Analysis (IPMA).
Keywords: *SME innovation, product innovation, process innovation, innovation ecosystems, institutional support, innovation finance, intangible investment, absorptive capacity, service-sector SMEs, emerging economies*

INTRODUCTION

Innovation in products and processes is widely recognized as a strategic pillar for competitiveness and sustained economic growth, particularly among service-sector firms in emerging economies. In these contexts, innovation supports firm development and market differentiation while contributing to national strategies aimed at technological upgrading and productive diversification (Croitoru, 2012; Glückler & Bathelt, 2017; Gomes et al., 2018; OECD/Eurostat, 2018).

Research on innovation in small and medium-sized enterprises (SMEs) has been grounded in complementary theoretical perspectives. The resource-based view (Barney, 1991) highlights how valuable, rare, and difficult-to-imitate resources—often intangible—can underpin competitive advantage. The dynamic capabilities approach, in turn, emphasizes the firm's ability to sense and seize opportunities and to reconfigure resources in response to environmental change (D. Teece et al., 1997; D. J. Teece, 2007, 2018). Absorptive capacity theory further underscores the importance of recognizing, assimilating, and applying external knowledge as a prerequisite for innovation and learning-based upgrading (Cohen & Levinthal, 1990; Zahra & George, 2002).

At the systemic level, the triple and quadruple helix models conceptualize innovation as the outcome of interactions among academia, industry, government, and civil society, stressing the role of institutional arrangements and knowledge intermediation in shaping national innovation ecosystems (Carayannis & Campbell, 2012; Etzkowitz & Leydesdorff, 2000). Yet, empirical applications of these systemic frameworks in emerging economies remain limited and fragmented. Much of the evidence is still derived from industrialized contexts, which limits external validity when transferred to settings characterized by institutional fragility, asymmetric access to funding, and persistently low levels of R&D investment (Barbosa et al., 2014; Paus et al., 2022; Spanos et al., 2015).

A persistent challenge in this literature lies in articulating how these system-level conditions are operationalized through firm-level metrics. This research addresses this multi-level linkage by conceptualizing the firm as a functional node that internalizes systemic environmental signals into strategic capabilities (Hessels & Terjesen, 2010; Lundvall, 2010). Systemic conditions—such as financial liquidity, knowledge infrastructure, and public policy incentives—are captured via the firm's effective engagement with these external structures (Edquist, 2005). Specifically, funding sources and institutional linkages are treated not merely as isolated variables, but as proxies for the firm's integration within the National Innovation System (NIS) (Nelson, 1993; Radicic et al., 2016). By quantifying these interactions using firm-level microdata, the study translates macro-environmental pressures into direct correlates of innovation behavior, thereby strengthening the theoretical coherence between the institutional framework and the empirical strategy.

Recent scholarship, therefore, calls for innovation models that are more explicitly contextualized to the structural conditions of developing countries. Common constraints include weak coordination among innovation actors, limited investment in intangible assets, and restricted access to external financing (Asheim & Gertler, 2009; Carvache-Franco et al., 2022; Paus et al., 2022). These contributions converge on a core premise: innovation does not unfold in an institutional vacuum but is embedded in country-specific environments shaped by macroeconomic disparities, institutional fragmentation, and underinvestment in science and technology. Consequently, direct application of frameworks developed in advanced economies may obscure the mechanisms through which firms innovate in less developed contexts. Although prior studies have examined internal capabilities and external linkages as moderators or enablers of innovation, a salient gap persists regarding the joint role of financing conditions, institutional linkages, and innovation-related investment in shaping product and process innovation—particularly in service activities, where innovation is frequently intangible-intensive and operationally oriented (Le & Ha, 2024; Stanko et al., 2015).

To address this empirical and methodological gap, this study estimates two Partial Least Squares Structural Equation Models (PLS-SEM) to examine the relationships between three explanatory composites—Funding Sources (FS), Institutional Support (IS), and Innovation Investment (II)—and two innovation outcomes: Product Innovation (PrI) and Process Innovation (PsI). All constructs are specified as first-order composites and operationalized using non-redundant binary indicators derived from the 2020–2021 Technological Development and Innovation Survey (EDITS VIII), conducted by Colombia's National Administrative Department of Statistics (DANE). Importantly, the analytical sample is restricted to

service-sector firms that report innovation activity; accordingly, the findings should be interpreted as evidence on the factors associated with the incidence of innovation outcomes, conditional on firms being innovation-active.

PLS-SEM is suitable for this setting because the model is composite-based and uses binary indicators that may depart from normality. The approach enables simultaneous estimation of measurement and structural components and supports inference through resampling procedures. Consistent with best practice for composite models, the empirical assessment emphasizes diagnostics aligned with formative specifications—such as indicator collinearity and bootstrapped relevance—and reports bootstrapped uncertainty for structural paths, complemented by predictive-oriented evaluation (Hair et al., 2021).

Conceptually, the study distinguishes two innovation pathways to avoid conflating outcomes that differ in nature and resource requirements. The first model treats product innovation (PrI) as a market-facing outcome plausibly more dependent on ecosystem connectivity, access to external knowledge, and institutional intermediation. The second model treats process innovation (PsI) as an internally configured outcome more closely associated with capability building and organizational upgrading through tangible and intangible investments. This dual-model strategy contributes to the debate on innovation in emerging economies by (i) disaggregating innovation into product and process domains to reveal differentiated patterns of association, (ii) providing context-sensitive evidence for the service sector, and (iii) clarifying that financing channels may be necessary but not sufficient, insofar as their contribution depends on complementarity with institutional connectivity and strategic investment in innovation-related capabilities.

The study makes three contributions. First, it empirically validates a multidimensional conceptual model tailored to innovative service-sector SMEs in an emerging economy. Second, it clarifies how aggregate financing conditions, institutional linkages, and innovation-oriented investment relate to product and process innovation outcomes, highlighting differences in their relative importance across innovation types. Third, it offers policy- and practice-relevant implications for strengthening institutional connectivity and investment capacity in contexts where firm innovation is constrained by asymmetric access to resources and fragmented support infrastructures.

Consistent with the dual-model strategy, the results reveal a differentiated pattern across innovation outcomes. Institutional Support (IS) shows the strongest association with Product Innovation (PrI), suggesting that ecosystem connectivity and intermediation by public and academic actors are particularly salient for market-facing innovation among Colombian service SMEs. In contrast, Innovation Investment (II)—especially intangible-oriented investment—shows the strongest association with Process Innovation (PsI), underscoring the role of internal capability building and organizational upgrading in operational improvements. Funding Sources (FS) are positively associated with both outcomes but exhibit comparatively weaker effects, indicating that financial access alone is insufficient unless complemented by institutional linkages and strategic investment in innovation capabilities.

The rest of the paper is organized as follows: Section 2 reviews the theoretical background and develops the research hypotheses. Section 3 describes the EDITS VIII data, the operationalization of constructs, and the PLS-SEM estimation strategy, including the rationale for estimating separate models for product and process innovation. Section 4 presents the empirical results and model diagnostics. Section 5 discusses the findings in light of the literature and the Colombian service-sector context. Section 6 concludes by presenting implications for policy and management, limitations, and directions for future research.

LITERATURE REVIEW

Theoretical approaches to innovation

Innovation has long been conceptualized as a dynamic and systemic process through which firms generate value by introducing new or significantly improved products, processes, organizational methods, or marketing techniques (Freeman & Soete, 1997; OECD/Eurostat, 2018; Schumpeter, 1935). This systemic perspective of innovation as a multidimensional phenomenon has been reinforced by contributions from various theoretical frameworks that underscore its complexity, interdependence, and contextual nature (Dzikowski, 2022; Godin, 2006).

Among these, the Triple Helix model (Etzkowitz & Leydesdorff, 2000) emphasizes the synergistic interaction between universities, industry, and government in fostering innovation, while the Quadruple Helix extends this perspective by incorporating civil society as a co-creator of knowledge and legitimacy (Carayannis & Campbell, 2012; Galvão et al., 2017). In recent developments, the Quintuple Helix model has been considered in relation to environmental concerns, thereby aligning innovation with the imperatives of ecological sustainability and green transformation (Machado et al., 2024).

The open innovation paradigm, introduced by Chesbrough (2003), challenges the conventional firm boundary by advocating the strategic utilization of external knowledge sources to complement internal capabilities. The hypothesis posits that firms can accelerate innovation processes, reduce costs, and increase flexibility through inbound flows of ideas from research institutions, customers, competitors, and suppliers (Caloghirou et al., 2021; Wang et al., 2020). The outbound dimension further suggests that unused internal knowledge can be externally commercialized to create value (Dahlander & Gann, 2010).

In addition, the dynamic capabilities framework posits that sustained competitive advantage arises from the ability of companies to integrate, build, and reconfigure internal and external resources to address rapidly changing environments (Teece et al., 1997; Teece, 2007, 2018). Innovation is contingent not only on access to novel technologies but also on the capacity to adapt and reconfigure organizational routines and capabilities continuously (Alves et al., 2017; Grant, 1991; Peteraf, 1993).

According to the resource-based view (RBV), innovation emerges from the deployment of valuable, rare, inimitable, and non-substitutable resources, including knowledge assets, skilled human capital, and institutional linkages (Barney, 1991; Grant, 1991; Caloghirou et al., 2021). These capabilities often interact with institutional factors such as public policy and financial support, especially in low- and middle-income economies (Crowley, 2017; Machado et al., 2024). For instance, Xicang et al. (2024) demonstrate that in high-tech firms operating in emerging economies, internal organizational routines and skills are decisive for translating external support into effective innovation outcomes. This reinforces the idea that innovation capacity rests not only on access to resources, but also on the firm's ability to convert them into value through strategic and organizational capabilities.

The absorptive capacity theory further contributes to the extant literature by conceptualizing the ability of companies to identify, assimilate, transform, and exploit external knowledge as a crucial antecedent to innovation (Cohen & Levinthal, 1990; Zahra & George, 2002). Empirical research has confirmed the strong association between absorptive capacity and enhanced innovation outcomes, particularly when firms engage in cooperation with external actors such as universities, governments, and industry associations (Dimos et al., 2024; Moura et al., 2020; Vo et al., 2024).

In Latin America, and particularly in Colombia, innovation capacity is often constrained by institutional weaknesses, underinvestment in research and development (R&D), and limited access to external finance (Acevedo & Diaz-Molina, 2021; Del Carpio-Gallegos & Miralles, 2019; Gómez & Robledo, 2011). In such contexts, firms tend to rely more on internal financing, a practice that, according to Brown et al. (2009), limits their capacity to engage in high-risk innovation. Consequently, the nexus among internal capabilities, institutional support, and external financing is particularly significant in fostering innovation performance.

Taken together, these theoretical perspectives: dynamic capabilities, the resource-based view (RBV), absorptive capacity, and systemic innovation models, provide a comprehensive analytical lens for examining the structural conditions and resource configurations associated with innovation in firms operating in contexts of intermediate technological development and institutional asymmetry, such as those observed in Colombia and other emerging economies.

Key factors associated with innovation in emerging economies

Funding sources

Access to funding is a crucial factor in fostering innovation, particularly for small and medium-sized enterprises (SMEs). Hall and Lerner's (2010) seminal study demonstrated that the availability of financial resources exerts a substantial influence on innovation development, with different funding sources yielding disparate effects. Venture capital, for instance, is often associated with the emergence of disruptive innovations, while bank credit typically supports incremental improvements (Brown et al., 2013). In emerging economies, self-financing remains the predominant funding mechanism for most firms despite its limitations in sustaining long-term innovative activities (Aiello et al., 2020; Kwak, 2021).

The relationship between financing and innovation is far from homogeneous. It varies according to firm size, R&D intensity, and the availability of public and private resources (Littunen et al., 2021). External funding sources, such as venture capital and government grants, tend to encourage riskier, more radical innovations. In contrast, bank loans and internal resources are more likely to support incremental product improvements and process optimization (Calabrese et al., 2024).

In resource-constrained contexts, funding diversification becomes a strategic imperative. Firms that combine public programs, private capital, and alternative mechanisms like equity crowdfunding can broaden their innovation capacity (Aiello et al., 2020; Eldridge et al., 2021; Panitkulpong et al., 2024). Moreover, foreign direct investment and venture capital not only provide liquidity but also foster knowledge transfer, technology assimilation, and the enhancement of organizational capabilities (Bakhouche, 2022; Guadalupe et al., 2012).

Nevertheless, the effectiveness of funding strategies depends on firms' internal capacities to manage financial and technological risk. Empirical research on capital structure suggests that misaligned funding choices may hinder innovation, especially in firms with limited absorptive or managerial capabilities (Martinez et al., 2019). In emerging markets, where information asymmetries and institutional weaknesses are pervasive, these challenges are exacerbated. This reinforces the need for targeted public funding schemes to complement private investments and mitigate systemic gaps (Mardones & Zapata, 2018; Mateut, 2018).

Conceptually, it is important to distinguish between private banking finance and private non-banking finance, as they involve different instruments and governance mechanisms. Bank credit reflects a debt-based relationship between the firm and a financial intermediary, typically shaped by collateral requirements, screening, and repayment capacity. By contrast, private non-banking finance encompasses resources provided by non-bank private agents—such as private investors or firms—and may involve equity or quasi-equity positions, strategic involvement, and complementary networks. This distinction matters for innovation because the bank–firm relationship tends to support projects with more predictable cash flows, whereas non-banking private finance may better accommodate uncertainty and provide "patient" or strategic capital for innovation-oriented activities.

In the Colombian context, the financing environment for innovation is characterized by a marked reliance on internal resources and persistent frictions in accessing external funding. Evidence reported from the national innovation surveys indicates that, among firms attempting to innovate, the scarcity of internal funds and the difficulty of obtaining external finance are recurrently identified as the most binding constraints, while the observed financing mix follows a clear hierarchy in which own resources dominate, followed by private bank credit, whereas public funds, private equity-type instruments, and cooperation/donations play a comparatively marginal role (Gálvez-Albarracín et al., 2018). Sector-focused evidence for Colombian service and commerce firms is consistent with this pattern: internal resources are the primary source for innovation activities, banking funds are mainly allocated to process innovations, and the use of public credit/co-financing remains minimal, in part due to administrative and informational barriers that hinder access to these instruments (Restrepo-Ramírez et al., 2022). This configuration suggests that internal funding in Colombian SMEs often reflects a structural constraint rather than a purely strategic choice, underscoring the need to distinguish between private banking finance (debt-based) and private non-banking finance (equity/quasi-equity and relational capital) when conceptualizing the composite Funding Sources (FS). Complementarily, cross-industry evidence suggests that financing constraints are correlated with the allocation of direct public support in several Colombian industries, underscoring the policy relevance of public instruments as potential mechanisms to relax market failures affecting innovation finance (Busom & Vélez-Ospina, 2017).

In this study, the construct Funding Sources (FS) reflects this multidimensional perspective and is operationalized using four binary indicators from the EDITS VIII survey: internal funding, private banking finance (bank credit), private non-banking finance (private capital), and cooperation or donations. Because these indicators jointly define the composite, the estimated structural coefficient captures the aggregate association of the financing structure with innovation outcomes, rather than the isolated effect of each specific source. Accordingly, the following hypotheses are proposed:

H1a: Funding Sources (FS), considered as an aggregated financing structure, are positively associated with product innovation outcomes in innovative service-sector SMEs.

H1b: Funding Sources (FS), considered as an aggregated financing structure, are positively associated with process innovation outcomes in innovative service-sector SMEs.

Institutional support and cooperation

Support institutions play a fundamental role in enabling innovation by acting as catalysts for knowledge transfer, facilitators of collaboration, and providers of complementary resources that help firms overcome structural barriers. A growing body

of research underscores the importance of universities, research centers, public agencies, and innovation intermediaries in building technological capabilities and diffusing knowledge (Feldman, 2016; Kafetzopoulos et al., 2021; Le & Ha, 2024).

Within the Triple Helix framework, collaboration among academia, industry, and government is regarded as essential for fostering integrated innovation systems (Etzkowitz & Leydesdorff, 2000; Ranga & Etzkowitz, 2013). These interactions are particularly significant in emerging economies, where market failures and institutional deficiencies hinder firms' innovation efforts (Inzelt, 2015; Mêgnigbêto, 2015). Empirical studies show that collaboration with academic and public institutions enhances absorptive capacity, facilitating more complex and sustainable innovation (Hervás-Oliver et al., 2018; Xia & Jia, 2023).

In Colombia, the institutional architecture that supports innovation has evolved since the early 1990s through policy efforts to activate the Sistema Nacional de Innovación (SNI) and strengthen the broader *Sistema Nacional de Ciencia, Tecnología e Innovación* (SNCTI). This institutional arrangement has sought to create an enabling environment for technological development in the productive sector, to connect firms with the scientific system, and to deploy instruments that support and finance I+D+i activities (Velez Agudelo, 2021). Policy implementation has historically relied on public entities such as *COLCIENCIAS* (Administrative Department of Science, Technology and Innovation; currently *Ministerio de Ciencia, Tecnología e Innovación*—MinCiencias) and SME-oriented programs, including *FOMIPYME* (*Fondo Colombiano de Modernización y Desarrollo Tecnológico de las Micro, Pequeñas y Medianas Empresas*), which have framed initiatives for innovation and technology transfer among Colombian SMEs (Villamizar, 2005). In parallel, regional articulation mechanisms—particularly the *Comités Universidad–Empresa–Estado* (CUEE) and the *Alianza Universidad–Empresa–Estado de Bogotá-Región*—have promoted collaborative dynamics through activities such as mapping university research capacities, identifying sectoral innovation needs, and strengthening managerial and intellectual property capabilities, thereby operationalizing knowledge transfer across actors (Ramírez Salazar & García Valderrama, 2010). Nevertheless, qualitative assessments warn that, despite the proliferation of governmental initiatives, instruments are frequently designed in generic terms and remain difficult to access for SMEs, while weak coordination among actors persists—reinforcing the analytical relevance of institutional linkages as a critical but uneven driver of innovation outcomes in the Colombian context (Briceño Marín & Morales Rubiano, 2017).

The expansion into Quadruple and Quintuple Helix models introduces civil society and environmental concerns as additional drivers of inclusive innovation (Carayannis & Campbell, 2012; Mineiro et al., 2021). Within this broader paradigm, technology parks, incubators, and public-private platforms function as coordination nodes that support joint knowledge creation and capability development (Rantala et al., 2021).

From a strategic perspective, cooperative R&D initiatives serve as effective mechanisms to enhance innovation returns by allowing firms to share risks, reduce costs, and access complementary resources (Najib et al., 2021; Ramsza & Karbowski, 2020). These arrangements are particularly relevant in knowledge-intensive sectors, where firm–university–government alliances foster innovation in both products and processes (Luengo-Valderrey, 2018).

However, the outcomes of institutional support vary across contexts. Studies by Dimos et al. (2024) and Trang (2024) caution that the mere availability of resources does not guarantee innovation success, particularly for SMEs with low absorptive capacity or limited managerial competencies. Inappropriately designed programs may even create dependency or opportunistic behavior (Dimos & Pugh, 2016).

Recent evidence highlights the growing relevance of institutional support for process innovation through initiatives such as digital transformation programs, technology transfer services, and knowledge management platforms (Cho & Lee, 2024; Le & Ha, 2024). These environments facilitate tacit knowledge exchange and foster durable innovation networks (Inzelt, 2015; Mineiro et al., 2021).

In this study, the construct Institutional Support (IS) is operationalized using five binary indicators from the EDITS VIII survey, capturing support from public agencies, academic or research institutions, private partners, international organizations, and training entities. As with FS, the estimated coefficient reflects the aggregate association of institutional linkages with innovation outcomes. The following hypotheses are derived from the reviewed literature:

H2a: Institutional Support (IS), understood as an aggregated set of linkages with public, academic, private, international, and intermediary organizations, is positively associated with product innovation outcomes in innovative service-sector SMEs.

H2b: Institutional Support (IS), understood as an aggregated set of linkages with public, academic, private, international, and intermediary organizations, is positively associated with process innovation outcomes in innovative service-sector SMEs.

R&D investment

Investment in research and development (R&D) is a foundational pillar for building technological capabilities and fostering firm-level innovation. A robust body of evidence confirms the positive association between R&D intensity and the emergence of new products, enhanced processes, and productivity gains (Kasych et al., 2021). However, this relationship is influenced by contextual, financial, and organizational conditions.

Among SMEs, financial constraints are a major impediment to R&D investment. Barriers include limited collateral, high uncertainty, and the lack of instruments tailored to innovation finance (Barona-Zuluaga & Rivera-Godoy, 2017; Ferraro et al., 2011). The intangible nature of many R&D outputs heightens risk perceptions, rendering debt-based financing less accessible (Hall & Lerner, 2010).

Public investment emerges as a key lever to counterbalance these barriers. Through subsidies, tax incentives, and co-financing schemes, governments can reduce opportunity costs and stimulate innovation, particularly in strategic sectors (Brautzsch et al., 2015; Liu & Guo, 2024). However, in Latin America, these mechanisms often face design and implementation challenges (Barona-Zuluaga & Rivera-Godoy, 2017; Guarín & García-Estévez, 2021).

The relationship between R&D, innovation, and productivity is increasingly understood as systemic and dynamic. The CDM model (Crépon et al., 1998) and its extensions conceptualize innovation as part of a cumulative process shaped by feedback between performance and investment (Bong & Park, 2021). Successful R&D depends not only on financial input but also on organizational learning and strategic alignment (Guarín & García-Estévez, 2021).

Firm-level factors, such as human capital, governance, and strategy, further shape R&D outcomes. Firms with skilled personnel, absorptive capacity, and explicit innovation goals tend to extract higher returns from R&D (Indrawati et al., 2020; Kasych et al., 2021).

In Colombia, most innovation expenditures are allocated to equipment acquisition, while internal R&D remains a minor share of total investment (Barona-Zuluaga & Rivera-Godoy, 2017; Hurtado & Guzmán, 2014). This pattern reflects a technology adoption model rather than a strategy focused on knowledge creation, potentially limiting the transformative potential of innovation.

In this study, the construct Innovation Investment (II) comprises both tangible and intangible innovation expenditures, operationalized through two binary indicators from the EDITS VIII survey: investment in physical assets (tangible) and investment in R&D, training, software, and intellectual property (intangible). This distinction allows us to assess the individual and combined effects of both investment types on firm-level innovation. Accordingly, the following hypotheses are proposed:

H3a: Innovation Investment (II), capturing tangible and intangible innovation-related investment, is positively associated with product innovation outcomes.

H3b: Innovation Investment (II), capturing tangible and intangible innovation-related investment, is positively associated with process innovation outcomes.

Conceptual model

As a synthesis of the previous hypotheses, the conceptual model of this study is presented in Figure 1. Given that product and process innovation are estimated as separate endogenous constructs, each hypothesis is specified in two parallel forms, one for product innovation and one for process innovation.

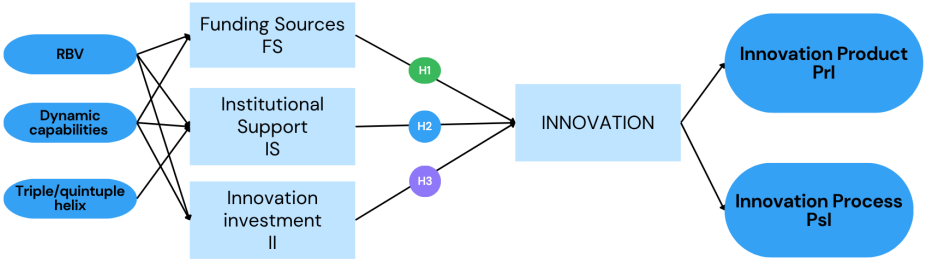

Figure 1. Conceptual model linking funding structures, institutional support, and innovation investment to product and process innovation in service-sector SMEs

The conceptual model integrates three complementary theoretical perspectives—the resource-based view (RBV), dynamic capabilities theory, and the Triple/Quadruple Helix frameworks—to explain how organizational and contextual factors are associated with innovation outcomes in service-sector SMEs operating in an emerging economy. As illustrated in Figure 1, the model links these theoretical foundations to three composite constructs—Funding Sources (FS), Institutional Support (IS), and Innovation Investment (II)—which represent aggregated resource configurations shaping firms' innovation performance.

From the perspective of the resource-based view, firms achieve competitive advantages when they possess valuable, rare, and strategically deployable resources (Barney, 1991; Grant, 1991). In this framework, financial capacity, knowledge access, and organizational investment are critical inputs that enable innovation activities. Accordingly, the constructs FS, IS, and II are conceptualized as complementary resource domains capturing firms' access to financing mechanisms, external knowledge and institutional linkages, and investments oriented toward innovation capabilities.

Dynamic capabilities theory extends this resource-based logic by emphasizing the firm's ability to integrate, reconfigure, and renew its resource base in response to changing environments (Teece et al., 1997; Teece, 2007, 2018). This perspective is particularly relevant for Innovation Investment (II), which encompasses both tangible and intangible investments supporting learning, capability upgrading, and internal transformation. Institutional Support (IS) also reflects dynamic capability processes, as external relationships facilitate knowledge recombination, access to complementary resources, and adaptive responses to technological and market changes.

The Triple and Quadruple Helix frameworks add a systemic dimension by highlighting the role of interactions among universities, government, industry, and civil society in shaping innovation ecosystems (Etzkowitz & Leydesdorff, 2000; Carayannis & Campbell, 2012). These interactions are especially captured through the Institutional Support construct, which reflects firms' engagement with public agencies, research institutions, private organizations, and innovation intermediaries that facilitate knowledge diffusion and collaborative learning.

Building on these theoretical perspectives, the model proposes three sets of direct relationships between the composite constructs and firms' innovation outcomes. Hypotheses H1a and H1b propose that Funding Sources (FS), representing an aggregated financing structure combining internal, public, private, and cooperative funding channels, are positively associated with product innovation (PrI) and process innovation (PsI), respectively. Hypotheses H2a and H2b posit that Institutional Support (IS), capturing firms' external linkages with public institutions, academic actors, private partners, international organizations, and innovation intermediaries, is positively associated with product and process innovation outcomes. Finally, Hypotheses H3a and H3b propose that Innovation Investment (II), reflecting tangible and intangible investments oriented toward innovation activities, is positively associated with both types of innovation outcomes.

These relationships are tested using two separate PLS-SEM models, with product innovation (PrI) and process innovation (PsI) specified as endogenous constructs. Distinguishing between these two outcomes is theoretically and empirically relevant, as product innovation tends to be more market-oriented and influenced by external ecosystem interactions, whereas process innovation is often more closely related to internal capability development and resource reconfiguration. Estimating separate models, therefore, allows a clearer assessment of how aggregated resource configurations influence distinct innovation pathways in service-sector SMEs.

METHODOLOGY

Measures and instrument development

This study utilizes firm-level microdata from the VIII Technological Development and Innovation Survey (EDIT VIII 2020–2021), conducted by Colombia's National Administrative Department of Statistics (DANE). Although the reference period (2020–2021) precedes the current year, EDIT VIII represents the most recent comprehensive dataset available for the Colombian service sector. In emerging economies, national innovation surveys often face structural lags due to the complexity of multi-stage data collection, institutional validation, and public release; as a result, these data remain the empirical frontier for analyzing innovation dynamics in this context.

To ensure methodological rigor, all constructs were operationalized as first-order composites (formative measurement). The use of dichotomous variables (0 = No; 1 = Yes) aligns with the survey's structure and the Oslo Manual guidelines (OECD/Eurostat, 2018). This binary format is also compatible with composite-based structural equation modeling, which does not require distributional normality assumptions (Hair et al., 2021).

The analytical sample was restricted to innovative service-sector firms (TIPOLO ≠ "NOINNO"), yielding 2,782 observations. This restriction creates a conditional scope for interpretation: the estimated relationships represent correlates of innovation incidence among firms already engaged in innovation activities, rather than explanations of the transition from non-innovator to innovator status. This conditioning is practically necessary because several key indicators—such as innovation funding and institutional support—are structurally unavailable in the survey for firms that report no innovation activity. Consequently, the results characterize the pathways associated with innovation outcomes among firms already embedded in the innovation ecosystem.

To document the empirical distribution of novelty levels in the original EDITS VIII indicators, we examined the prevalence of product innovations new to the firm, the national market, and the international market prior to constructing the final Product Innovation (PrI) composite. The results reported in Appendix 4 show that firm-level novelty is substantially more frequent (21.5% for new goods and 15.2% for improved goods), whereas novelty at the national market level is uncommon (1.37% and 1.08%, respectively) and novelty at the international market level is extremely rare (0.11% and 0.07%, respectively). This distribution confirms that higher novelty categories exhibit very limited variance in the sample. Accordingly, national and international novelty indicators were aggregated into broader market-novelty variables in order to preserve the conceptual distinction between firm-level and market-level novelty while ensuring sufficient variability for stable model estimation.

The model includes two dependent constructs that represent distinct innovation outcomes:

- Product Innovation (PrI): Measured through four indicators capturing the introduction of new or significantly improved goods/services (new_goods_firm, improved_goods_firm, new_goods_market, improved_goods_market). Market novelty indicators aggregate national and international levels;
- Process Innovation (PsI): Captures internal operational improvements through six indicators: *production, organization, marketing, distribution, information systems,* and *accounting methods*.

These innovation outcomes are explained by three independent, multidimensional constructs:

- Funding Sources (FS): A composite of four indicators (*internal, banks, private, donations*) reflecting the firm's financing configuration (Czarnitzki, 2006; Sohn et al., 2007);
- Institutional Support (IS): Captures linkages with five external pillars: *public, academic, private, international,* and *training* entities. This aligns with Triple and Quadruple Helix frameworks (Etzkowitz & Leydesdorff, 2000; Carayannis & Campbell, 2012);
- Innovation Investment (II): Distinguishes between *tangible* (physical capital) and *intangible* investment (R&D, software, IP, training), allowing for an assessment of knowledge-based vs. structural modernization (Liu & Guo, 2024).

Each construct consists of non-overlapping, theory-informed indicators. As detailed in Appendix 1, these indicators represent distinct yet complementary aspects of firm-level dynamics, reinforcing the formative nature of the measurement model. To ensure the adequacy of the composite measurement specification, the measurement model was evaluated using criteria appropriate for formative (composite) constructs. Variance Inflation Factors (VIF) were computed to assess potential multicollinearity among indicators, using a conservative threshold of 3.3. Bootstrapping with 5,000 replications was used to obtain sampling-based uncertainty estimates for composite weights and structural paths (Hair et al., 2021). Given the composite (formative) specification, traditional reflective reliability and validity metrics (e.g., Cronbach's alpha, composite reliability, AVE, Fornell–Larcker) are not used as decision criteria for measurement quality in this study.

Data collection

The empirical analysis draws on firm-level microdata from the Eighth Technological Development and Innovation Survey (EDIT VIII) conducted by Colombia's National Administrative Department of Statistics (DANE) for the 2020–2021 period. As previously noted, EDIT VIII represents the most recent comprehensive firm-level evidence available for the Colombian service sector. The survey provides detailed information on innovation-related inputs—including financing channels, institutional support, and strategic investments—making it particularly suitable for examining innovation dynamics in an emerging-economy context characterized by structural asymmetries and fragmented support infrastructures.

To ensure analytical precision and maintain consistency between the systemic innovation framework and firm-level empirical indicators, the original dataset of 8,812 firms was refined through a sequential filtering strategy.

First, firms classified as "non-innovators" were excluded using the survey's typology variable (TIPOLO = "NOINNO"). This step yields an analytical sample of firms that report active engagement in innovation activities. Consequently, the estimated models are not intended to explain the transition into innovation activity; rather, they are specified to examine the correlates of product and process innovation incidence among firms that have already crossed the threshold of innovation engagement. This conditioning is methodologically necessary because several key indicators—particularly those related to innovation funding and institutional support—are structurally unavailable in the survey for firms that do not report innovation activity.

Second, the analysis was restricted to the service sector, as defined by the International Standard Industrial Classification (ISIC Rev. 4). This focus enhances comparability, acknowledging that innovation patterns and capability requirements in services differ fundamentally from those in manufacturing (Stanko et al., 2015). The final analytical sample consists of 2,782 innovative service-sector firms with valid responses across all indicators. This sample size comfortably exceeds the recommended minimum requirements for Partial Least Squares Structural Equation Modeling (PLS-SEM), even under composite-based specifications with multiple binary indicators (Hair et al., 2021).

Third, following the official SME classification established by Colombian regulations (Law 590 of 2000; Law 905 of 2004) and consistent with previous empirical applications using EDIT microdata (Romero-Alvarez et al., 2025), the sample was explicitly restricted to small and medium-sized enterprises (SMEs). In line with the criteria set by Colombia's Ministry of Commerce, Industry, and Tourism, firms were categorized by total number of employees. Specifically, the sample includes only small firms (between 11 and 50 employees) and medium-sized firms (between 51 and 200 employees). Large firms (exceeding 200 employees) and micro-enterprises (fewer than 10 employees) were excluded to ensure the theoretical framework's focus on resource constraints and financial asymmetries remains internally valid.

Following these three sequential filters—(i) innovation activity, (ii) service sector, and (iii) size constraints—the final analytical sample consists of 2,782 innovative service-sector SMEs. This explicit restriction ensures that the subsequent findings and policy implications are properly aligned with the structural characteristics and resource dependencies inherent to the SME segment in an emerging economy.

Data were collected through structured questionnaires and validated by DANE following international protocols. In line with Oslo Manual guidelines, key variables are recorded as dichotomous indicators. This operational logic is consistent with widely used Community Innovation Survey (CIS) applications and supports the application of PLS-SEM to examine how systemic and internal conditions are associated with specific innovation outcomes within the sub-sample of active firms (Bou & Satorra, 2019).

Method of data analysis

Prior to model estimation, the microdata were screened for missing values, internal inconsistencies, and implausible codings. Given the survey-based nature of EDITS VIII and the predominance of dichotomous indicators, the analysis proceeded by retaining complete and valid responses for the indicator sets used to operationalize the composites. Observations were included when they provided non-missing values for the relevant blocks, thereby ensuring consistent construct construction across the estimated models.

The analysis employed Partial Least Squares Structural Equation Modeling (PLS-SEM), implemented using the *seminr* package (v2.3.4) in R (v4.3.1). Estimations were conducted locally on a Windows 11 system. PLS-SEM was selected because it is appropriate for composite-based (formative) model specifications, accommodates categorical and potentially non-normal indicators, and supports predictive-oriented research designs (Hair et al., 2017; Sarstedt et al., 2019; Hair et al., 2021). In addition, the operationalization of key outcomes and inputs using binary incidence indicators is consistent with the logic of Oslo-based innovation surveys and CIS applications, where innovation is frequently measured as the introduction (yes/no) of product and process innovations during a reference period (Bou & Satorra, 2019; Rosário et al., 2024).

The estimation followed the sequential procedure summarised in Figure 2. First, all indicators were recoded into binary variables (0 = No; 1 = Yes) in line with the EDITS VIII questionnaire design. Second, two independent PLS-SEM models were estimated: one for product innovation (PrI) and one for process innovation (PsI). Both models included the same set of exogenous composites—Funding Sources (FS), Institutional Support (IS), and Innovation Investment (II)—to preserve comparability across outcomes while enabling differentiated innovation pathways. This dual-model strategy was adopted after an initial joint specification (with the PrI and PsI models simultaneously modeled as endogenous

constructs) exhibited instability under the binary composite measurement blocks. Estimating separate models improved convergence and interpretability without altering the substantive conceptual framework.

Third, model evaluation followed criteria appropriate for composite (formative) measurement. Indicator collinearity was assessed using variance inflation factors (VIF). Indicator relevance was examined using bootstrapped weights and their percentile confidence intervals from 5,000 resamples. Structural model assessment relied on explained variance (R^2 and adjusted R^2) and bootstrap-based inference for path coefficients (bootstrap means, standard errors, t-statistics, and percentile confidence intervals). Because the endogenous innovation constructs are formed from binary indicators, particular attention was paid to indicator variability to ensure stable resampling-based inference. In the product innovation model, two ultra-rare novelty indicators were aggregated into broader "market novelty" indicators to increase variance while preserving the conceptual intent of novelty beyond the firm level.

Finally, predictive relevance was assessed using Stone–Geisser's Q^2. An Importance–Performance Map Analysis (IPMA) was also conducted to identify constructs that combine higher importance (total effects on the endogenous construct) with comparatively lower performance (average construct scores), thereby supporting a more actionable interpretation of the estimated relationships. The sequential analytical procedure applied in the PLS-SEM models is summarised in Figure 2.

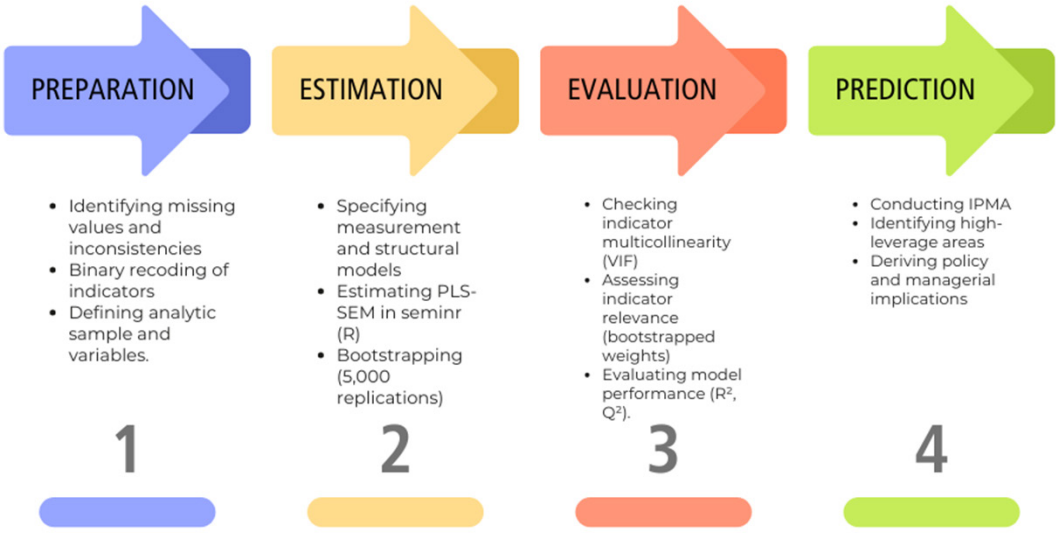

Figure 2. Sequential analytical procedure applied in the PLS-SEM models

Source: Authors' elaboration based on Hair et al. (2021).

RESULTS

Descriptive statistics of constructs

To contextualize the innovation-related profile of the sampled firms, Table 1 reports the frequency and percentage of observations associated with each construct included in the final model. For the innovation outcomes, the table presents a descriptive prevalence measure—coded as 1 when the firm reports at least one indicator within the corresponding innovation block—whereas, in the PLS-SEM estimation, both outcomes are modeled as multi-indicator composites (PrI: four binary indicators; PsI: six binary indicators). Table 1 also summarises the prevalence of institutional support (IS), funding sources (FS), and innovation investment (II) across the 2,782 innovative service-sector firms.

Overall, process innovation (PsI) is substantially more prevalent than product innovation (PrI): 69.2% of firms report at least one process-related innovation indicator, whereas 30.3% report at least one product-related innovation indicator. This pattern suggests that, within the service sector, innovation activity more frequently targets internal operational improvements than market-facing outputs. Regarding institutional support, engagement with public institutions (29.8%) and private-sector actors (28.0%) is relatively common, while academic or research support is less frequent (14.9%).

Support from international organizations/NGOs (4.49%) and training/intermediation entities (7.05%) is comparatively limited, indicating that these channels play a smaller role in the observed innovation dynamics.

With respect to financing, internal resources are the dominant funding channel (76.7%), whereas access to bank loans (9.24%), cooperation/donations (5.57%), and private funds (1.94%) is relatively uncommon. Finally, intangible investment—covering activities such as R&D, training, and software—shows a higher prevalence (72.9%) than tangible investment (41.1%), consistent with the intangible-intensive nature of innovation in service-sector firms.

Table 1. Descriptive statistics of composites and binary indicators (N = 2,782)

Construct	Variable	Description	Count	Total	Percentage (%)
Innovation outcomes	PrI	Firms reporting ≥1 product-innovation indicator (descriptive prevalence)	844	2,782	30.30
Innovation outcomes	PsI	Firms reporting ≥1 process-innovation indicator (descriptive prevalence)	1,925	2,782	69.20
IS – Institutional Support	support_public	Firms that received support from public institutions	830	2,782	29.80
IS – Institutional Support	support_academic	Firms that received support from academic or research institutions	414	2,782	14.90
IS – Institutional Support	support_private	Firms that received support from private-sector actors	780	2,782	28.00
IS – Institutional Support	support_international	Firms that received support from international organizations and/or NGOs	125	2,782	4.49
IS – Institutional Support	support_training	Firms that received support from training/intermediation entities	196	2,782	7.05
FS – Funding Sources	funding_internal	Firms that financed innovation using internal resources	2,135	2,782	76.70
FS – Funding Sources	funding_banks	Firms that financed innovation through bank loans	257	2,782	9.24
FS – Funding Sources	funding_private	Firms that financed innovation using private funds	54	2,782	1.94
FS – Funding Sources	funding_donations	Firms that financed innovation through cooperation and/or donations	155	2,782	5.57
II – Innovation Investment	investment_tangible	Firms that invested in tangible assets for innovation	1,143	2,782	41.10
II – Innovation Investment	investment_intangible	Firms that invested in intangible assets for innovation	2,027	2,782	72.90

Note: PrI is operationalized as a first-order composite with four binary indicators: new_goods_firm, improved_goods_firm, new_goods_market (=1 if national or international new goods =1), and improved_goods_market (=1 if national or international improved goods =1). PsI is operationalized as a first-order composite with six binary indicators capturing innovations in production, organization, marketing, distribution, information management, and administrative practices.

Although firm size and export status were initially considered as additional covariates, preliminary estimations indicated that their inclusion did not improve model stability or explanatory performance for the innovation outcomes examined. Therefore, in line with the principle of parsimony, these variables were excluded from the final structural models.

Evaluation of the measurement model

To assess the adequacy of the measurement model in both innovation specifications, the analysis followed evaluation procedures recommended for composite (formative) constructs in PLS-SEM. Because all latent variables were specified as first-order composites, internal consistency metrics such as Cronbach's alpha, composite reliability (ρC), and average variance extracted (AVE) are not applicable and therefore were not reported. These indices assume reflective measurement and indicator interchangeability, whereas composite indicators represent distinct and non-redundant facets of the construct (Hair et al., 2021).

Accordingly, measurement model evaluation focused on: (i) multicollinearity among indicators, assessed via variance inflation factors (VIF), and (ii) indicator relevance, assessed through bootstrapped weights (5,000 replications). Tables 2a and 2b report the indicator-level VIF values for all composites included in each model.

Two higher-level novelty indicators were extremely rare in the sample. Specifically, only 1.37% of firms reported goods/services new to the national market and 0.11% to the international market, while the corresponding rates for improved goods/services were 1.08% and 0.07%, respectively (Appendix 4). To avoid instability in resampling-based inference while preserving the distinction between firm-level and market-level novelty, these indicators were aggregated into broader market-novelty measures. This approach maintains conceptual consistency with the Oslo Manual classification while ensuring sufficient variability for reliable composite estimation.

Across both models, all VIF values remained well below the conservative threshold of 3.3 (maximum VIF = 1.649), indicating no problematic multicollinearity within the formative blocks and supporting the interpretability of indicators as distinct contributors to their composites. In addition, bootstrapped weights were examined to evaluate the statistical contribution of each indicator. Overall, the weight patterns were consistent with the conceptual specification of each composite and provided an appropriate basis for interpreting the subsequent structural relationships.

Table 2a. Variance Inflation Factors (VIF) for formative indicators — Product innovation model (PrI)

Construct	Indicator	VIF
Product innovation (PrI)	improved_goods_firm	1.06920331
Product innovation (PrI)	improved_goods_market	1.10807788
Product innovation (PrI)	new_goods_firm	1.0778143
Product innovation (PrI)	new_goods_market	1.12395865
Funding Sources (FS)	funding_banks	1.33967903
Funding Sources (FS)	funding_donations	1.53942221
Funding Sources (FS)	funding_internal	1.01734068
Funding Sources (FS)	funding_private	1.40685323
Innovation Investment (II)	investment_intangible	1.04344841
Innovation Investment (II)	investment_tangible	1.04344841
Institutional Support (IS)	support_academic	1.64879251
Institutional Support (IS)	support_international	1.28424585
Institutional Support (IS)	support_private	1.32326737
Institutional Support (IS)	support_public	1.49848142
Institutional Support (IS)	support_training	1.43817195

Source: Authors' elaboration in R.

Table 2b. Variance Inflation Factors (VIF) for formative indicators — Process innovation model (PsI)

Construct	Indicator	VIF
Process innovation (PsI)	new_method_account	1.07662276
Process innovation (PsI)	new_method_distribution	1.07788344
Process innovation (PsI)	new_method_information	1.16348604
Process innovation (PsI)	new_method_marketing	1.05109906
Process innovation (PsI)	new_method_organization	1.18313074
Process innovation (PsI)	new_method_production	1.06894236
Funding Sources (FS)	funding_banks	1.33967903
Funding Sources (FS)	funding_donations	1.53942221
Funding Sources (FS)	funding_internal	1.01734068
Funding Sources (FS)	funding_private	1.40685323
Innovation Investment (II)	investment_intangible	1.04344841
Innovation Investment (II)	investment_tangible	1.04344841
Institutional Support (IS)	support_academic	1.64879251
Institutional Support (IS)	support_international	1.28424585
Institutional Support (IS)	support_private	1.32326737
Institutional Support (IS)	support_public	1.49848142
Institutional Support (IS)	support_training	1.43817195

Source: Authors' elaboration in R.

Because all constructs were specified as formative composites, internal consistency and convergent validity metrics developed for reflective measurement (e.g., Cronbach's alpha, composite reliability, and AVE) were not used as evaluation criteria. Instead, the assessment of the measurement model relied on: (i) indicator collinearity, examined through variance inflation factors (VIF), and (ii) the statistical relevance of indicators, evaluated via bootstrapped indicator weights and 95% confidence intervals (see Appendices 2–3). In formative composites, negative weights may arise due to informational overlap among indicators or suppression effects; accordingly, they should be interpreted as the indicator's net relative contribution, conditional on the presence of the other indicators, and considered jointly with collinearity diagnostics.

Construct distinctiveness and patterns of interrelationships

Given the composite (formative) specification of all constructs, traditional convergent and discriminant validity assessment based on Average Variance Extracted (AVE) and the Fornell–Larcker criterion is not applicable. Therefore, the inter-construct score matrix is not used as a formal validity test but as a diagnostic tool. Instead, construct distinctiveness is supported through three complementary considerations: (i) the deliberate, non-overlapping design of indicators across composites; (ii) the absence of problematic multicollinearity among indicators, as evidenced by the low VIF values reported in Tables 2a and 2b; and (iii) an examination of interrelationship patterns among construct scores as a descriptive diagnostic to identify potential empirical redundancy.

Figure 3 presents the inter-construct scores, showing that the observed associations are directionally consistent with theoretical expectations and do not suggest redundancy among the composites. Because this matrix is used solely for descriptive diagnostics, statistical significance is not reported here. Formal inference is conducted in the structural model analysis (Section 4.4), where path coefficients are evaluated using bootstrapping.

Several patterns emerge from this diagnostic stage. First, Funding Sources and Innovation Investment exhibit a meaningful positive association ($r = 0.655$), suggesting that firms with broader access to financial resources also tend to report a higher incidence of tangible and intangible investment in innovation activities. Institutional Support is likewise positively linked with Innovation Investment ($r = 0.215$), indicating that engagement with external support organizations co-occurs with firms' resource mobilization.

Second, the inter-construct patterns involving innovation outcomes align with the study's conceptual framing. Product innovation (PrI) shows its strongest association with Institutional Support ($r = 0.451$), consistent with the view that linkages with public agencies and universities are especially relevant for market-facing innovation. In contrast, process innovation (PsI) is most strongly associated with Innovation Investment ($r = 0.393$), underscoring the role of resource allocation for internal operational improvements. Finally, the association between PrI and PsI is positive but modest ($r = 0.257$), indicating that they are distinct outcomes. This empirical pattern further validates the decision to estimate separate structural models to capture the distinct association patterns characterizing each innovation type.

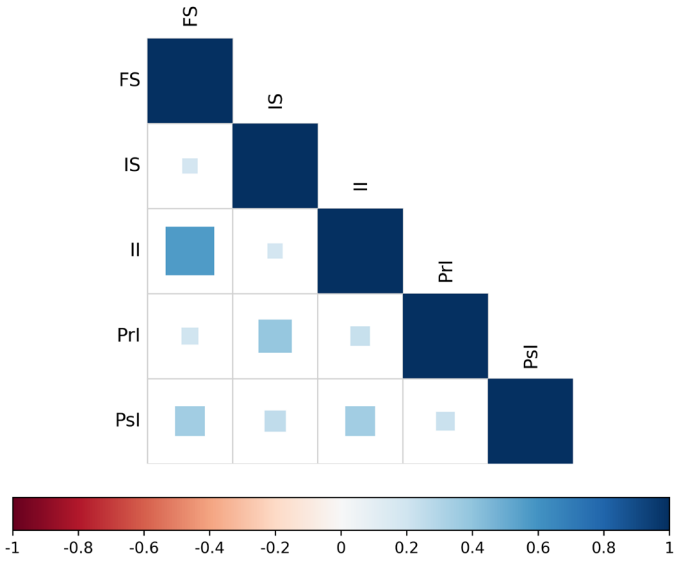

Figure 3. Matrix of interrelationships between construct scores

Structural model estimation

Consistent with the composite-based specification of the explanatory constructs, the estimated structural coefficients capture the aggregated effects of funding sources and institutional support rather than the isolated contributions of individual sources. This modeling choice reflects the systemic and complementary nature of financial and institutional resources in shaping innovation outcomes in service-sector firms.

Product innovation model

To estimate the structural relationships between the explanatory constructs and product innovation, a PLS-SEM model was specified using the *seminr* package in R. The measurement model incorporated three first-order composites—Funding Sources (FS), Institutional Support (IS), and Innovation Investment (II)—each operationalized using non-redundant binary indicators derived from the EDITS VIII dataset.

The endogenous construct, Product Innovation (PrI), was specified as a first-order composite measured by four dichotomous indicators, capturing the introduction of new or significantly improved goods/services at the firm level and at broader market novelty levels. This specification reflects an aggregation of low-frequency novelty indicators to ensure sufficient variability and statistical stability in the estimation.

The structural model included direct paths from FS, IS, and II to PrI and was estimated using 2,782 observations from innovative firms in the service sector. Table 3 reports the standardized path coefficients and the model's explanatory power.

Table 3. PLS-SEM Structural Model Results – Product Innovation

Path	Coefficient	Bootstrap mean	Std. Dev.	t-statistic	p-value	95% CI (2.5%–97.5%)
FS → Product Innovation (PrI)	0.071	0.075	0.0289	2.46	0.014	[0.019, 0.132]
IS → Product Innovation (PrI)	0.416	0.419	0.0234	17.74	<0.001	[0.373, 0.464]
II → Product Innovation (PrI)	0.138	0.136	0.0295	4.67	<0.001	[0.078, 0.193]
R^2	0.246					
Adj. R^2	0.246					

Source: Authors' estimation in R with seminr (v2.3.4), 5,000 bootstrap resamples.

Overall, the model explains 24.6% of the variance in product innovation ($R^2 = 0.246$), which represents a meaningful level of explanatory power given the exploratory scope of the study and the binary nature of the indicators. Among the constructs, Institutional Support (IS) shows the strongest association with product innovation ($\beta = 0.416$), highlighting the relevance of engagement with public programs, universities, and support organizations for product-oriented innovation in service-sector firms. Innovation Investment (II) is also positively related to product innovation ($\beta = 0.138$), suggesting that allocating resources to tangible and intangible innovation assets contributes to the introduction of new or improved products/services. By contrast, Funding Sources (FS) exhibits the smallest coefficient ($\beta = 0.071$), indicating that variation in financing modalities is less strongly associated with product innovation than institutional linkages and innovation-oriented investment in this sample.

For statistical inference, a bootstrapping procedure with 5,000 resamples was implemented after aggregating low-frequency novelty indicators to ensure sufficient variability in the measurement model. The bootstrapped results confirm the statistical significance of all structural paths, with confidence intervals that exclude zero. Accordingly, the estimated coefficients can be interpreted as statistically supported associations within the composite-based PLS-SEM framework. Figure 4 provides a graphical representation of the estimated structural model.

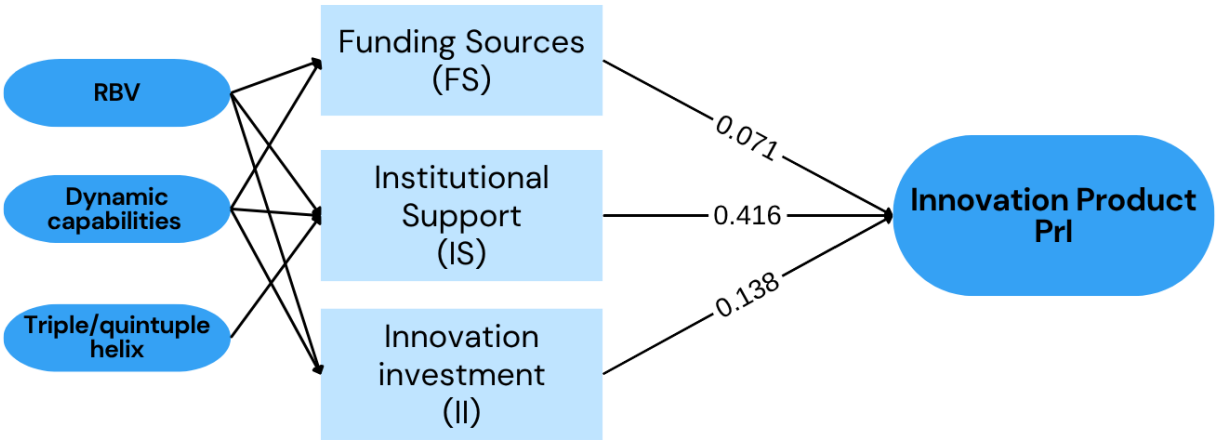

Figure 4. Structural model for product innovation (PLS-SEM standardized path coefficients)

Process innovation model

To examine the correlates of process innovation, a second structural model was estimated using the same three first-order composites: Funding Sources (FS), Institutional Support (IS), and Innovation Investment (II). The endogenous construct, Process Innovation (PsI), was specified as a composite measured by six binary indicators reflecting innovations in production methods, organizational routines, marketing techniques, distribution systems, information management, and administrative practices. The model was estimated using the same analytical sample of 2,782 innovative service-sector firms from the EDIT VIII dataset. The standardized path coefficients and explanatory power, indicating the strength of these associations within the innovation-active sub-sample, are reported in Table 4.

Table 4. PLS-SEM Structural Model Results – Process Innovation

Path	Coefficient	Bootstrap mean	Std. Dev.	t-statistic	p-value	95% CI (2.5%–97.5%)
FS → Process Innovation (PsI)	0.079	0.081	0.0265	2.99	<0.001	[0.027, 0.133]
IS → Process Innovation (PsI)	0.203	0.204	0.0234	8.67	<0.001	[0.157, 0.250]
II → Process Innovation (PsI)	0.371	0.370	0.0257	14.44	<0.001	[0.321, 0.422]
R^2	0.272					
Adj. R^2	0.271					

Source: Authors' estimation in R with seminr (v2.3.4); bootstrapping with 5,000 resamples.

Overall, the model explains 27.2% of the variance in process innovation outcomes, indicating a moderate explanatory capacity that slightly exceeds the product innovation model. Among the constructs, Innovation Investment (II) shows the strongest association with process innovation (β = 0.371), suggesting that firms allocating tangible and intangible resources—such as equipment, training, and software—are more likely to report internal innovation activities. Institutional Support (IS) also exhibits a positive association (β = 0.203), indicating that engagement with external support organizations is linked to process innovation, plausibly through channels such as technical assistance, knowledge diffusion, and skills development. Funding Sources (FS) presents the smallest coefficient (β = 0.079), implying that variation in financing modalities is less strongly associated with process innovation than innovation-oriented investment and institutional linkages in this sample.

For statistical inference, a bootstrapping procedure with 5,000 resamples was implemented. The results indicate that all structural paths are statistically significant, with confidence intervals that exclude zero (Table 4), supporting the robustness of the estimated relationships within the composite-based PLS-SEM framework. Figure 5 summarises the estimated structural relationships and the measurement specification for the Process Innovation (PsI) composite.

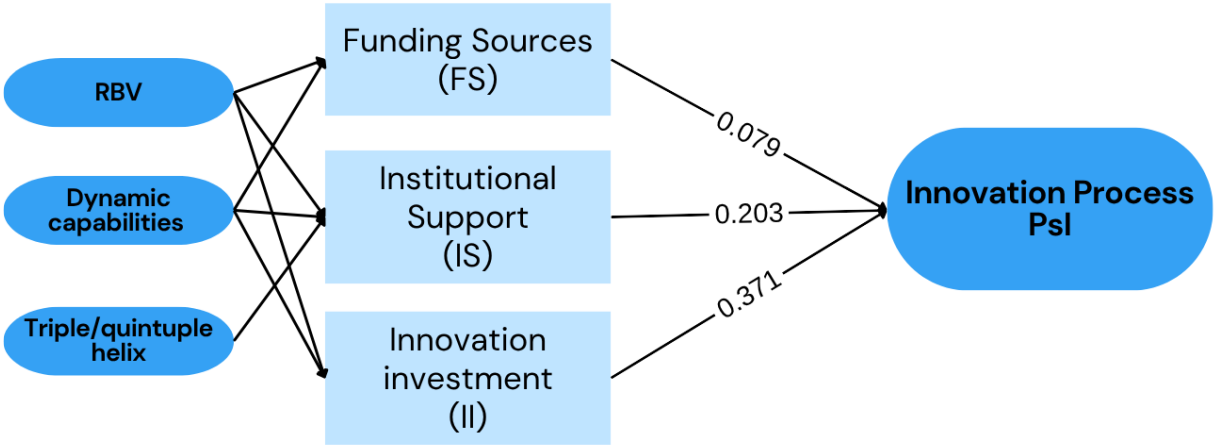

Figure 5. PLS-SEM Model for Process Innovation

Predictive relevance and importance-performance analysis

To evaluate the predictive capability of the estimated PLS-SEM models, Stone–Geisser's Q^2 values were computed using a blindfolding procedure. The results indicate positive predictive relevance for both endogenous constructs, with Q^2 = 0.125 for Product Innovation (PrI) and Q^2 = 0.192 for Process Innovation (PsI). As both values exceed the recommended threshold of zero, the models demonstrate out-of-sample predictive relevance appropriate for an exploratory assessment of innovation outcomes in emerging-economy settings (Hair et al., 2019).

In addition, an Importance–Performance Map Analysis (IPMA) was conducted to identify constructs that combine relatively high importance (i.e., total effects on the endogenous construct) with comparatively low performance (i.e., average construct score). This complementary diagnostic facilitates a more actionable interpretation of the model results by highlighting where improvements could yield greater potential gains in innovation outcomes. Table 5 reports the IPMA results for both the product and process innovation models.

Table 5. Importance–Performance Analysis (IPMA) for Product and Process Innovation

Construct	Mean score	Importance on PrI	Importance on PsI
FS	0.430	0.075	0.079
IS	0.321	0.406	0.203
II	0.556	0.139	0.371

Source: Authors' calculation in R.

The IPMA results point to differentiated leverage areas across innovation outcomes. For product innovation, Institutional Support (IS) emerges as the most important construct (importance = 0.406) while also exhibiting the lowest performance (mean score = 0.321). This configuration positions IS as a high-leverage domain where strengthening linkages with public agencies, universities, and support organizations could be particularly relevant for enhancing product-oriented innovation. For process innovation, Innovation Investment (II) shows the highest importance (importance = 0.371) and also the highest performance (mean score = 0.556), reinforcing the central role of tangible and intangible resource allocation—such as equipment, training, and digital and knowledge-related investments—in internal operational improvements.

By contrast, Funding Sources (FS) is comparatively less important in both models (0.075 for PrI; 0.079 for PsI) and has a mid-range performance level (mean score = 0.430). This pattern suggests that, within the observed institutional and market context, financing modalities alone are less closely aligned with innovation outcomes than institutional linkages and innovation-oriented investment, and that their contribution may depend on how effectively financial resources are translated into capability-building inputs.

Figure 6 summarises these findings by mapping each construct according to its relative importance and empirical performance, thereby offering a practical lens for prioritizing managerial and policy interventions.

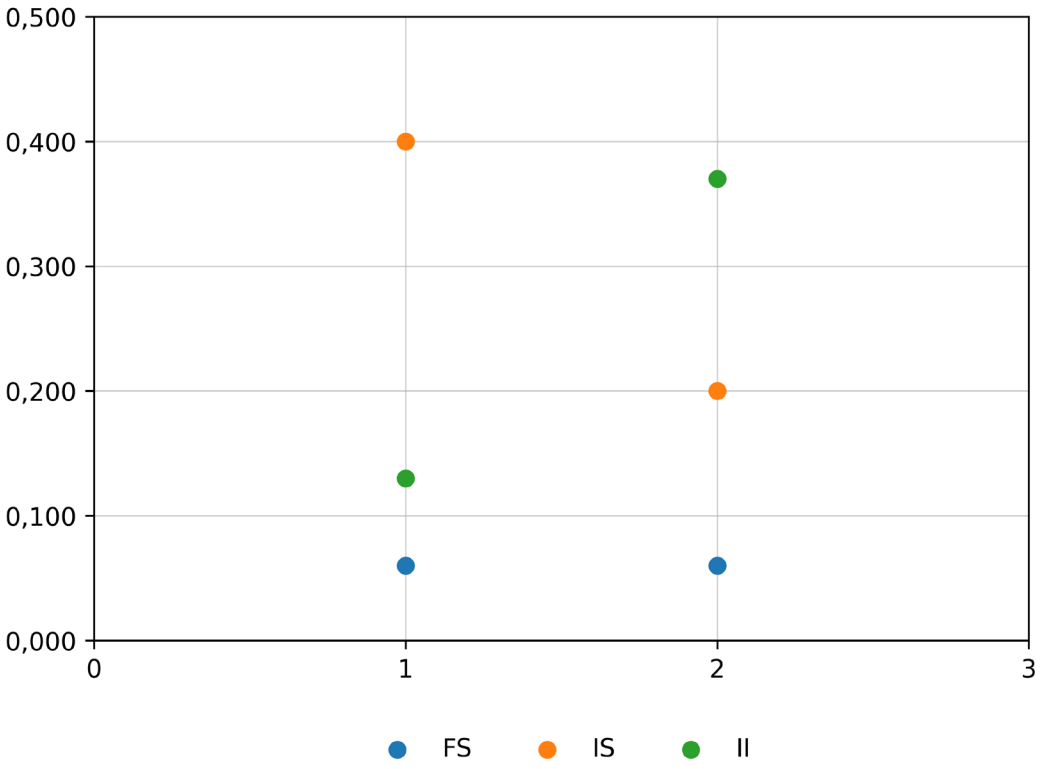

Figure 6. Importance–Performance Map (IPMA) for Product and Process Innovation

DISCUSSION

This study contributes to the literature on innovation in emerging economies by providing empirical evidence on how aggregated (formative) funding structures, institutional linkages, and innovation-oriented investment are associated with two distinct innovation outcomes among innovative service-sector SMEs in Colombia. By estimating two independent PLS-SEM models—one for product innovation and another for process innovation—the analysis addresses the conceptual and empirical argument that these outcomes are related but not interchangeable, particularly in service sectors where innovation frequently materializes through both market-facing offerings and internal organizational and digital upgrading (Busom & Vélez-Ospina, 2017; Pertuz & Ojeda Ramírez, 2023). In addition, operationalizing innovation outcomes using binary incidence indicators is consistent wits and widely used CIS applications, in which innovation is typically measured as a dichotomous "introduced versus not introduced" outcome within a given reference period (Bou & Satorra, 2019; Rosário et al., 2024). This approach, therefore, captures the occurrence of innovation among firms reporting innovation activities rather than the magnitude of innovation outputs.

A central finding of the study is the differentiated pattern of associations observed across innovation outcomes. Institutional Support (IS) shows the strongest association with product innovation (β = 0.416), whereas Innovation Investment (II) exhibits the strongest association with process innovation (β = 0.371). Although the two models have comparable explanatory power (R^2 = 0.246 for product innovation and R^2 = 0.272 for process innovation), their internal structures reveal theoretically meaningful differences. Because FS, IS, and II are specified as composite constructs, the estimated coefficients capture the joint association of their underlying indicators with innovation outcomes rather than the isolated effect of individual funding mechanisms or institutional actors.

The prominence of institutional linkages in explaining product innovation is consistent with systemic perspectives of innovation, particularly in emerging-economy contexts where firms often rely on external knowledge channels to

complement limited internal research capabilities. In Colombia, empirical evidence suggests that public support and institutional infrastructure for innovation play a significant role in shaping firms' innovation trajectories, including in the service sector (Busom & Vélez-Ospina, 2017). For service SMEs, access to universities, innovation intermediaries, technical assistance, and market-based knowledge sources can accelerate learning, validation, and commercialization. Recent empirical evidence indicates that innovative Colombian service firms combine internal knowledge with market-based sources and technical assistance, while university knowledge can differentiate firms' innovation profiles (Pertuz & Ojeda Ramírez, 2023). From this perspective, Institutional Support functions not merely as a source of resources but also as an ecosystem mechanism that expands firms' knowledge access and strengthens their absorptive and commercialization capabilities in contexts where internal research infrastructure is limited.

In contrast, the stronger association between innovation investment and process innovation reflects the importance of internal capability development and resource reconfiguration for operational improvements. Process innovation in service SMEs often involves investments in intangible assets, such as training, organizational redesign, digital infrastructure, software, and information systems. These investments facilitate incremental improvements in service delivery, administrative processes, and information management, thereby enhancing organizational efficiency and adaptability. This interpretation aligns with evidence showing that discrete technological breakthroughs drive less intangible-intensive innovation than sustained investments in organizational capabilities and learning processes. Moreover, intangible assets are often difficult to collateralize, particularly for SMEs, which influences both the structure of financing and the mechanisms through which investment translates into innovation outcomes (Norkio, 2024). In this context, Innovation Investment represents the internal accumulation and deployment of innovation-related inputs that support continuous process upgrading.

Funding Sources (FS) shows a positive but comparatively modest association with both innovation outcomes (β = 0.071 for product innovation and β = 0.079 for process innovation). Substantively, this result suggests that financing—when conceptualized as an aggregated structure—functions primarily as an enabling condition rather than a direct explanatory factor of innovation outcomes. This interpretation is consistent with empirical evidence indicating that self-financing remains highly prevalent among Colombian SMEs and is closely associated with innovation activities, while external financing is often constrained by risk aversion, information asymmetries, and limited specialized financial instruments (Gálvez-Albarracín et al., 2018). Additional evidence highlights that financial barriers continue to influence firms' innovation performance and interact with knowledge networks and human capital conditions (Barrios et al., 2022). International research similarly suggests that innovative SMEs frequently face persistent frictions in accessing suitable financing instruments, particularly under conditions of uncertainty, reinforcing the idea that financial availability alone does not automatically translate into innovation unless it is effectively transformed into innovation investment and complemented by institutional support (Cowling et al., 2024).

The empirical distinction between product and process innovation is further supported by the moderate correlation between the two constructs (r = 0.257), which reinforces the methodological decision to estimate separate models. Conceptually, this distinction suggests that product innovation outcomes in service SMEs are more strongly influenced by ecosystem connectivity and institutional interfaces, whereas process innovation is more closely linked to internal investment intensity and the accumulation of intangible capabilities. From a policy perspective, this differentiation implies that uniform innovation support instruments may be insufficient: strengthening institutional bridges and specialized support infrastructures may be particularly relevant for product innovation, while policy instruments that encourage sustained investment in innovation capabilities—especially in intangible assets—may be more effective in promoting process upgrading.

The empirical results provide differentiated support for the proposed hypotheses. Hypotheses H1a and H1b receive support, as Funding Sources (FS) are positively associated with both product and process innovation, although the relatively small coefficients suggest a facilitating rather than dominant influence (Gálvez-Albarracín et al., 2018). Hypothesis H2a receives strong support, with Institutional Support showing the largest association with product innovation outcomes, highlighting the importance of institutional knowledge channels and innovation ecosystems in the Colombian service sector (Busom & Vélez-Ospina, 2017; Pertuz & Ojeda Ramírez, 2023). Finally, hypothesis H3b receives strong empirical support, as Innovation Investment shows the strongest association with process innovation, consistent with the capability-building role of intangible investment and internal implementation capacity (Norkio, 2024).

Overall, the findings underscore a key contextual insight for emerging economies: innovation in service-sector SMEs is less a linear outcome of increased financial availability and more a function of how financial resources are transformed

into innovation investment and combined with institutional linkages that enable learning, legitimacy, and access to complementary knowledge resources. From a policy perspective, strengthening institutional connectivity and mechanisms that support capability-building investment may therefore be as important as expanding financial channels, particularly in service sectors characterized by asymmetric access to resources and fragmented innovation support infrastructures (Busom & Vélez-Ospina, 2017; Cowling et al., 2024).

CONCLUSION

This study examines how aggregated funding structures, institutional support, and innovation-oriented investment relate to product and process innovation outcomes among innovation-active service-sector SMEs in Colombia. Using firm-level microdata from the EDITS VIII survey and estimating two PLS-SEM models, the analysis provides new empirical insights into how financial and institutional resources are associated with innovation outcomes in an emerging-economy service context.

A first contribution of the study is theoretical. By integrating the resource-based view, dynamic capabilities theory, and the Triple/Quadruple Helix perspectives within a composite-based SEM framework, the study proposes a holistic analytical model linking financial structures, institutional ecosystems, and investment patterns to distinct innovation outcomes. The results suggest that these domains operate as complementary resource configurations rather than independent explanatory factors. In particular, the findings indicate that institutional support is more strongly associated with product innovation, whereas innovation investment appears more strongly related to process innovation, highlighting differentiated innovation pathways among innovation-active service-sector SMEs.

A second contribution is empirical. Evidence from Colombian service-sector SMEs engaged in innovation activities indicates that institutional linkages are closely associated with product innovation outcomes, suggesting that connections with universities, support institutions, and market actors may facilitate access to knowledge and commercialization opportunities. In contrast, internal investment in innovation-related assets—particularly intangible resources—appears more strongly associated with process innovation, reflecting the importance of internal capability development and operational upgrading. Funding structures exhibit a positive but comparatively weaker association with both innovation outcomes, suggesting that financial resources may primarily serve as enabling conditions rather than direct explanatory factors.

A third contribution relates to methodological advancement. By operationalizing funding sources, institutional support, and innovation investment as formative composite constructs and modeling product and process innovation separately, the study provides a structured approach for capturing the multidimensional nature of innovation inputs in emerging-economy contexts. This approach allows the analysis to reflect the aggregated configuration of financial and institutional resources available to firms rather than focusing on isolated indicators.

From a policy and managerial perspective, the findings suggest that innovation support policies for innovation-active service-sector SMEs should move beyond purely financial instruments. Strengthening institutional linkages—such as collaboration with universities, technical assistance organizations, and innovation intermediaries—appears particularly relevant for fostering product innovation. At the same time, policies that encourage sustained investment in innovation-related assets, including training, digital infrastructure, and organizational capabilities, may be more conducive to supporting process innovation and operational upgrading.

Finally, several limitations should be acknowledged. The study relies on cross-sectional survey data, which limits causal inference regarding the direction of relationships between financing structures and innovation outcomes. Moreover, the measurement of innovation outcomes relies on binary indicators that capture the occurrence of innovation rather than its economic magnitude or technological depth. These limitations suggest that innovation in emerging economies should be understood not as a single process but as a set of differentiated pathways shaped by the interaction between financial structures, institutional ecosystems, and internal capability development. Future research could extend this approach by incorporating longitudinal data, intensity-based innovation indicators, and comparative analyses across sectors or countries to further explore the dynamics linking financial structures, institutional ecosystems, and innovation performance.

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Appendix 1. Operationalization of constructs: Latent variables, descriptions, and EDITS VIII survey codes

Construct	Indicator (binary)	Description	EDITS Code
PrI – Product Innovation	new_goods_firm	New goods or services for the firm (already available in national/international markets)	I1R1C1N
	improved_goods_firm	Improved goods or services for the firm (already available in national/international markets).	I1R1C1M
	new_goods_market	New goods/services with market novelty (1 if national or international novelty = 1)	I1R2C1N and I1R3C1N
	improved_goods_market	Improved goods/services with market novelty (1 if national or international novelty = 1)	I1R2C1M and I1R3C1M
PsI – Process Innovation	new_method_production	New or improved methods for delivery service or goods production.	I1R4C1
	new_method_organization	New or improved organizational methods within the firm.	I1R5C1
	new_method_marketing	New or improved marketing techniques.	I1R6C1
	new_method_distribution	New or improved distribution, delivery, or logistics systems.	I1R8C1
	new_method_information	New or improved information processing or communication methods.	I1R9C1
	new_method_account	New or improved accounting or administrative operations methods.	I1R10C1
FS – Funding Sources	funding_internal	Own financial resources.	III1R1C1, III1R1C2
	funding_banks	Bank loans from domestic or international institutions.	III1R4C1–III1R4C4
	funding_private	Private equity or funding from other companies (domestic or international).	III1R6C1–III1R6C4
	funding_donations	Funds from cooperation or donations.	III1R7C1–III1R7C4
II – Innovation Investment	investment_tangible	Machinery, equipment, or facilities acquired for innovation purposes.	II1R3C1, II1R3C2, II1R11C1, II1R11C2
	investment_intangible	Internal/external R&D, ICT, software, marketing, intellectual property, technical assistance, training, etc.	II1R1C1–II1R12C2
IS – Institutional Support	support_public	Public and governmental institutions (e.g., ministries, SENA, INNPulsa, Colombia Productiva).	V2R1C1–V3R12C1
	support_academic	Universities, research centers, technology parks, and academic entities.	V2R7C1–V3R10C1
	support_private	Private sector entities: clients, suppliers, business groups, consultants.	V2R15C1–V3R5C1
	support_international	International organizations and NGOs.	V2R17C1, V3R11C1
	support_training	Technical training entities, regional science and technology councils (CODECyT), regional competitiveness commissions.	V2R13C1, V2R14C1, V2R19C1

Note: The sequence of process innovation indicators follows the original EDITS VIII questionnaire structure. After item I1R6C1 (marketing methods), the survey includes I1R7C1, which refers to a follow-up question on marketing innovation rather than a distinct type of process innovation. Consequently, the next indicator corresponding to a different innovation category is I1R8C1 (distribution and logistics methods). The numbering therefore reflects the original questionnaire coding rather than a missing variable.

Appendix 2. Bootstrapped indicator weights (PrI model)

Construct	Indicator	Weight	SE	t	CI 2.5%	CI 97.5%
Product Innovation (PrI)	new_goods_firm	0.495***	0.028	17.429	0.439	0.551
Product Innovation (PrI)	improved_goods_firm	0.445***	0.030	15.013	0.386	0.502
Product Innovation (PrI)	new_goods_market	0.399***	0.034	11.621	0.330	0.464
Product Innovation (PrI)	improved_goods_market	0.276***	0.038	7.332	0.199	0.345
Funding Sources (FS)	funding_internal	0.636***	0.066	9.577	0.515	0.773
Funding Sources (FS)	funding_banks	0.281***	0.063	4.478	0.145	0.393
Funding Sources (FS)	funding_private	-0.122***	0.047	-2.592	-0.216	-0.033
Funding Sources (FS)	funding_donations	0.579***	0.062	9.316	0.446	0.688
Institutional Support (IS)	support_public	0.544***	0.031	17.613	0.485	0.605
Institutional Support (IS)	support_academic	0.484***	0.017	27.805	0.451	0.516
Institutional Support (IS)	support_private	0.259***	0.013	19.248	0.233	0.286
Institutional Support (IS)	support_international	0.286***	0.021	13.333	0.245	0.328
Institutional Support (IS)	support_training	0.277***	0.017	16.440	0.242	0.309
Innovation Investment (II)	investment_tangible	0.797***	0.026	31.066	0.744	0.844
Innovation Investment (II)	investment_intangible	0.462***	0.033	13.963	0.396	0.526

Note: Weights were estimated using bootstrapping with 95% confidence intervals. *** p < 0.01; ** p < 0.05; * p < 0.10 (normal approximation based on the t-statistic).

Appendix 3. Bootstrapped indicator weights (PsI model)

Construct	Indicator	Weight	SE	t	CI 2.5%	CI 97.5%
Process Innovation (PsI)	new_method_production	0.339***	0.017	19.460	0.305	0.372
Process Innovation (PsI)	new_method_ organization	0.343***	0.012	28.326	0.319	0.366
Process Innovation (PsI)	new_method_marketing	0.274***	0.016	17.346	0.242	0.304
Process Innovation (PsI)	new_method_distribution	0.209***	0.015	13.699	0.178	0.239
Process Innovation (PsI)	new_method_information	0.413***	0.015	28.367	0.385	0.442
Process Innovation (PsI)	new_method_account	0.517***	0.018	29.124	0.481	0.552
Funding Sources (FS)	funding_internal	0.756***	0.034	22.048	0.687	0.822
Funding Sources (FS)	funding_banks	0.261***	0.031	8.465	0.197	0.318
Funding Sources (FS)	funding_private	0.111***	0.031	3.533	0.047	0.171
Funding Sources (FS)	funding_donations	0.323***	0.030	10.575	0.258	0.380
Institutional Support (IS)	support_public	0.665***	0.023	28.893	0.620	0.710
Institutional Support (IS)	support_academic	0.489***	0.017	29.469	0.457	0.522
Institutional Support (IS)	support_private	0.349***	0.023	15.283	0.308	0.397
Institutional Support (IS)	support_international	0.250***	0.023	10.651	0.202	0.293
Institutional Support (IS)	support_training	0.209***	0.022	9.414	0.163	0.249
Innovation Investment (II)	investment_tangible	0.410***	0.026	15.677	0.357	0.459
Innovation Investment (II)	investment_intangible	0.832***	0.019	43.332	0.794	0.869

Note: Weights were estimated using bootstrapping with 95% confidence intervals. *** p < 0.01; ** p < 0.05; * p < 0.10 (normal approximation based on the t-statistic).

Appendix 4. Prevalence of original product innovation novelty indicators

Indicator	Count	Total	Percentage (%)
new_goods_firm	598	2,782	21.50
new_goods_national	38	2,782	1.37
new_goods_international	3	2,782	0.11
improved_goods_firm	423	2,782	15.20
improved_goods_national	30	2,782	1.08
improved_goods_international	2	2,782	0.07

Note: National and international novelty indicators were subsequently aggregated into the broader variables *new_goods_market* and *improved_goods_market* for the estimation of the Product Innovation composite.

Biographical notes

Yaneth P. Romero-Alvarez is a Ph.D. in Innovation and a Full Professor at Universidad de Sucre (Colombia). Her research integrates innovation, financing strategies, and technological capabilities in SMEs, with a particular focus on developing and peripheral regions. She has an extensive background in financial analysis, project evaluation, and public investment, and has contributed to studies on innovation determinants using econometric techniques, including logistic regression and PLS-SEM, applied to large-scale datasets. Her work emphasizes the role of financial structures and institutional environments in shaping innovation outcomes and regional development.

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Author Contributions Statement

Yaneth P. Romero-Alvarez: Conceptualization, Data Curation, Formal Analysis, Methodology, Investigation, Visualization, Writing – Original Draft Preparation, Writing – Review & Editing.
Katherinne Salas-Navarro: Conceptualization, Supervision, Investigation, Writing – Review & Editing. **Lisana B. Martinez:** Resources, Supervision, Writing – Review & Editing.

Conflicts of Interest

The authors declare no conflicts of interest.

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Entrepreneurial finance and risk in portfolio management: Drawdown-based systematic exposure in European equities

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Abstract

PURPOSE: *The objective of the article is to calculate new systematic risk measures – Expected Regret of Drawdown (ERoD) Beta and Conditional Drawdown-at-Risk (CDaR) Beta – that account for the drawdowns (a decline in the value from a peak to a subsequent low) of the STOXX Europe 600 index in the period 2004–2024 across European countries and industries. These drawdown betas show how the securities behaved during market drawdowns, especially during the Great Financial Crisis and the COVID-19 crisis.* ***METHODOLOGY:*** *ERoD and CDaR Beta are new dynamic portfolio performance risk characteristics measuring portfolio drawdowns. Similar to the standard beta, the drawdown betas relate the expected return of an asset to the expected return of the market but are based on the concept of drawdowns.* ***FINDINGS:*** *The numerical results show that drawdown beta directly measures the performance of the securities during drawdowns. The drawdown betas have negative values, suggesting a safe-haven property for certain companies during financial crises, whereas the standard beta is positive. We demonstrate that the drawdown beta is a useful tool for portfolio construction and can indicate the different performance of Healthcare, Technology, and small-value companies during the COVID-19 crisis. It can imply that those securities can provide a hedge during a similar crisis.* ***IMPLICATIONS:*** *If the negative drawdown beta is identified, it could be used as insurance to lessen risk or to perform well in the event of a crisis in active management strategies.* ***ORIGINALITY & VALUE:*** *The drawdown beta is an innovative dynamic portfolio performance risk measure used on the European stock market data across an extended period (2004–2024). We investigated the impact of different factors on the resilience of the company during drawdowns, including firm-size deciles, countries, and industries, providing valuable insights into the relationship between company size and resilience during downturns. The drawdown beta framework delivers a powerful tool for both academics and practitioners seeking to assess asset resilience during market drawdowns.*

Keywords: *drawdown beta, Conditional Drawdown-at-Risk (CDaR) beta, Expected Regret of Drawdown (ERoD) beta, downside risk, systematic risk, Capital Asset Pricing Model (CAPM), portfolio risk management, safe-haven assets, financial crises, European equity markets*

INTRODUCTION

The relationship between risk and expected return is a significant challenge in financial theory. The traditional Capital Asset Pricing Model (CAPM) explains how to measure risk and the relationship between expected return and risk (Sharpe, 1964; Lintner, 1965; Mossin, 1966). CAPM shows that investors are rewarded for taking on non-diversifiable

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risk (systematic risk), which is measured by beta. Beta is the tendency of the stock's return to respond to changes in the market, represented by the stock market index. Beta coefficients are a fundamental concept in finance, particularly within the realm of portfolio management, as they serve as a key measure of an asset's riskiness.

While the single-period CAPM uses beta to explain returns on risky assets, beta alone cannot capture all variations in expected returns. The standard approach to estimate beta is to estimate covariances and variances from a time series of historical stock returns. However, this approach faces the problem of time-varying beta coefficients (e.g., Blume, 1975; Ferson and Harvey, 1991; and Groenewold and Fraser, 1999). Empirical studies across international markets, including the US (Fabozzi and Francis, 1978; Feder-Sempach et al., 2023) and Europe (Wells, 1994; Chauveau and Maillet, 1998), have demonstrated the instability of the beta parameter. Beta is mainly evaluated over relatively short periods (typically five years) because the CAPM's performance tends to be better over shorter periods, likely due to beta's instability over time. This phenomenon may stem from a conceptual limitation of the standard CAPM risk measure, which fails to distinguish between losses and gains within a portfolio. A new approach, represented by the drawdown beta, could better assess portfolio performance during market drawdowns.

Various risk measures have been proposed as alternatives to variance, including the latest drawdown-based risk measures, the Conditional Drawdown-at-Risk beta (CDaR beta), introduced by Zabarankin et al. (2014), and the Expected Regret of Drawdown Beta (ERoD beta), proposed by Ding and Uryasev (2022). Both metrics, like the standard or traditional beta, relate the returns of an asset to the returns of the market but are based on the concept of drawdowns: the decline in the value of an asset from a peak to a subsequent low. The CDaR and ERoD Betas differ in their approach to determining which drawdowns to include. The former is based on a percentage of worst-case market drawdowns, while the latter is based on drawdowns with a known threshold.

The main aim of the paper is to examine standard beta and the new drawdown betas during stock market drawdowns in Europe, applying the methodologies proposed by Zabarankin et al. (2014) and Ding and Uryasev (2022). To show the impact of unprecedented events – the Great Financial Crisis (GFC), the COVID-19 crisis, and Russia's invasion of Ukraine – the sample covers two 10-year subperiods: 2004–2014 and 2014-2024, with March 1, 2014, serving as the cutoff date. The drawdown beta evaluates portfolio performance, accounting for the drawdowns of the STOXX Europe 600 index across countries, industries, and company sizes, to differentiate between the causes and the nature of the crisis.

The research sample comprises companies in the STOXX Europe 600 index, listed in both euros and in their respective domestic currencies. This index comprises 600 components from European countries, covering large-, mid-, and small-capitalisation companies. The index provides coverage across country and industry allocations, offering a portfolio of developed European economies and replicating almost 90% of the underlying investable market.

This paper contributes to the literature in three significant ways. First, it assesses the two risk measures (CDaR and ERoD Betas) over a 20-year horizon, including two ten-year subperiods. The drawdown periods are defined differently based on their respective formulas. Second, it analyses these risk measures in different countries, industries and market capitalization deciles to illustrate the impact of the GFC and COVID-19 market turmoil. Third, by comparing the standard beta and drawdown betas, the aim is to supplement the existing portfolio management literature with a diversification perspective. The main research hypothesis is that drawdown beta is much more sensitive to market distress and can exhibit negative values, potentially working as a downside protection measure indicator, unlike the standard beta, which is positive. A downside protection measure indicator not based on correlation is similar to the notion of safe-haven assets, which maintain or increase their value during periods of market turmoil, protecting investors when most other assets decline. The above-mentioned sensitivity to crises could be effectively leveraged in active portfolio management strategies in European stock markets amid market volatility.

The remainder of the article is structured as follows: Section two provides a literature review, and Section three presents the research sample and methodology. Section four discusses the empirical results, and the last section concludes the paper.

LITERATURE REVIEW

The standard beta is a key indicator of stock performance in portfolio management, measuring the relationship between the expected return of a security and the expected excess return of a market index. According to the classical CAPM formula, this relationship is based on three implications: (1) expected returns on all assets are linearly related to their

betas, (2) the beta premium is positive, and (3) the beta premium equals the expected market return minus the risk-free rate (Fama and French, 2004).

Early empirical tests of the CAPM revealed that beta estimates for individual assets are imprecise and that regression residuals exhibit common sources of variation, such as industry effects in average returns. To improve beta estimation, researchers shifted their focus from individual securities to portfolios. For example, Blume (1970, 1975), Friend and Blume (1973), and Black, Jensen, and Scholes (1972) demonstrated that beta estimates for diversified portfolios are more precise than those for individual securities. Vasicek (1973) proposed a method of adjusting historical betas towards the average beta, modifying each estimate based on its sampling error. In other words, an estimate is considered more reliable if it predicts stock returns more accurately than simply assuming all stocks have a beta of one. Fama and MacBeth (1973) addressed inference problems caused by correlated residuals in cross-sectional regressions. Instead of using a single cross-sectional regression of average monthly returns on beta estimates, they proposed conducting month-by-month cross-sectional regressions of monthly returns on estimated betas.

The central question is whether market betas can explain expected returns. The Sharpe-Lintner and Black (1972) version of the CAPM implies that differences in expected return across securities and portfolios are entirely explained by differences in market beta. No other variables contribute to explaining expected returns – highlighting the prominent role of beta in modern financial theory. The risk premium for beta is assumed to be positive, and under these conditions, the model provides a good description of expected stock returns.

Furthermore, it is vital to know if the relationship between beta and return holds under different stock market conditions, such as bull and bear markets. Several studies have examined this using individual securities, including Fabozzi and Francis (1977, 1979), Clinball et al. (1993), Kim and Zumwalt (1979), and Dębski et al. (2016). Most of these studies find that the beta parameter varies with different market conditions. For example, Spiceland et al. (1983) observed that the parameters exhibit nonstationarity during market advances and market declines for certain stock groups. For instance, parameters of stocks in high-risk and low-risk schemes behave differently, suggesting they are affected by the alternating forces of bull and bear market conditions. Wiggins (1992) demonstrated that conditioning beta on the sign of the market risk premium provides a better explanation of monthly cross-sectional returns, on average. These studies commonly used the Dual Beta Market (DBM) model and t-tests and F-tests, along with up- and down-market definitions of bull and bear markets, to investigate this relationship. Notably, there is no single definition of a bull or bear market. For instance, Chen (1982) used a continuously changing time-varying parameter model to study beta nonstationarity across bull and bear market cycles.

As a consequence of these findings, the CAPM has been extended by using different risk measures for portfolio valuation, like the concept of drawdown measures. Initially, Markowitz (1959) proposed the mean-semi-variance approach to portfolio selection. Both standard deviation and lower semi-deviation are treated as general deviation measures that are not symmetric with respect to the rising and declining market trends of a random variable. Afterward, various non-symmetric risk measures have been proposed as an alternative to the standard beta, which is calculated over long periods to account for different market cycles. One of the proposals was the downside beta, which measures a stock's sensitivity to market downturns by focusing only on periods when the overall market's return is negative. This downside beta builds on the idea of downside risk. Jahankhani (1976) tested the risk and return relationships for a mean-variance and a mean-semivariance CAPM, but he did not find any improvement of the downside beta over the standard beta when predicting portfolios' returns. In contrast, Ang and Chen (2007) demonstrated that the usual downside beta has strong explanatory power for returns over the same period, but not for future returns. Even though Estrada (2002) showed that the downside beta explains the variation in the cross-section of asset returns in emerging markets, proposing the downside CAPM, or D-CAPM for short. He strongly supported the downside beta and the D-CAPM idea. Lettau, Maggiori, and Weber (2014) proved the explanatory power of the downside beta by the cross-section of currency returns. They showed that downside risk CAPM could rationalize the cross-section of equity, equity index options, commodity, sovereign bond, and currency returns, thus offering a unified risk view of the selected financial instruments. A new approach to portfolio optimization and risk reduction was proposed by Rockafellar and Uryasev (2000), who suggested minimizing the Conditional Value-at-Risk (CVaR) rather than the value-at-risk (VaR). This approach has gained popularity among investment companies, mutual funds, and international investors as a way to evaluate risk (Rockafellar and Uryasev, 2002, 2013).

Building on this, Rockafellar et al. (2006) extended classical CAPM by introducing non-symmetric risk measures known as Generalized Deviations. The classical portfolio theory goes beyond the traditional reliance on standard deviation. Rockafellar et al. (2006) stated that the CAPM equations are necessary optimality conditions for portfolio

optimization, where beta can be computed for CVaR and the lower semi-deviation (the square root of the semi-variance). Liu (2023) introduced a novel measure of downside beta, the ES-implied beta, based on expected shortfall, to improve the prediction of the cross-section of asset returns. The ES-implied beta explains stock returns similarly to the widely used downside beta, but it can be associated with high persistence. Finally, Krokhmal et al. (2011) provided a comprehensive review of these non-symmetric risk measures and the latest advances in decision-making under uncertainty. Their paper also introduced new formulas for estimating beta.

An important lesson from this discussion is that portfolio managers aim to construct portfolios that avoid drawdowns and minimize losses. Market drawdowns are commonly assessed using the widely recognized Maximum Drawdown, which measures the largest cumulative portfolio loss within a specified time interval (Daehwan, 2014). However, from an investor's perspective, the maximum drawdown is not an ideal risk measure as it reflects only one specific event on a price sample path.

To address this limitation, Goldberg and Mahmoud (2016) introduced the Conditional Expected Drawdown (CED), defined as the tail mean of the maximum drawdown distribution. Similarly, Chekhlov et al. (2004) proposed Conditional Drawdown at Risk (CDaR), which averages a specified percentage of the largest portfolio drawdowns over the whole investment horizon. CDaR has been used to identify systemic dependencies in the financial market and is conceptually similar to the CVaR, applied specifically to the drawdowns of cumulative portfolio returns. Ding and Uryasev (2022) employed CDaR regression to measure systemic risk contributions of financial institutions and for fund style classification. Allen et al. (2016) also analysed the downside risk metrics as a portfolio diversification strategy in a European market context by using CVaR optimisers and drawdown optimisers (MaxDD, AveDD, CDaR95, CDaRMin95).

Zabarankin et al. (2014) introduced the CAPM with drawdown beta, which provides the necessary optimization conditions in the form of CAPM equations. In this model, drawdown alpha and beta are defined analogously to the classical CAPM. The new formula for CDaR Beta was derived similarly to the standard beta, but it quantifies the relationship between market returns and individual asset returns exclusively during market drawdown periods. Both the drawdown beta and alpha were used to prioritize hedge fund strategies designed to mitigate market downturn risks. In summary, drawdown beta and standard beta have a clear distinction: drawdown beta focuses solely on asset performance during market drawdowns, effectively identifying hedging properties, whereas standard beta reflects the correlation between asset and market returns across all market conditions[4].

Broadly defined, a safe-haven asset is one that either retains or increases in value during periods of market turmoil or extreme financial stress. This concept has been extensively explored in academic literature, particularly in the context of financial crisis and portfolio risk management (Baur & Lucey, 2010; Baur et al., 2021). When describing the safe-haven behaviour, the main idea is to reduce portfolio risk in extreme market conditions, acting as a stabilizer when financial markets are under stress. Empirical identification of safe-haven assets remains contingent on various factors. The concept of drawdown risk measures as downside protection indicators is perfectly suited here, as the notion of drawdown beta has emerged as a complementary framework for understanding asset performance under adverse market conditions. A low or negative drawdown beta indicates that an asset either resists or inversely responds to market drawdowns, thereby providing protection during a crisis.

By refining the concept of drawdown beta, Ding and Uryasev (2022) introduced the Expected Regret of Drawdown (ERoD), a novel portfolio performance risk measure that computes the average drawdown exceeding a specified threshold. Essentially, the ERoD beta is constructed by dividing the average stock losses during market drawdowns that exceed the threshold by the corresponding average market drawdowns. This ERoD beta yields different results than the downside beta based on lower semi-deviation. While the ERoD beta is similar to CDaR beta, which averages a specified percentage of the largest drawdowns, it offers the advantage of explicitly quantifying the magnitude of the drawdowns. Although the CDaR and ERoD portfolio optimization problems are equivalent and yield the same optimal portfolios, they capture different drawdown characteristics. Empirical applications of ERoD and CDaR beta could enrich the existing literature on safe-haven assets by providing a quantitative metric for evaluating their effectiveness across different markets, by using the non-correlation definitions. Specifically, stocks that qualify as safe-haven assets should exhibit a low or negative drawdown beta. Both drawdown betas can be used effectively to identify safe-haven behaviour, especially when used together: CDaR Beta reveals how much an asset can lose in a worst-case drawdown. ERod Beta indicates whether an asset moves with or against the market during a crisis. This makes them valuable tools in risk-based asset selection and portfolio hedging.

4 See more about beta parameter and drawdown beta concept in Feder-Sempach E., (2024). Portfolio Management in Times of Elevated Risk. Safe-Haven and Hedge Assets in CAPM Setting, Journal of Finance and Financial Law.

METHODOLOGY

To calculate the ERoD and CDaR Betas, the European stock market was selected, represented by the STOXX Europe 600 index. It encompasses 600 large, mid, and small-cap companies across 17 European countries, denominated in both euros and their domestic currencies. It provides country and industry coverage, replicating almost 90% of the underlying investable market. This study uses daily and monthly closing prices of STOXX Europe 600 companies listed on the main European stock exchanges. All companies' quotations were converted into euros before calculating beta coefficient values, and we used the full time series with 428 stocks. The return frequency is daily for the drawdown beta (i.e., drawdown periods can vary in length) and monthly for the standard beta. According to the formulas below, the period of drawdown is selected, which means that drawdown betas are inherently conditional. They focus only on periods when the market is experiencing a drawdown, which are irregular intervals of stock returns. All stock data, including the STOXX Europe 600 index (price, net return in EUR), was collected between March 2004 and March 2024 from the LSEG Refinitiv EIKON database.

All companies were classified according to the Refinitiv Business Classifications (TRBC), the most comprehensive and up-to-date industry classification for analyzing companies and sectors across European markets[5]. This classification represents 10 main industries: Energy, Basic Materials, Consumer Cyclicals, Consumer Non-Cyclicals, Financials, Healthcare, Technology, Utilities, Real Estate, and Industrials.

This paper compares two drawdown betas – CDaR Beta and ERoD Beta – with the traditional beta. The CDaR Beta is defined as the average loss of a security over a percentage of the largest market drawdown periods, divided by the average market loss during those same periods. The ERoD beta is calculated as the average losses of a security during periods when the market experiences a drawdown exceeding a specified threshold ϵ, divided by the average market losses during those same periods (Ding & Uryasev, 2022). The formula for calculating the CdaR Beta and ERoD beta for security *i* is as follows:

$$\hat{\beta}^i_{CDaR,\alpha} = \frac{\sum_{t=1}^{T} q_t\left(w^i_{\tau(t)} - w^i_t\right)}{\sum_{t=1}^{T} q_t\left(w^M_{\tau(t)} - w^M_t\right)},$$

$$\hat{\beta}^i_{ERoD,\epsilon} = \frac{\frac{1}{T}\sum_{t=1}^{T} q^*_t\left(w^i_{\tau(t)} - w^i_t\right)}{\frac{1}{T}\sum_{t=1}^{T} q^*_t\left(w^M_{\tau(t)} - w^M_t\right)},$$

where:
i – index of security $i = 1, \ldots I$,
t – time, $t = 1, \ldots, T$,
w^i_t – compounded cumulative return of asset i at time t,
w^M_t – compounded cumulative return of the market portfolio at time t,
$d^M_t = w^M_{\tau(t)} - w^M_t$ drawdowns of the market portfolio,
q_t –indicator function, which is equal to $1/\left((1-\alpha)T\right)$ if d^M_t is one of the largest $(1-\alpha)T$ drawdowns $d^M_1, d^M_2, \ldots, d^M_T$ of the market portfolio, and 0 otherwise,
$q^*_t = 1(d^M_t \geq \epsilon)$ – indicator function, which is equal to 1 for $d^M_t \geq \epsilon$, and 0 otherwise.
$\tau(t) = \max\{k | 1 \leq k \leq t, w^M_k = \max_{1 \leq l \leq t} w^M_l\}$.

For the CdaR Beta, the parameter $\alpha \in [0,1]$ controls the percentage of the largest drawdowns included in the calculation. Specifically, $\alpha = 0$ includes all market drawdowns, while $\alpha = 0$ considers only the maximum (i.e., the single largest) market drawdown. For example, the $CdaR_{0.9}$ beta accounts for the largest 10% of drawdowns in the market portfolio.

For the ERoD beta, the parameter $\epsilon \in (0,+\infty)$ determines the magnitude of the market drawdowns to be considered. Ding and Uryasev (2022) proposed a threshold of 0 + with $\epsilon = 10^{-6}$ to account for all non-zero drawdowns. In the empirical part of the study, we calculated drawdown betas with the following parameters: the CdaR beta with $\alpha = 0.9$ ($CdaR_{0.9}$) and

5 Our sample does not include any companies from Luxembourg.

the ERoD beta with a threshold of $\epsilon = 10^{-6}$ ($EroD_{0+}$), both based on daily returns[6]. The standard beta was calculated using monthly returns based on Fama and French's (2004) formula:

$$\hat{\beta}^i_{standard} = \frac{cov(r^i_t, r^M_t)}{var(r^M_t)},$$

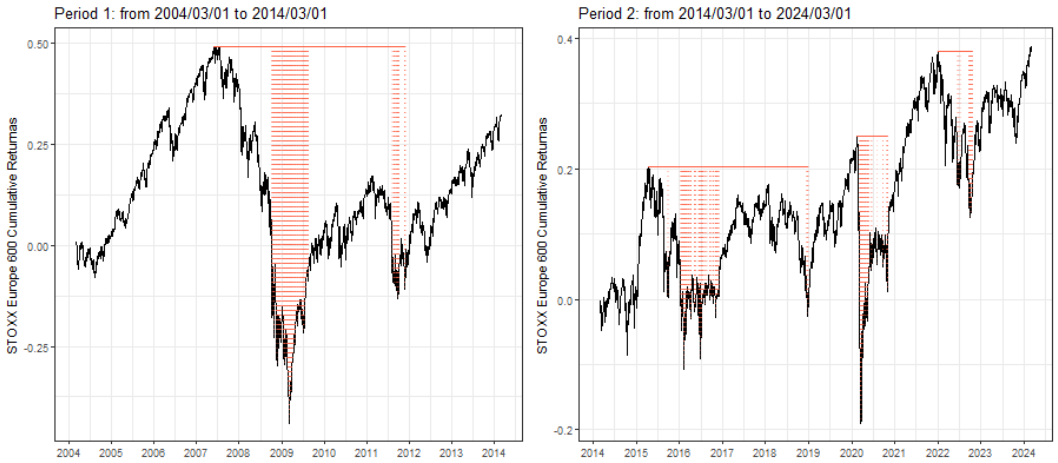
where:
i – index of security $i = 1, \ldots I$,
t – time, $t = 1, \ldots, T$,
r^i_t – return of asset i at time t,
r^M_t – return of the market portfolio at time t.

It is important to note that the CdaR Beta and the ERoD Beta capture different drawdown characteristics. The CdaR Beta focuses on unique market conditions, such as the GFC and the COVID-19 crisis, which are unlikely to recur. In contrast, the EroD Beta accounts for all nonzero drawdowns in the STOXX Europe 600. Thus, the EroD Beta should be treated as an alternative to the CdaR Beta.

RESULTS AND DISCUSSION

We begin by comparing the ERoD Beta, the CDaR Beta, and the standard beta for European companies in two subperiods. Comparing drawdown betas with the standard beta demonstrates that, although the traditional beta is more stable, it provides little additional information during periods of market distress. In contrast, drawdown betas are more sensitive to market distress during unexpected events. Their tendency to take on negative values during such times may indicate potential safe-haven characteristics (cf. Bogołębska et al. 2024), offering greater informative power to investors focused on European markets.

Below, we compare the values of betas across two distinct periods. The first period reflects the impact of the GFC and the Eurozone crisis, while the second period encompasses several major events, including Donald Trump's first election, the Brexit crisis, the COVID-19 economic crisis, and Russia's invasion of Ukraine (Figure 1):



Note: The 10% largest drawdowns are highlighted in red. Period 1: 2004 – 2014, dominated by the GFC; Period 2: 2014 – 2024, dominated by the COVID-19 economic crisis.

Figure 1. STOXX Europe 600 in Periods 1 and 2
Source: Own elaboration based on LSEG Refinitiv EIKON data.

6 The drawdown betas are not computed on daily intervals, but the return time series is daily.

The analysis is based on cross-country and industry patterns, as well as on deciles of European companies ranked by the means of year-end market capitalization[7]. The first decile represents the 10% of companies with the smallest market cap, while the tenth decile covers the 10% biggest companies. Table 1 presents average beta values by country; Table 2 shows average beta values by industry; and Table 3 displays average beta values by market capitalization deciles for Periods 1 and 2. The corresponding results based on medians are reported in Tables A1–A3 in the appendix.

Table 1. Average beta values by country in Periods 1 and 2

Country of exchange	Period 1			Period 2			N
	$ERoD_{0+}$	$CDaR_{0.9}$	Standard	$ERoD_{0+}$	$CDaR_{0.9}$	Standard	
Austria	1.456	1.160	1.212	0.002	0.914	1.068	6
Belgium	1.059	0.936	0.879	-0.252	0.383	0.825	12
Denmark	1.068	1.091	0.978	0.258	0.699	1.095	20
Finland	1.156	1.083	1.034	0.398	0.719	0.929	12
France	1.040	0.975	1.048	0.154	0.682	1.068	58
Germany	0.783	0.899	1.031	0.464	0.738	1.089	47
Ireland; Republic of	2.966	1.229	1.028	1.479	0.820	0.951	6
Italy	1.711	1.102	0.936	1.643	1.140	1.191	25
Netherlands	0.930	0.987	1.074	0.787	0.998	1.114	18
Norway	0.996	0.943	1.102	-0.265	0.386	0.749	11
Poland	0.551	1.074	1.079	0.407	1.125	1.040	6
Portugal	1.277	0.702	0.727	2.881	1.142	0.930	3
Spain	1.082	0.832	0.928	0.962	0.935	0.948	17
Sweden	0.766	1.038	1.096	0.279	0.675	1.087	43
Switzerland	0.431	0.705	0.675	-0.121	0.497	0.771	44
United Kingdom	1.179	1.077	0.953	1.118	0.978	1.100	100
Total	1.022	0.983	0.973	0.572	0.788	1.033	428

Source: Own elaboration based on LSEG Refinitiv EIKON data.

Table 2. Average beta values by industry in Periods 1 and 2

Sector	Period 1			Period 2			N
	$ERoD_{0+}$	$CDaR_{0.9}$	Standard	$ERoD_{0+}$	$CDaR_{0.9}$	Standard	
Basic Materials	0.750	0.952	1.141	0.424	0.881	1.069	39
Consumer Cyclicals	1.087	1.100	1.027	0.914	0.979	1.160	60
Consumer Non-Cyclicals	0.493	0.760	0.649	0.147	0.359	0.753	38
Energy	0.797	0.806	1.053	1.166	0.916	1.068	17
Financials	1.863	1.223	1.255	1.768	1.291	1.206	80
Healthcare	0.530	0.717	0.596	-0.551	0.170	0.833	34
Industrials	0.814	0.971	1.022	0.179	0.717	1.084	75
Real Estate	1.165	1.072	0.752	1.079	0.936	0.884	19
Technology	0.807	0.922	0.905	-0.561	0.392	0.977	46
Utilities	1.165	0.865	0.733	0.860	0.823	0.808	20
Total	1.022	0.983	0.973	0.572	0.788	1.033	428

Source: Own elaboration based on LSEG Refinitiv EIKON data.

7 First, end-of-year market capitalizations were selected; then, their means were calculated; finally, companies were assigned to deciles based on these means.

Table 3. Average beta values in Periods 1 and 2, relative to deciles of company value

Deciles of company value	Period 1			Period 2			N
	$ERoD_{0+}$	$CDaR_{0.9}$	Standard	$ERoD_{0+}$	$CDaR_{0.9}$	Standard	
1st decile	0.858	0.922	0.726	-0.054	0.685	0.949	43
2nd decile	1.227	1.107	0.901	0.178	0.610	1.066	43
3rd decile	1.011	0.950	0.928	0.599	0.704	0.986	43
4th decile	1.309	1.121	1.034	0.610	0.791	1.076	42
5th decile	1.124	0.987	0.935	0.417	0.764	1.039	43
6th decile	0.979	0.912	0.916	0.491	0.695	0.978	43
7th decile	1.009	0.996	1.029	0.606	0.862	1.052	42
8th decile	1.207	1.054	1.095	0.999	0.987	1.072	43
9th decile	0.844	0.902	1.111	0.726	0.869	1.073	43
10th decile	0.658	0.887	1.061	1.150	0.915	1.039	43
Total	1.022	0.983	0.973	0.572	0.788	1.033	428

Source: Own elaboration based on LSEG Refinitiv EIKON data.

According to Table 1, CDaR and standard beta are always positive on average, making it impossible to identify European companies that can hedge a portfolio by moving in the opposite direction from the STOXX Europe 600 index. However, for the ERoD beta, the average value for Belgian, Norwegian, and Swiss companies is negative in Period 2, which covers the COVID-19 pandemic. Norway and Switzerland, which are not members of the European Union, are at a different stage of the business cycle than EU countries[8]. One explanation is that changes in the external environment tend to impact Norwegian and Swiss companies differently from those in the EU. Although the global economy is increasingly interdependent during a crisis due to spillover effects, some Norwegian and Swiss companies remain unaffected and could be used to hedge European portfolios (Reskiyah, 2023). Belgian companies were also relatively resilient to the recent crisis despite Belgium being an EU and eurozone member. It is also worth noting the exceptionally high ERoD Beta values for Irish companies – 2.966 in Period 1 and 1.479 in Period 2, along with similarly elevated values for Italian and Portuguese issuers. This may indicate that Irish, Italian, and Portuguese companies were highly sensitive to the crisis, or they may simply reflect an overweight of financial firms or the dominance of small-cap companies, rather than a genuine country-specific effect.

As shown in Table 2, the situation remains largely the same: the CDaR and standard beta values are positive on average. However, the ERoD beta shows negative values for the Healthcare and Technology industries in Period 2, which coincided with the COVID-19 pandemic crisis. These results show that Healthcare and Technology companies may have experienced accelerated returns due to heightened demand for medical and digital services caused by the COVID-19 crisis in Europe. The pandemic accelerated the digital transformation of many services and positively impacted companies in the Healthcare and Technology industries. Those industries became strategically important during the pandemic due to vaccine development, increased demand for medical products, and global lockdowns and remote work. Technology and healthcare stocks acted as resilient during the pandemic, similarly to gold, which is traditionally seen as a safe-haven asset (Baur & McDermott, 2010). Investors buy gold when uncertainty is high (e.g., during geopolitical turmoil, pandemics, or financial crises) because gold is viewed as a store of value not tied to the performance of economies. The pandemic created a unique situation where both gold and certain stocks performed well.

Gained investor interest as defensive stocks — demand for healthcare tends to remain stable even during economic downturns. According to Nassar et al. (2023), portfolio analysis indicates that investors should include the Healthcare and Technology sectors in their equity portfolios to reduce investment risk and protect expected returns during a pandemic.

Conversely, the highest beta values are observed in the Financial industry, which appears more unstable relative to the market than other industries, not only during periods of elevated risk but also under normal market conditions.

As shown in Table 3, similar results are observed in the ERoD Beta values for smaller, listed European companies. Specifically, for firms in the first decile based on market capitalization, the average ERoD Beta value is negative in Period

8 Norway and Switzerland are ranked as the most developed and richest countries from the global perspective while Norway is a member of the European Economic Area whereas Switzerland can participate and access the European single market through a set of bilateral agreements with the EU.

2 for the smallest 10% of companies by market capitalization. Generally, ERoD and CDaR Beta values are much smaller in Period 2, with nearly all values below 1.

In accordance with the study results, the ERoD and CDaR Beta values are, in some cases, lower than standard beta values, which are generally close to 1. Furthermore, during Period 1 (which covered the GFC), the ERoD and CDaR Betas were much higher than in Period 2 (which covered COVID-19), suggesting that European companies reacted differently to the distinct nature of each crisis. The ERoD Beta appears to deliver the best results because it captures the hedging attributes of selected European companies across countries, industries, and market capitalization, thereby improving portfolio efficiency. The average CDaR and standard beta contribution values remain positive across both periods despite the contrasting market shocks.

Tables 4–6 present the correlation coefficients for ERoD, CDaR, and standard betas between Period 1 and Period 2 across countries, industries, and company market capitalization, respectively. The negative correlation coefficients between these two periods show that European companies reacted differently to the distinct market drawdowns of the GFC and COVID-19.

Table 4. Beta correlations (Pearson correlation coefficients with 95% confidence intervals in parentheses) between Periods 1 and 2 in individual countries

Country of Exchange	Correlation			N
	$ERoD_{0+}$	$CDaR_{0.9}$	Standard	
Austria	-0.145 (-0.856; 0.755)	0.164 (-0.747; 0.861)	0.704 (-0.250; 0.965)	6
Belgium	0.309 (-0.322; 0.750)	0.760 (0.331; 0.929)	0.798 (0.414; 0.941)	12
Denmark	-0.231 (-0.611; 0.236)	0.220 (-0.246; 0.604)	0.864 (0.682; 0.945)	20
Finland	0.117 (-0.490; 0.647)	0.021 (-0.559; 0.588)	0.900 (0.676; 0.972)	12
France	0.241 (-0.019; 0.470)	0.345 (0.095; 0.554)	0.735 (0.588; 0.835)	58
Germany	0.185 (-0.108; 0.448)	-0.023 (-0.308; 0.266)	0.787 (0.647; 0.876)	47
Ireland; Republic of	0.797 (-0.040; 0.977)	0.666 (-0.316; 0.959)	0.855 (0.142; 0.984)	6
Italy	0.629 (0.311; 0.820)	0.610 (0.283; 0.810)	0.771 (0.541; 0.894)	25
Netherlands	0.261 (-0.235; 0.649)	0.586 (0.164; 0.827)	0.809 (0.549; 0.926)	18
Norway	-0.068 (-0.642; 0.555)	-0.197 (-0.713; 0.457)	0.776 (0.330; 0.939)	11
Poland	0.840 (0.090; 0.982)	0.861 (0.165; 0.985)	0.247 (-0.706; 0.882)	6
Portugal	0.965	0.981	0.996	3
Spain	0.024 (-0.462; 0.499)	0.246 (-0.266; 0.650)	0.751 (0.422; 0.905)	17
Sweden	-0.093 (-0.382; 0.214)	-0.011 (-0.311; 0.290)	0.610 (0.380; 0.770)	43
Switzerland	-0.074 (-0.362; 0.228)	0.223 (-0.079; 0.488)	0.832 (0.710; 0.905)	44
United Kingdom	0.294 (0.104; 0.464)	0.380 (0.198; 0.536)	0.741 (0.637; 0.818)	100
Total	0.311 (0.223; 0.394)	0.300 (0.211; 0.384)	0.722 (0.673; 0.764)	428

Note: No confidence interval is reported for Portugal due to an insufficient number of observations.
Source: Own elaboration based on LSEG Refinitiv EIKON data.

Table 5. Beta correlations (Pearson correlation coefficients with 95% confidence intervals in parentheses) between Periods 1 and 2 in individual industries

Sector	Correlation			N
	$ERoD_{0+}$	$CDaR_{0.9}$	Standard	
Basic Materials	-0.069 (-0.376; 0.252)	0.094 (-0.228; 0.398)	0.867 (0.759; 0.929)	39
Consumer Cyclicals	0.221 (-0.035; 0.450)	0.298 (0.047; 0.513)	0.639 (0.460; 0.768)	60
Consumer Non-Cyclicals	0.326 (0.007; 0.584)	0.380 (0.069; 0.624)	0.390 (0.080; 0.631)	38
Energy	0.244 (-0.268; 0.649)	0.550 (0.095; 0.815)	0.562 (0.111; 0.821)	17
Financials	0.479 (0.290; 0.632)	0.486 (0.299; 0.638)	0.580 (0.413; 0.710)	80
Healthcare	-0.468 (-0.696; -0.154)	-0.399 (-0.649; -0.070)	0.577 (0.296; 0.766)	34
Industrials	-0.013 (-0.240; 0.214)	0.064 (-0.165; 0.287)	0.614 (0.450; 0.738)	75
Real Estate	0.260 (-0.220; 0.639)	0.463 (0.012; 0.758)	0.809 (0.560; 0.924)	19
Technology	0.069 (-0.226; 0.352)	0.037 (-0.256; 0.324)	0.524 (0.276; 0.707)	46
Utilities	-0.247 (-0.622; 0.219)	0.028 (-0.420; 0.465)	0.595 (0.207; 0.821)	20
Total	0.311 (0.223; 0.394)	0.300 (0.211; 0.384)	0.722 (0.673; 0.764)	428

Note: No confidence interval is reported for Portugal due to an insufficient number of observations.
Source: Own elaboration based on LSEG Refinitiv EIKON data.

Table 6. Beta correlations (Pearson correlation coefficients with 95% confidence intervals in parentheses) between periods 1 and 2 in individual deciles of the company value

Deciles of company value	Correlation			N
	$ERoD_{0+}$	$CDaR_{0.9}$	Standard	
1st decile	0.072 (-0.233; 0.365)	0.275 (-0.027; 0.532)	0.729 (0.549; 0.845)	43
2nd decile	0.264 (-0.039; 0.523)	0.351 (0.057; 0.589)	0.625 (0.400; 0.779)	43
3rd decile	0.510 (0.248; 0.703)	0.350 (0.055; 0.588)	0.752 (0.584; 0.859)	43
4th decile	0.303 (-0.001; 0.556)	0.403 (0.113; 0.630)	0.664 (0.451; 0.805)	42
5th decile	0.110 (-0.197; 0.397)	0.065 (-0.240; 0.359)	0.732 (0.554; 0.847)	43
6th decile	0.617 (0.389; 0.774)	0.596 (0.360; 0.760)	0.721 (0.537; 0.839)	43
7th decile	0.286 (-0.020; 0.543)	0.296 (-0.009; 0.550)	0.835 (0.711; 0.908)	42
8th decile	0.566 (0.320; 0.741)	0.541 (0.287; 0.724)	0.897 (0.816; 0.943)	43
9th decile	-0.196 (-0.469; 0.111)	0.026 (-0.276; 0.324)	0.610 (0.379; 0.769)	43
10th decile	0.515 (0.254; 0.706)	0.331 (0.035; 0.575)	0.643 (0.425; 0.791)	43
Total	0.311 (0.223; 0.394)	0.300 (0.211; 0.384)	0.722 (0.673; 0.764)	428

Source: Own elaboration based on LSEG Refinitiv EIKON data.

Tables 4–6 show the Pearson correlation coefficients with 95% confidence intervals in parentheses between the two periods. Tables A4–A6 in the appendix show the corresponding Spearman correlations. All correlation coefficients calculated for the standard beta between the two periods are, on average, positive, indicating that the standard beta cannot capture variations in stock behavior across unrelated market crises. In contrast, the correlation coefficients for the ERoD and CDaR Betas are negative, suggesting that stock performance differed by crisis type.

Notably, Austrian, Danish, Norwegian, Swedish, and Swiss companies displayed distinct behavior in terms of the ERoD Beta. A similar pattern is observed across industries such as Basic Materials, Healthcare, Industrials, and Utilities, as well as among companies with higher market capitalizations. The CDaR Beta showed fewer negative correlation coefficients, primarily among companies from Germany, Norway, and Sweden, and in the Healthcare sector. Consistent with earlier findings, this supports the inclusion of Healthcare companies in equity portfolios to reduce investment risk during periods such as the COVID-19 crisis.

According to the numerical results, there is no relationship between a company's market capitalization and its beta during the drawdown periods of the GFC and COVID-19. This finding contradicts the results of Ding and Uryasev (2022), who reported that larger companies tend to exhibit stronger correlations in beta coefficients across crisis periods.

According to the classic CAPM interpretation, beta measures the sensitivity of a stock's return to variation in the market index return (Fama & French, 2004). As such, a positive beta indicates that the asset moves in the same direction as the market, while a negative beta would indicate the opposite. In the context of portfolio optimization, a contingency analysis of positive and negative ERoD and CDaR Beta values is proposed. Tables 7 and 8 present the number of companies with negative and positive ERoD and CDaR Betas across the two periods. In the case of the standard beta, no company has a negative beta in any period.

Table 7. Contingency table of positive and negative $ERoD_{0+}$ beta values in Periods 1 and 2

$ERoD_{0+}$ Beta	**Period 2**		
Period 1	Negative (-)	Positive (+)	Total
Negative (-)	21	30	51
Positive (+)	129	248	377
Total:	150	278	428

Source: Own elaboration based on LSEG Refinitiv EIKON data.

Table 8. Contingency table of positive and negative $CDaR_{0.9}$ beta values in Periods 1 and 2

$CDaR_{0.9}$ Beta	**Period 2**		
Period 1	Negative (-)	Positive (+)	Total
Negative (-)	2	5	7
Positive (+)	58	363	421
Total:	60	368	428

Source: Own elaboration based on LSEG Refinitiv EIKON data.

The contingency tables show the number of stocks with negative and positive ERoD and CDaR Beta values in Periods 1 and 2. No negative standard beta values – that would indicate an inverse relationship with the market – were observed. According to Table 7, 21 companies have a negative ERoD Beta in Periods 1 and 2, while 30 companies have a negative ERoD Beta in Period 1 but a positive one in Period 2. Conversely, 129 companies have an ERoD Beta that is positive in Period 1 but negative in Period 2. Meanwhile, 248 companies maintain a positive ERoD Beta across both periods.

Table 8 reveals that only two companies exhibit a negative CDaR Beta in both periods. Five companies have a negative CDaR Beta in Period 1 and a positive value in Period 2. In contrast, 58 companies have a CDaR Beta that is positive in Period 1 but negative in Period 2. The vast majority – 363 companies – have a positive CDaR Beta across both periods. These results indicate that the majority of European stocks moved in the same direction as the market, as indicated by the ERoD and CDaR Beta evaluations. However, these two new beta measures can potentially identify stocks that can rise during market distress and help investors diversify their portfolios.

In line with Ding and Uryasev's (2022) research on the American market, this study finds that ERoD and CDaR Betas applied to the European market are better at identifying stocks that can hedge portfolios and might serve as

indicators of downside protection measures in effective risk management strategies. In classical financial theory, safe-haven stocks tend to maintain or even gain value during market downturns. Consistently low or negative ERoD and CDaR Beta during crises could be considered safe from drawdown risk and extremely useful for strategies concerned with capital preservation. Surprisingly, there is no relationship between the market capitalization of the analyzed European companies and the beta in the two main drawdown periods of the GFC and COVID-19, which contrasts with the results observed in the US market. Larger stocks tend to have more stable betas on average and more stable downside exposure, due to greater diversification, better financing, more elastic access to capital, and, generally, a more stable business as a whole (Ding & Uryasev, 2022).

CONCLUSION

The drawdown betas extend beyond the traditional beta, which measures sensitivity to market movements (market exposure coefficient), and specifically focuses on an asset's performance during market downturns (drawdown exposure coefficient). In essence, drawdown betas capture stock performance when the market is in a drawdown. The study revealed that drawdown betas are more sensitive to market downturns than the standard beta. While the standard beta is always positive for all firms (the minimum value observed in the sample is 0.078), some European stocks exhibit negative drawdown betas, indicating that these stocks generate positive returns when the market is in drawdown and can work as diversifying assets. These findings support the hypothesis that drawdown betas have fundamentally different characteristics from traditional betas and can be negative when the standard beta is positive. Relying solely on the standard beta might cause investors to miss the safe-haven effect and fail to adequately hedge their portfolios in the event of a crisis. The drawdown betas provide a valuable tool for portfolio construction.

Our empirical analysis across European countries, industries and market capitalization deciles indicates that standard beta are always positive and cannot identify companies that could hedge or diversify portfolios. Only the ERoD and CDaR Beta display negative values. The industry analysis showed that companies in the Healthcare and Technology sectors may have safe-haven attributes during market drawdowns, as reflected by their ERoD and CDaR Beta values, which are negative or below 1. This outcome is consistent with the context of the COVID-19 pandemic crisis, which disproportionately benefited Healthcare companies during the market collapse, making them similar to gold that serves its classic role as a safe-haven asset.

The correlation coefficients between Periods 1 and 2 of the ERoD, CDaR, and standard betas across countries, industries, and market capitalization values once again showed that the standard beta cannot capture differences in stock behavior across unrelated market downturns. Industries such as Basic Materials, Healthcare, Industrials, and Utilities exhibited different ERoD Beta behaviors during the GFC and COVID-19 crisis. Moreover, no consistent relationship was found between market value and beta values during the GFC drawdown period and the COVID-19 period, in contrast to the results of Ding and Uryasev (2022).

In line with the contingency table, most European stocks moved in the same direction as the market, but we hope that new beta measures can identify stocks that may help diversify portfolios. The ERoD and CDaR Beta values tend to be lower than standard beta values, which are mostly close to 1. The study revealed that drawdown betas, especially ERoD, are more sensitive to market drawdowns and hold greater informational value than the standard beta. Our findings shed light on a new significant risk measure: the drawdown beta.

A more precisely estimated investment risk is highly desirable and effective in financial market analysis, offering better returns on investments. The findings of this research could help investors quantify investment risk across European companies when unprecedented events, such as the GFC or the COVID-19 crisis, present challenges for both investors and financial analysts. The drawdown beta offers valuable insights for constructing more resilient portfolios, effectively managing risk, and evaluating performance amidst market fluctuations. This study shifts the focus from static correlation measures to dynamic, downside-sensitive risk metrics, aligning theoretical definitions with real-world investor concerns about capital preservation during drawdowns. This gives rise to a legitimate hope that the drawdown beta can be applied in other highly developed European markets or, perhaps, in emerging economies.

This study, however, is not without its limitations. Thus, future research should incorporate the two-factor International Capital Asset Pricing Model (ICAPM) to account for exchange-rate risk premiums across European countries. We also identified the weaknesses of the dataset. We have included 428 companies, but they should be taken with caution due to the survivorship bias, as only surviving companies were included in the analysis.

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Appendix

Table A1. Median beta values by country in Periods 1 and 2

Country of exchange	Period 1			Period 2			N
	$ERoD_{0+}$	$CDaR_{0.9}$	Standard	$ERoD_{0+}$	$CDaR_{0.9}$	Standard	
Austria	1.378	1.234	1.180	-0.181	0.912	1.160	6
Belgium	0.778	0.850	0.796	-0.169	0.357	0.804	12
Denmark	1.226	1.194	0.986	0.423	0.882	1.144	20
Finland	0.955	1.091	0.965	0.298	0.802	0.936	12
France	0.983	0.966	1.032	0.453	0.821	1.035	58
Germany	0.707	0.881	1.030	0.353	0.805	1.071	47
Ireland; Republic of	1.838	1.264	0.987	0.262	0.348	1.023	6
Italy	1.675	1.110	0.911	0.795	1.265	1.203	25
Netherlands	0.836	1.030	1.020	0.384	0.991	1.183	18
Norway	1.085	1.158	1.100	-0.306	0.494	0.773	11
Poland	0.544	1.090	1.148	1.547	1.727	1.062	6
Portugal	1.019	0.774	0.704	1.102	0.930	0.804	3
Spain	1.276	0.919	0.888	0.679	0.775	0.985	17
Sweden	0.580	0.988	1.031	0.510	0.933	1.090	43
Switzerland	0.311	0.641	0.608	0.099	0.608	0.783	44
United Kingdom	0.899	1.017	0.931	1.254	1.043	1.077	100
Total	0.842	0.996	0.955	0.509	0.868	1.033	428

Source: Own elaboration based on LSEG Refinitiv EIKON data.

Table A2. Median beta values by industry in Periods 1 and 2

Sector	Period 1			Period 2			N
	$ERoD_{0+}$	$CDaR_{0.9}$	Standard	$ERoD_{0+}$	$CDaR_{0.9}$	Standard	
Basic Materials	0.600	1.027	1.165	0.496	0.926	1.042	39
Consumer Cyclicals	0.848	1.112	1.068	1.157	1.115	1.170	60
Consumer Non-Cyclicals	0.410	0.806	0.633	0.017	0.335	0.734	38
Energy	0.708	0.781	1.043	1.022	0.844	1.151	17
Financials	1.580	1.301	1.254	1.307	1.214	1.181	80
Healthcare	0.542	0.679	0.583	0.156	0.440	0.832	34
Industrials	0.891	0.996	1.047	0.082	0.780	1.104	75
Real Estate	1.337	1.248	0.869	0.760	0.891	0.939	19

Sector	Period 1			Period 2			N
	$ERoD_{0+}$	$CDaR_{0.9}$	Standard	$ERoD_{0+}$	$CDaR_{0.9}$	Standard	
Technology	0.705	0.960	0.907	-0.472	0.461	0.985	46
Utilities	1.087	0.857	0.721	1.030	0.772	0.803	20
Total	0.842	0.996	0.955	0.509	0.868	1.033	428

Source: Own elaboration based on LSEG Refinitiv EIKON data.

Table A3. Median beta values in Periods 1 and 2, relative to deciles of company value

Deciles of company value	Period 1			Period 2			N
	$ERoD_{0+}$	$CDaR_{0.9}$	Standard	$ERoD_{0+}$	$CDaR_{0.9}$	Standard	
1st decile	0.850	0.979	0.692	0.170	0.762	0.957	43
2nd decile	1.237	1.142	0.948	0.008	0.716	1.057	43
3rd decile	0.707	0.956	0.901	0.407	0.696	0.946	43
4th decile	1.154	1.090	1.013	0.691	0.929	1.132	42
5th decile	1.015	0.915	0.908	0.243	0.872	0.988	43
6th decile	0.538	0.856	0.870	0.428	0.607	0.984	43
7th decile	1.068	0.995	0.952	0.904	0.981	1.058	42
8th decile	1.045	1.026	1.031	0.873	0.998	1.053	43
9th decile	0.737	0.927	1.065	0.800	0.953	1.090	43
10th decile	0.424	0.895	1.060	0.798	0.941	1.104	43
Total	0.842	0.996	0.955	0.509	0.868	1.033	428

Source: Own elaboration based on LSEG Refinitiv EIKON data.

Table A4. Beta correlations (Spearman correlation coefficient) between Periods 1 and 2 in individual countries

Country of exchange	Correlation			N
	$ERoD_{0+}$	$CDaR_{0.9}$	Standard	
Austria	-0.086	-0.029	0.714	6
Belgium	0.420	0.210	0.783	12
Denmark	-0.205	0.238	0.879	20
Finland	-0.182	-0.182	0.846	12
France	0.369	0.380	0.769	58
Germany	0.179	0.104	0.787	47
Ireland; Republic of	0.600	0.543	0.771	6
Italy	0.512	0.556	0.744	25
Netherlands	0.399	0.575	0.849	18
Norway	-0.127	-0.145	0.782	11
Poland	0.829	0.771	0.371	6
Portugal	1.000	1.000	1.000	3
Spain	-0.140	0.346	0.718	17
Sweden	-0.072	-0.068	0.592	43
Switzerland	-0.118	0.237	0.818	44
United Kingdom	0.305	0.436	0.776	100
Total	0.219	0.358	0.721	428

Source: Own elaboration based on LSEG Refinitiv EIKON data.

Table A5. Beta correlations (Spearman correlation coefficient) between Periods 1 and 2 in individual industries

Sector	Correlation			N
	$ERoD_{0+}$	$CDaR_{0.9}$	Standard	
Basic Materials	-0.051	0.220	0.857	39
Consumer Cyclicals	0.239	0.328	0.684	60
Consumer Non-Cyclicals	0.100	0.326	0.486	38
Energy	0.181	0.525	0.520	17
Financials	0.512	0.478	0.571	80
Healthcare	-0.500	-0.329	0.485	34
Industrials	-0.010	0.093	0.611	75
Real Estate	0.140	0.560	0.653	19
Technology	0.018	0.113	0.508	46
Utilities	-0.343	-0.077	0.573	20
Total	0.219	0.358	0.721	428

Source: Own elaboration based on LSEG Refinitiv EIKON data.

Table A6. Beta correlations (Spearman correlation coefficient) between periods 1 and 2 in individual deciles of the company value.

Deciles of company value	Correlation			N
	$ERoD_{0+}$	$CDaR_{0.9}$	Standard	
1st decile	0.040	0.183	0.730	43
2nd decile	0.317	0.422	0.642	43
3rd decile	0.387	0.518	0.762	43
4th decile	0.232	0.406	0.622	42
5th decile	0.125	0.141	0.742	43
6th decile	0.282	0.600	0.689	43
7th decile	0.237	0.384	0.839	42
8th decile	0.545	0.599	0.876	43
9th decile	-0.137	0.099	0.681	43
10th decile	0.143	0.314	0.612	43
Total	0.219	0.358	0.721	428

Source: Own elaboration based on LSEG Refinitiv EIKON data.

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Author contributions statement

Ewa Feder-Sempach: Conceptualization, Data Curation, Writing – Original Draft Preparation, Writing – Review & Editing. **Piotr Szczepocki**: Conceptualization, Formal Analysis, Methodology, Writing – Original Draft Preparation. **Stan Uryasev**: Conceptualization, Methodology, Supervision.

Conflicts of interest

The authors declare no competing interests.

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Data availability

The data used to support the findings of this study are available from the corresponding author upon request.

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Behavioral finance and perceived ethnic entrepreneurial investment success: The dual role of project management methodology

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Abstract

PURPOSE: *The study aims to investigate the effects of behavioral finance (BF) on ethnic entrepreneurship investment success (EEIS), with a particular focus on ethnic entrepreneurs operating in host-country contexts. It further hypothesizes that project management methodology (PM2) both moderates and mediates this relationship.* ***METHODOLOGY:*** *A quantitative research design was employed using survey data collected in 2024 from a sample of 183 ethnic entrepreneurs in the province of Quebec. The study is grounded in a descriptive-analytical approach and forms part of a broader empirical investigation examining behavioral and contextual determinants of entrepreneurial investment outcomes.* ***FINDINGS:*** *The results indicate that behavioral finance has a significant negative impact on ethnic entrepreneurs' decisions; however, the PM2 methodology both moderates and mediates this relationship. A detailed examination of behavioral finance factors revealed that heuristic effects and framing-dependent biases had significant impacts, whereas market conditions exhibited weaker associations. The findings also suggest that the convergence of heuristic effects, framing-dependent biases, and ethnic market conditions, when integrated with project management methodology, significantly enhances the decision-making processes of ethnic entrepreneurs.* ***IMPLICATIONS:*** *This study offers valuable insights for immigrant investors and ethnic entrepreneurs operating in host countries. The findings suggest that adopting the PM2 methodology can serve as both a moderator and a mediator of behavioral finance's influence on decision-making processes.* ***ORIGINALITY & VALUE:*** *Despite the growing prominence of behavioral finance in the financial sector, its impact on the decisions of non-financial investors, particularly entrepreneurs, remains insufficiently understood. This study is among the first to empirically examine the combined roles of behavioral finance and PM2 methodology in shaping ethnic entrepreneurship decisions.*

Keywords: *behavioral finance, ethnic entrepreneurship, immigrant entrepreneurship, cognitive biases, entrepreneurial investment, methodology, venture performance.*

INTRODUCTION

Entrepreneurship and small business ownership are key pathways through which immigrants pursue economic integration and financial advancement in host countries such as Canada and the United States (Kloosterman & Rath, 2001; Waldinger et al., 1990), a phenomenon commonly referred to as ethnic entrepreneurship (EE). Self-employment and business ownership are generally more prevalent among immigrants than native-born individuals. In Canada, 11.9% of immigrants

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aged 25–69 owned a private incorporated company or were primarily self-employed in 2016, compared with lower rates among second- and third-generation Canadians (Picot & Ostrovsky, 2021). These trends underscore the substantial economic contribution of immigrant entrepreneurs and highlight the importance of studying ethnic entrepreneurship to understand investment outcomes, decision-making processes, and policy implications in host countries.

However, a body of international research suggests that immigrant-owned businesses have shorter durations of survival than businesses owned by the native born (Fertala, 2005; Mueller, 2014; Vinogradov & Isaksen, 2008). Studies conducted in Sweden, Norway, Germany, and the United States confirm these results (Barth & Zalkat, 2020; Lofstrom & Wang, 2019; Vinogradov, et al., 2008), but there is little evidence to support this in Canada. According to Government of Canada (2018) recent immigrants (that is, those in Canada for less than 10 years) had higher exit rates from ownership and shorter durations of ownership than did the Canadian-born or longer-term immigrants (that is, those in Canada for 10 or more years). While, Statistics Canada study finds that, "on average, there was little difference in the duration of ownership between immigrant and Canadian-born owners of private incorporated companies" (Ostrovsky & Picot, 2018). Based on studies by Green et al. (2016), among recent immigrants, business-class immigrants had the highest exit rates and the shortest duration of ownership. Owners in real estate and leasing, food and accommodation, professional services and wholesale trade generally had the shortest duration of ownership.

Although ethnic businesses may face higher risks of failure, scholars have proposed several explanations for immigrants' relatively high rates of entrepreneurial entry. Immigrants often pursue business ownership as a strategy to overcome barriers in the labor market, including discrimination, credential recognition issues, or limited employment opportunities (Salehi, 2026). In particular, immigrant entrepreneurs are motivated by a combination of opportunity- and necessity-driven factors (Kloosterman et al., 2001; Dana, 1995), with some seeking to capitalize on unique market niches and others engaging in entrepreneurship out of economic necessity. These motivations shape the type, scale, and risk profile of the ventures they undertake, influencing both strategic decisions and long-term outcomes. These conditions may shape both their decision-making processes and the outcomes of their ventures.

Entrepreneurial investment outcomes are inherently the result of prior investment decisions, which are influenced by a combination of cognitive, emotional, and contextual factors. Behavioral finance (BF) provides a theoretical framework to understand these influences, emphasizing how heuristics, biases, and framing effects systematically shape decision-making under uncertainty (Guzavicius et al., 2014; Belsky & Gilovich, 2010). While this study does not directly observe investment decisions themselves, it is grounded in the theoretical premise that these decisions are the mechanisms through which behavioral factors manifest. Consequently, the outcomes of these decisions, captured here as perceived ethnic entrepreneurial investment success (EEIS), serve as a valid and meaningful reflection of the effectiveness and quality of the underlying investment choices.

Perceived ethnic entrepreneurial investment success is conceptualized as a multidimensional construct, comprising performance, adaptation, satisfaction, social effects, and sustainability. Each dimension captures a distinct facet of venture outcomes, providing a holistic perspective that integrates financial, strategic, social, and long-term considerations. In this framework, behavioral finance factors drive investment decisions, while perceived investment success serves as the observable outcome through which the effects of these latent decisions can be empirically studied.

Although behavioral finance is well-established in financial markets, its application to entrepreneurial contexts, particularly ethnic entrepreneurship, remains limited. This study extends the relevance of behavioral finance by examining how cognitive and emotional biases, heuristics, and decision-making anomalies manifest in the outcomes of investment projects of ethnic entrepreneurs. Traditional theories of the "fully rational agent" assume that decisions are based solely on complete information and mathematically optimal calculations (Prosad et al., 2015). In reality, entrepreneurs operate in complex, uncertain, and dynamic environments where market conditions shift, information is incomplete, and patterns of overreaction or underreaction are common. Such conditions provide strong evidence that investment outcomes are shaped by more than purely rational calculation. By framing perceived ethnic entrepreneurial investment success as the observable reflection of underlying investment decisions, this research captures how behavioral and contextual factors influence venture outcomes. Understanding these effects is critical not only for extending behavioral finance beyond traditional financial settings but also for identifying strategies, such as effective project management methodologies, that enhance the effectiveness, adaptability, and sustainability of ethnic entrepreneurial ventures.

Building on this background, the present study addresses the following research questions: 1) How do behavioral finance factors influence the investment success of ethnic entrepreneurs? And 2) in what ways does the PM2 project management methodology moderate and mediate the relationship between behavioral finance and ethnic entrepreneurial decision-making outcomes?

To answer these questions, the study surveys 183 ethnic entrepreneurs in Quebec, Canada, and empirically examines the effects of heuristics, framing biases, and market conditions on perceived investment success. The remainder of the paper is structured as follows: Section 2 presents the theoretical background and literature review; Section 3 develops the research model and hypotheses; Section 4 describes the methodology; Section 5 reports the results and findings; Section 6 provides a discussion, including interpretations, theoretical contributions, practical implications, limitations, and directions for future research; and Section 7 concludes the study.

THEORETICAL FOUNDATIONS

Ethnic entrepreneurship

The literature on entrepreneurship uses several related terms to describe entrepreneurial activities undertaken by individuals with a shared cultural or migration background. Among these, ethnic entrepreneurship is the most frequently used concept. Ethnic entrepreneurship can be defined as the process by which "an individual identifies, assesses, and exploits opportunities through a business he or she starts, acquires, or inherits, and that maintains close relationships with the ethnic community to which the individual belongs" (Allali, 2010). This definition emphasizes both the entrepreneurial activity itself and the embeddedness of the venture within an ethnic or cultural community. More broadly, ethnic entrepreneurship encompasses business activities undertaken by individuals whose group membership is tied to a common cultural heritage or origin and who are recognized by out-group members as possessing such shared traits (Honig et al., 2010).

Related terms such as immigrant entrepreneurship and migrant entrepreneurship are often used interchangeably with ethnic entrepreneurship but reflect important conceptual distinctions. The term immigrant entrepreneur typically refers to foreign-born individuals who have immigrated within recent decades and subsequently established businesses in their host countries (Brzozowski, Cucculelli, & Surdej, 2017). While this definition captures first-generation immigrant business owners, it excludes members of ethnic minority groups who may have resided in the host country for multiple generations but continue to operate businesses shaped by ethnic identity and community ties. Similarly, migrant entrepreneurship refers to individuals who move to another country for a minimum period, commonly defined as at least twelve months, and engage in entrepreneurial activity in the host country (Salehi, 2026; Sinkovics & Reuber, 2021). The primary distinction between immigrant and migrant entrepreneurship lies in the degree of permanence in the host country, rather than in the nature of entrepreneurial activity itself.

In this study, the term ethnic entrepreneurship is adopted because it provides the most inclusive and theoretically appropriate framework for capturing entrepreneurial investment activities shaped by cultural background, migration experience, and ethnic embeddedness. This broader conceptualization is particularly suitable for examining investment behavior and outcomes, as it acknowledges the enduring influence of ethnic identity, social networks, and contextual constraints on entrepreneurial decision-making and venture performance. Empirical evidence indicates that immigrant entrepreneurs constitute a substantial and economically significant segment of small business owners in North America; for example, in Canada, 11.9% of immigrants aged 25–69 owned a private incorporated company or were primarily self-employed in 2016 (Picot & Ostrovsky, 2021). This prevalence underscores the relevance of studying this population, as their investment decisions and venture strategies provide meaningful insights into ethnic entrepreneurship and the application of behavioral finance principles.

Behavioral finance

Behavioral finance provides a theoretical framework for understanding how cognitive and emotional factors systematically shape investment decisions under conditions of uncertainty (Barberis & Thaler, 2003; Shefrin, 2002). While traditional finance assumes fully rational actors, entrepreneurs operate in complex environments characterized by incomplete information, market volatility, and high ambiguity, making decision outcomes inherently influenced by heuristics, biases, and contextual cues. Despite its extensive application in financial markets, the relevance of behavioral finance for ethnic entrepreneurial investment outcomes remains underexplored. This study draws on the behavioral finance micro (BFMI) perspective, emphasizing individual-level cognitive and emotional biases that indirectly manifest in observable venture outcomes, here conceptualized as perceived ethnic entrepreneurial investment success (Taylor, 2024; Noah & Lingga, 2020; Hamidon, & Kehelwalatenna, 2019).

Recent research highlights that entrepreneurs are particularly susceptible to biases in evaluating opportunities and allocating resources under uncertainty. Overconfidence, loss aversion, and representativeness heuristics can lead to suboptimal investment decisions, affecting both venture performance and sustainability (Shepherd et al., 2015; Baron & Shane, 2007). For ethnic entrepreneurs, these effects may be compounded by contextual factors, such as limited access to financial networks, institutional barriers, and the necessity-driven motivations underlying venture creation (Kloosterman & Rath, 2001; Picot & Ostrovsky, 2021). Studies indicate that the influence of behavioral biases extends beyond immediate financial decisions to strategic choices and long-term project outcomes, reinforcing the importance of a behavioral lens in entrepreneurship research (McMullen & Shepherd, 2006; Zhao & Seibert, 2006).

Despite these insights, the current behavioral finance literature exhibits several limitations. Most empirical work remains anchored in stock markets or institutional investor behavior, with relatively few studies addressing the entrepreneurial context, particularly for ethnic entrepreneurs (Hamidon & Kehelwalatenna, 2020). Existing research often treats behavioral mechanisms in isolation, neglecting the interaction between cognitive biases and the contextual environment, including informational asymmetries, market trends, and social influences, which can amplify or mitigate the effects of individual-level heuristics (Shiller, 2003; Bikhchandani & Sharma, 2000). Furthermore, prior studies rarely link behavioral factors to observable outcomes, such as venture performance or perceived investment success, limiting their practical and theoretical utility for understanding ethnic entrepreneurial decision-making.

Although behavioral finance has been widely applied in financial markets, its application to ethnic entrepreneurial investment remains limited. Existing research often focuses on individual investors rather than entrepreneurs and rarely links cognitive and emotional biases to observable outcomes such as perceived investment success. Integrating contextual factors, including informational environments and decision-making frameworks, can help clarify how these biases shape entrepreneurial investment outcomes. These considerations provide a natural bridge to project management methodologies, which may influence the effectiveness of entrepreneurial decision-making under uncertainty.

Project management methodologies provide structured frameworks for planning, executing, monitoring, and controlling projects to achieve predefined objectives within constraints of time, cost, and scope. PM^2 is a standardized project management methodology designed to enhance transparency, governance, and consistency in project implementation, particularly in complex and uncertain environments (Kourounakis & Maraslis, 2018). It incorporates defined roles, formal planning processes, risk management practices, and performance monitoring tools that support systematic decision-making across the project life cycle.

PM2 is composed of three integrated components: Agile Management, Portfolio Management, and Program Management (European Commission, 2021). Agile emphasizes adaptive planning, iterative execution, and responsiveness to change, which is especially useful in uncertain and dynamic entrepreneurial environments (European Commission, Directorate-General for Digital Services, 2021). Portfolio Management provides guidance for selecting, prioritizing, and monitoring multiple projects to ensure strategic alignment and optimal resource allocation (European Commission, Directorate-General for Digital Services, & Council of the European Union, General Secretariat, 2022). Program Management focuses on coordinating interrelated projects to achieve overarching objectives, facilitating stakeholder engagement, and ensuring that project outcomes collectively deliver intended benefits (European Commission, Directorate-General for Digital Services, & Council of the European Union, 2021).

In entrepreneurial investment contexts, PM2 can be conceptualized as both a decision-structuring and decision-enabling mechanism. By introducing formal procedures, evaluation criteria, and control checkpoints, PM2 reduces ambiguity and reliance on intuition-driven judgments, while simultaneously enabling entrepreneurs to translate strategic intentions into organized investment actions (European Commission, Directorate-General for Digital Services. 2023; Fonrouge et al., 2019). This dual role is particularly relevant in settings characterized by uncertainty, limited resources, and high cognitive demands, such as ethnic entrepreneurial ventures.

From a behavioral finance perspective, PM2 can be understood as interacting with cognitive and emotional factors rather than operating independently of them. As a mediating mechanism, PM2 explains how behavioral finance factors may influence the way investment decisions are structured, planned, and executed. Behavioral tendencies such as overconfidence, herding effects, and loss aversion (Abideen et al., 2023) may affect the extent to which entrepreneurs adopt, apply, and adhere to formal project management practices, which may subsequently shape investment outcomes. In this sense, PM2 represents an intermediate mechanism through which behavioral influences are translated into observable investment decisions and outcomes.

At the same time, PM2 also serves a moderating role by shaping the strength and direction of the relationship between behavioral finance factors and investment outcomes. By providing structure, feedback, and governance, PM2 can

attenuate the negative effects of certain behavioral biases or enhance the positive effects of disciplined decision-making. Thus, PM2 influences not only whether behavioral tendencies affect outcomes, but also how strongly they do so.

Accordingly, in this study, PM2 is theorized as both a mediator and a moderator in the relationship between behavioral finance factors and perceived ethnic entrepreneurial investment success. This dual conceptualization allows for a nuanced examination of how structured project management practices both channel and condition the effects of cognitive and emotional influences on entrepreneurial investment outcomes.

CONCEPTUAL MODEL AND HYPOTHESES

Conceptual model overview

Entrepreneurial investment success does not emerge in isolation; it is the cumulative outcome of a series of investment-related decisions made under conditions of uncertainty. In the context of ethnic entrepreneurship, these decisions are often shaped by limited information, unfamiliar institutional environments, cultural distance, and heightened personal and financial risk (McMullen & Shepherd, 2006). Behavioral finance offers a robust theoretical lens for understanding how such conditions influence decision-making by emphasizing the role of cognitive heuristics, emotional biases, and contextual factors in shaping judgment and choice (Barberis & Thaler, 2003).

In this study, investment decisions are conceptualized as a latent, unobserved process through which behavioral finance factors exert their influence. While the decision-making process itself is not directly measured, it is treated as the underlying mechanism linking behavioral influences on observable outcomes, consistent with current behavioral finance literature (Taylor, 2024; Hamidon & Kehelwalatenna, 2019). This conceptualization is consistent with behavioral finance theory, which posits that biases and heuristics affect how individuals evaluate information, assess risk, and select courses of action, with the consequences of these decisions becoming evident only after implementation. Accordingly, the dependent construct in this research is perceived ethnic entrepreneurial investment success, which captures entrepreneurs' ex post evaluations of the outcomes of their investment activities. These perceived outcomes are understood as reflections of the effectiveness and quality of prior investment decisions, rather than as direct measures of the decision-making process itself. By focusing on outcomes, this study aligns with the view that the impacts of cognitive and emotional biases are most meaningfully observed in how entrepreneurs assess venture performance, adaptability, satisfaction, social impact, and long-term viability.

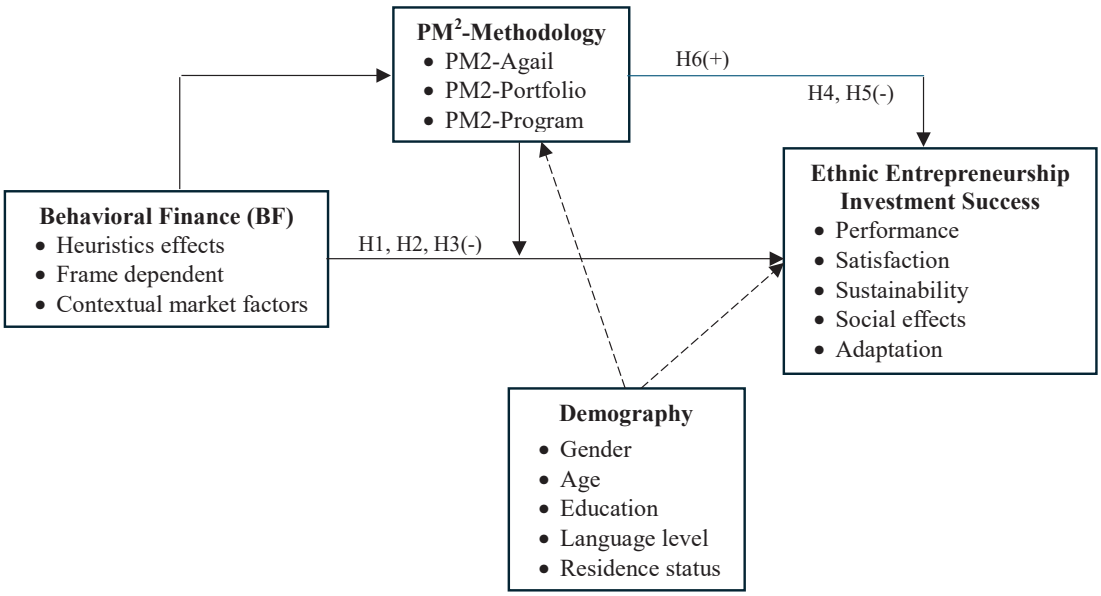

Figure 1. The proposed research model

Figure 1 illustrates the proposed conceptual model. Behavioral finance factors, comprising heuristics effects, frame-dependent biases, and contextual market condition, are theorized to influence investment decisions at the cognitive and evaluative level. These latent decisions, in turn, shape perceived investment success. Project management methodology (PM2) is incorporated as a critical contextual mechanism within this framework. On the one hand, PM2 provides structure, formalization, and discipline that can channel behavioral influences into more systematic decision processes. On the other hand, it can condition the strength and direction of behavioral effects by either mitigating or amplifying the consequences of biases under different project environments.

By explicitly distinguishing between latent investment decision processes and observable investment outcomes, the proposed model avoids conflating decision-making with performance. This distinction allows behavioral finance to be meaningfully applied to ethnic entrepreneurship while maintaining conceptual clarity and ensuring alignment between theoretical constructs and empirical measurement.

Behavioral finance factors and perceived ethnic entrepreneurial investment success

Researchers have proposed several frameworks for classifying behavioral finance factors that influence investment-related decision processes. Shefrin (2002), for instance, broadly distinguishes between heuristic-driven biases and frame-dependent biases, a classification that has been widely adopted in the behavioral finance literature (Lowies et al., 2013; Rajdev & Raninga, 2016). Similarly, Pompian (2011) categorizes behavioral biases into cognitive and emotional types, reflecting differences in their psychological origins. While these frameworks vary in emphasis, they collectively highlight that investment-related judgments are shaped by both mental shortcuts and evaluative distortions.

Building on Shefrin's (2002) classification and informed by the qualitative phase of this research, the present study organizes behavioral finance factors affecting ethnic entrepreneurs' investment-related decision processes into three analytically distinct yet interrelated categories: heuristics effects, frame-dependent biases, and market conditions. This categorization reflects not only established theoretical distinctions but also the contextual realities faced by ethnic entrepreneurs operating under uncertainty. These behavioral finance factors are theorized to influence investment decisions at a latent level, with their cumulative effects becoming observable through entrepreneurs' evaluations of investment outcomes, conceptualized here as perceived ethnic entrepreneurial investment success. The following subsections examine each category in turn.

Heuristics effects

The first group of factors is based on heuristics theory. Heuristics are simple, efficient rules of thumb proposed to explain how people make decisions, form judgments, and solve problems, particularly when facing complexity or incomplete information (Venkatapathy & Sultana, 2016). These rules often shorten decision-making time and allow individuals to function without extensive cognitive effort (Tversky & Kahneman, 1974); however, their systematic use can lead to predictable cognitive biases that affect the quality of investment-related judgments.

Heuristics theory suggests that investors rely on mental shortcuts to cope with complex decision environments, which may result in deviations from optimal choices (Schwartz, 2010). Overconfident investors, for example, tend to overestimate their knowledge and abilities, engage in excessive trading, and ignore transaction costs and fundamental information, thereby increasing the likelihood of suboptimal outcomes (ul Abdin et al., 2017). Similarly, investors may selectively attend to positive information while discounting negative signals, leading to delayed responses to adverse developments and poorer investment performance (De Goey, 2023).

Anchoring bias further illustrates how initial reference points, such as past prices, can distort valuation judgments when investors fail to adjust adequately toward intrinsic values (Shefrin, 2002). Availability bias causes decision-makers to rely disproportionately on recent or salient information, rather than conducting comprehensive analyses (Pompian, 2011). In entrepreneurial investment contexts, such heuristic-driven biases may affect not only immediate decisions, but also longer-term outcomes related to venture performance, adaptability, and sustainability. Key heuristic biases identified in the literature include optimism, overconfidence, availability, anchoring, and representativeness (Hamidon & Kehelwalatenna, 2020; Venkatapathy & Sultana, 2016; Tversky & Kahneman, 1974). Accordingly, these biases are expected to adversely affect the perceived success of entrepreneurial investments. Therefore, the following hypothesis is proposed:

H1. Heuristic-driven biases have a significant negative effect on perceived ethnic entrepreneurial investment success.

Frame dependent biases

Frame-dependent biases are central to prospect theory, which posits that individuals evaluate outcomes relative to reference points and exhibit loss aversion-placing greater weight on losses than on equivalent gains (Kahneman & Tversky, 2013). As a result, investment judgments are influenced by how options are framed, rather than by their objective expected value. This framing effect can lead entrepreneurs to favor risk-averse or risk-seeking behaviors depending on perceived gains or losses, with implications for investment outcomes.

Regret aversion is another key component of prospect theory. Investors often experience regret when recognizing missed opportunities or poor past choices, leading them to hold on to underperforming investments to avoid acknowledging mistakes (Shefrin & Statman, 1985). Such behavior may constrain learning and adaptation, negatively influencing perceived investment success. Also, self-control bias further affects decision-making when individuals struggle to regulate emotions and impulses (Pompian, 2011). For example, tax-related behaviors, such as selling losing assets to realize tax benefits (Keim, 1983), illustrate how emotional considerations can override long-term strategic reasoning. In entrepreneurial settings, these frame-dependent biases may shape satisfaction, persistence, and evaluations of investment outcomes beyond purely financial returns.

Based on prior studies and the qualitative findings of this research, the primary frame-dependent biases influencing ethnic entrepreneurs' investment-related judgments include regret aversion, loss aversion, mental accounting, self-control, and framing effects (Jahanzeb, 2012). These biases are therefore expected to negatively influence perceived ethnic entrepreneurial investment success. Thus, the second hypothesis is proposed as follows:

H2. Frame-dependent biases have a significant negative effect on perceived ethnic entrepreneurial investment success.

Contextual market factors

Market conditions represent external contextual pressures that influence investment judgments and strategies, rather than intrinsic cognitive or emotional biases. Investment strategy reflects how entrepreneurs interpret market signals, assess trade-offs, and commit to specific courses of action under uncertainty (Porter, 1996). De Bondt and Thaler (1995) argue that investors frequently overreact or underreact to price changes, extrapolate past trends into the future, and rely on seasonal or cyclical patterns, all of which can shape investment outcomes. Empirical studies confirm that market factors, such as price volatility, historical trends, and the availability of market information, significantly influence investment-related decisions (Waweru et al., 2008). In addition to internal cognitive and emotional biases, behavioral finance research recognizes that investor behavior is influenced by interactions with external environments and informational contexts (Shiller, 2003; Bikhchandani & Sharma, 2000). Market information and past trends serve as environmental cues that entrepreneurs use to make decisions, while herding reflects a behavioral response to these cues. Together, these factors may activate, amplify, or constrain individual behavioral tendencies, indirectly affecting perceptions of investment success.

Herding is a behavioral phenomenon in which individuals imitate the actions of others rather than relying solely on private information (Bikhchandani & Sharma, 2000). Herding has been shown to influence investment decisions, often amplifying market inefficiencies (Noah & Lingga, 2021; Spyrou, 2013). Although the efficient market hypothesis assumes that prices fully reflect all available information (Shiller, 2003), evidence shows that reliance on technical analysis or past trends may bias judgments and reduce the quality of investment-related evaluations (Hamidon & Kehelwalatenna, 2020). For ethnic entrepreneurs operating in unfamiliar or volatile markets, these contextual conditions may intensify behavioral responses and shape perceptions of investment outcomes. Accordingly, market conditions are modeled as environmental pressures that indirectly affect perceived ethnic entrepreneurial investment success, rather than as a direct cognitive or emotional bias. The third hypothesis is therefore proposed as follows:

H3. Market conditions have a significant impact on perceived ethnic entrepreneurial investment success.

The moderated-mediation role of PM2 in perceived EEIS

Entrepreneurial investment projects are often conducted under conditions of high uncertainty, limited resources, and complex decision-making requirements. In such contexts, structured project management practices can provide essential guidance, coordination, and feedback mechanisms. PM2, comprising Agile, Portfolio, and Program management, offers

a comprehensive framework that supports systematic planning, execution, and monitoring of investment projects, enhancing the likelihood of successful outcomes (Kerzner, 2025; European Commission, 2023; Batista et al., 2022).

Behavioral finance factors, including heuristics, frame-dependent biases, and responses to market conditions, shape investment decisions at a latent level. PM2 is theorized to influence perceived ethnic entrepreneurial investment success through two interconnected pathways. First, as a mediating mechanism, PM2 translates latent investment decisions into observable outcomes by structuring processes, providing checkpoints, and enforcing governance, thereby mitigating the negative effects of cognitive and emotional biases (Patanakul & Milosevic, 2009). Second, as a moderating mechanism, PM2 can buffer or amplify the effects of behavioral biases, such that the impact of heuristics, framing, or market perception on perceived investment success depends on the level of PM2 adoption (Acur et al., 2012).

Beyond these conditional effects, PM2 is also expected to exert a direct positive influence on perceived investment success by improving resource allocation, aligning project execution with strategic objectives, and facilitating adaptive responses to changing conditions. In sum, PM2 both channels the effects of behavioral finance factors (mediation) and conditions their strength (moderation), highlighting its dual role in shaping entrepreneurial investment outcomes. Based on this theoretical framework, the following hypotheses are proposed:

H4. PM2 adoption mediates the relationship between behavioral finance factors and perceived ethnic entrepreneurial investment success.
H5. PM2 adoption moderates the relationship between behavioral finance factors and perceived ethnic entrepreneurial investment success, such that higher PM2 adoption mitigates the negative effects of biases.
H6. PM2 adoption has a direct positive effect on perceived ethnic entrepreneurial investment success.

Given that the investor demographics are anticipated to affect the variables, their influence is incorporated into the proposed model because investors differ significantly from one another based on a range of factors, including demographic characteristics, socioeconomic status, education level, gender, age, race and ethnicity. In other words, investment decision-making is not solely governed by standardized methods or precise models (Schramm-Nielsen, 2001; VanderPal, 2021); emotional influences and personal temperament often accompany the logical and analytical aspects of the process.

METHODOLOGY

Study design and sample

This study is an empirical investigation that employs a quantitative design grounded in the descriptive-analytical method. Primary data were collected using a survey approach, as part of a larger research project conducted using a mixed-methods approach.

The survey targeted ethnic entrepreneurs in Quebec. Specifically, the study population consisted of ethnic entrepreneurs who had invested in small businesses and real assets, not in the stock market, and who had created at least one job in Quebec. This inclusion criterion ensured that respondents had achieved a minimum level of entrepreneurial activity and operational experience, allowing for a meaningful assessment of investment outcomes and decision-making processes. However, this criterion also represented a potential limitation to the study's external validity, as it may have biased the sample toward more established ventures, thereby weakening or distorting the observed relationships between behavioral biases, PM2 adoption, and perceived entrepreneurial venture success.

Given the large population size within the research framework, a convenience sampling approach was employed. Although this sampling method does not support probability-based inference, the final sample of 183 respondents was considered adequate for analysis using partial least squares structural equation modeling (PLS-SEM). This variance-based technique is particularly suitable for exploratory and complex models with small to medium sample sizes and allows for meaningful assessment of structural relationships under sampling constraints (Hair et al., 2021; Henseler et al., 2016).

The list of ethnic entrepreneurs was obtained from ethnic small business associations, consulting firms, and immigration service counseling centers. Additional sources included the Quebec Business Directory (QBL), Montreal Local Small Businesses (MLSM), the Directory of Entrepreneurship Support Organizations (DESO), and the Montreal Island Social Services Directory (MIDCS). Demographic variables such as age, gender, education etc. were considered to assess sample representativeness (see Table 1). The study was conducted in accordance with ethical guidelines, and

informed consent, confidentiality, and voluntary participation were ensured. Ethical approval was obtained from the UQO Research Ethics Committee prior to data collection.

Measures and instruments

A thirty-eight-item questionnaire was used to collect data on the impact of behavioral finance on the decision-making of ethnic entrepreneurs. The questionnaire was divided into two sections: the first collected demographic data, and the second was based on a conceptual model designed to assess the relationships between the variables.

Dependent variable: Ethnic Entrepreneurship Investment Success. Since this research focuses on ethnic entrepreneurship, which primarily involves investment in real and tangible assets, the decision-making criteria leading to success in this context differ from those used by investors in financial markets. Non-financial criteria are considered alongside traditional financial measures, reflecting the broader goals and values that guide ethnic entrepreneurial decisions. The models proposed by Shenhar et al. (2001) informed the identification of key factors, including project efficiency and performance, customer impact, business success, and future readiness. Subsequently, findings from our qualitative study were distilled into five key factors, performance, sustainability, adaptation, satisfaction, and social effects, and ten specific items. Respondents rated each item on a scale from 1 (strongly agree) to 5 (strongly disagree), with responses reverse-coded prior to analysis so that higher scores indicated higher levels of perceived success. A mean score was calculated for each respondent, reflecting decision-making effectiveness, business sustainability, entrepreneurial adaptation, satisfaction, and positive social impacts among co-ethnics.

Independent variable: Behavioral Finance. Behavioral finance measures were primarily based on Shefrin's model (2002), which classifies biases into heuristic-based and frame-dependent categories. Based on prior studies (Adil et al., 2022; Tseng, 2006) and qualitative findings, Contextual Market Factors were added as a third factor. Twenty-two items were used to assess behavioral finance factors: ten items for heuristic biases (optimism, overconfidence, availability, anchoring, and representativeness) adapted from Salem (2023) and Suresh et al. (2024); six items for frame-dependent biases (regret aversion, framing, mental accounting) adapted from Mbaluka et al., (2012) and Sattar et al. (2020); and six items for contextual market factors, including herding behavior and external informational cues, adapted from the qualitative study and prior research (Suresh, 2024; Noah & Lingga, 2021; Caparrelli et al., 2004; Bikhchandani & Sharma, 2000; Rajan et al., 2000). Respondents rated each item on a five-point scale, and mean scores were calculated for each subscale.

Moderator and mediator: PM2 Project Management Methodology. PM2, serving a moderated-mediation role between behavioral finance and entrepreneurial decisions, was measured using nine items across agile PM2, portfolio PM2, and program PM2. Item construction primarily relied on the PM2 Project Management Guide v3.1 (European Commission, 2023), supplemented by the PM2-Agile Guide 3.0.1, PM2 Programme Management Guide 1.0, and PM2 Portfolio Management Guide 1.5. Items were refined through several stages with input from experts and the authors. Respondents rated each item on a scale from 1 (not at all important) to 5 (very important), with higher mean scores indicating greater integration of PM2 practices.

Control variables: Demographics. Demographic characteristics, including age, gender, education level, language proficiency, residency status, ethnicity, and type of business, were included as control variables, given their potential influence on entrepreneurial decisions. Gender was coded as binary (1=male, 2=female). Age and language proficiency were measured in five categories, education in seven categories, and residency status as binary (1=permanent resident/citizen, 2=temporary resident). Ethnicity and business type were self-reported through open-ended questions.

Data analysis

This study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4 to test the proposed conceptual model and associated hypotheses. The choice of PLS-SEM is both theoretically and methodologically justified based on considerations related to sample size, model complexity, and research objectives. First, the sample size of 183 respondents is more suitable for PLS-SEM than for covariance-based SEM (CB-SEM), particularly given the complexity of the proposed model, which includes multiple latent constructs, mediation and moderation effects, and interaction terms and it does not require strict assumptions of multivariate normality (Hair et al., 2019). In addition, the primary objective of this research is theory extension and prediction, rather than strict theory confirmation. PLS-SEM is particularly appropriate when the goal is to explain variance in key dependent constructs, here, perceived ethnic entrepreneurial investment success (EEIS), and to assess the predictive relevance of behavioral finance factors and project

management methodology (PM2). Also, the model incorporates latent constructs representing cognitive, emotional, and contextual influences, along with a moderated-mediation structure in which PM2 simultaneously functions as a mediator and a moderator. Thus, its suitability for predictive modeling and handling complex, multivariate relationships aligns well with the objectives of this study.

RESULTS

Sample demographics

A total of 183 ethnic entrepreneurs completed the survey questionnaire; of these, 54% were male and 45.9% were female. The respondents' ages ranged from 23 to 70+, with > 41-year-olds accounting for 74% of participants. The French language level of 55.5% of the participants was below intermediate, and 45% was above intro. Almost 27.5% have been able to speak French fluently. This situation is slightly different in English language level: 17.8% (below intermediate) versus 80% (intermediate and above). 48.5% state they can speak English fluently. Also, more than 94% of the respondents had a college diploma/certificate, or higher. Also, 74.3% of the participants were permanent residents/citizens, while 25.7% were temporary residents or were seeking PR. The highest frequency of businesses among ethnic entrepreneurs was found in the food services and related industries -such as restaurants, bakeries and pastry shops, and coffee shops- which accounted for 23.8% of the total. This was followed by retailers, representing 18.2%.

Table 1. Status of the participants' demographics

	Variable	N	%
Gender	Male	99	54,1
	Female	84	45,9
Age	≤ 20	0	0,0
	21-30	11	6,0
	31-40	36	19,7
	41-50	66	36,1
	≥ 51	70	38,3
Language level (Fr. & En.)	Elementary	83	45,4
	Pre-intermediate	23	12,6
	Intermediate	24	13,1
	Upper-intermediate	32	17,5
	Advance	21	11,5
Education	Secondary	11	6,0
	Collage dip. / cert.	84	45,9
	Bachelor's degree	63	34,4
	Master's degree and higher	25	13,7
PR./ Citizen	Yes	136	74,3
		47	25,7

Measurement model assessment

Before evaluating the structural relationships, the measurement model was assessed to ensure that all constructs were reliable, valid, and empirically distinct. This assessment included checks for internal consistency, convergent validity, indicator reliability, discriminant validity, and collinearity, providing a robust foundation for subsequent structural model analysis.

Reliability and convergent validity

The reliability and convergent validity of all constructs were assessed using Cronbach's alpha (α), rho_A, composite reliability (CR), and average variance extracted (AVE). As shown in Table 2, Cronbach's alpha values ranged from 0.737 to 0.836, exceeding the recommended threshold of 0.70 and indicating satisfactory internal consistency. Similarly, rho_A values ranged from 0.743 to 0.840, confirming consistent reliability of the latent constructs. Composite reliability values, ranging from 0.828 to 0.901, further support the internal consistency of the measures. Convergent validity was established, with AVE values between 0.570 and 0.753, all above the 0.50 benchmark, demonstrating that each construct explains a substantial portion of the variance in its indicators.

Table 2. Reliability and validity of the constructs

Construct	Coronach- α	rho-A	Composite reliability	AVE
Perceived EEs' investment success	0.737	0.743	0.828	0.592
Heuristics effects	0.808	0.813	0.868	0.570
Market conditions	0.836	0.840	0.901	0.753
PM2-methodology	0.753	0.771	0.856	0.665
Frame dependent biases	0.741	0.746	0.853	0.659

Note: Thresholds — Cronbach's α > 0.7, rho_A > 0.7, CR > 0.7, AVE > 0.5 (Sarstedt et al., 2019; Fornell & Larcker al., 1981).

These results indicate satisfactory measurement quality; however, the findings should be interpreted with caution given the moderate loadings of several indicators.

Indicator loadings

Indicator reliability was evaluated by examining the outer loadings of all items on their respective latent constructs. Outer loadings indicate the strength of the relationship between an indicator and its latent variable. Loadings above 0.70 are considered strong, while items with loadings between 0.40 and 0.70 are acceptable if supported by theoretical justification (Hair et al., 2019; Henseler et al., 2016).

Table 3. Indicator loadings and bootstrapped t-values

Construct	Indicator	Standardized loading	t-values
Heuristics	Excessive optimism	0.747	17.531
	Over-confidence	0.782	21.516
	Availability	0.804	22.194
	Anchoring	0.813	25.685
	Representativeness	0.612	9.985
Frame dependent biases	Regret aversion	0.838	7.781
	Framing	0.767	6.779
	Mental accounting	0.828	8.538
Market conditions	Herding effects	0.839	5.058
	Market information	0.868	5.211
	Past trends	0.896	5.556
PM2	Agile management	0.821	13.228
	Portfolio management	0.837	13.186
	Programme management	0.789	6.090
Perceived EEs' investment success	Performance of the business	0.812	14.207
	Sustainability	0.675	8.134
	Clients and entrepreneurs' Satisfaction	0.662	5.054
	Adaptation in environment	0.741	10.812
	Social effects	0.598	7.743

Note: Loadings > 0.70 are considered strong, 0.40–0.70 are acceptable with theoretical justification. Bootstrapped t-values > 1.96 indicate significance at $p < 0.05$.

As shown in Table 3, most items demonstrated strong loadings, ranging from 0.662 to 0.896, with all bootstrapped t-values exceeding 1.96, confirming statistical significance at $p < 0.05$. For example, heuristic-related items such as Excessive optimism (0.747, t = 17.531), Over-confidence (0.782, t = 21.516), and Anchoring (0.813, t = 25.685) loaded strongly on the Heuristics construct, while Representativeness (0.612, t = 9.985) was slightly below 0.70 but retained due to theoretical relevance. Similarly, items for perceived EEs' investment success, including social effects (0.598, t = 7.743) and Clients and entrepreneurs' satisfaction (0.662, t = 5.054), were retained as acceptable indicators. All other constructs, including frame-dependent biases, market conditions, and PM2 methodology, showed strong loadings and statistically significant t-values, supporting the reliability of the measurement model.

Discriminant validity

Discriminant validity evaluates whether each construct is empirically distinct from the other constructs in the model. In this study, discriminant validity was assessed using both the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio, following recommended PLS-SEM guidelines (Henseler et al., 2015; Hair et al., 2019).

According to the Fornell–Larcker criterion, the square root of the AVE for each construct should exceed its correlations with all other constructs. As shown in Table 4, this condition is satisfied for all constructs: for example, Perceived EEs' investment success has an AVE square root of 0.702, which is greater than its correlations with Heuristics (−0.476), Market conditions (0.098), PM2 methodology (0.234), and Frame-dependent biases (−0.222). Similarly, all other constructs' AVE square roots exceed their correlations with the remaining constructs, confirming discriminant validity under the Fornell–Larcker criterion.

Table 4. Discriminant validity based on Fornell and Larcker and Heterotrait-Monotrait criteria

Construct	Fornell & Larcker ratio					HTMT ratio				
	PEEIS	HEU	MKC	PM2	FDB	PEEIS	HEU	MKC	PM2	FDB
Perceived EEIS	0.702					-				
Heuristics effects	-0.476	0.755				0.611	-			
Market conditions	0.098	-0.090	0.868			0.135	0.107	-		
PM2-methodology	0.234	-0.199	-0.089	0.816		0.380	0.232	0.112	-	
Frame dependent biases	-0.222	0.102	-0.016	0.097	0.812	0.323	0.143	0.134	0.150	-

Note: For Fornell–Larcker, the diagonal values (√AVE) should exceed all inter-construct correlations. HTMT values < 0.90 indicate acceptable discriminant validity (Henseler et al., 2015).

The HTMT ratio, a more stringent test, assesses construct distinctiveness, with values below 0.90 indicating adequate discriminant validity. In the current analysis, all HTMT values range from 0.107 to 0.611, well below the 0.90 threshold. This demonstrates that the constructs are conceptually and empirically distinct, and there is no indication of problematic overlap between latent variables. Overall, the results from both Fornell–Larcker and HTMT analyses provide strong evidence that the measurement model possesses satisfactory discriminant validity, supporting the robustness of subsequent structural model assessment.

Collinearity assessment

To examine potential multicollinearity among the predictor variables, both inter-construct correlations and variance inflation factors (VIFs) were assessed. Examining correlations provides a preliminary indication of overlap among independent constructs, whereas VIFs offer a more robust, model-consistent assessment in PLS-SEM.

First, a correlation matrix was inspected to identify whether any bivariate correlations among the independent constructs exceeded commonly accepted thresholds. As shown in Table 5, the correlations among Heuristics effects (HEU), Frame-dependent biases (FDB), and Market conditions (MKC) are low in magnitude, ranging from −0.090 to 0.102. All correlations are well below the threshold of 0.80, suggesting that multicollinearity is unlikely to be a concern at the bivariate level.

Table 5. Matrix of correlation between independent variables

		HEU	FDB	MKC
HEU	Heuristics effects	1		
FDB	Frame dependent biases	-0.090	1	
MKC	Market conditions	0.102	0.016	1

Note: Correlations above 0.80 are typically viewed as an indication of multicollinearity, suggesting that the variables may overlap and distort regression estimates (Dormann et al., 2013; Gujarati et al., 2009).

In addition to assessing multicollinearity at the construct level, collinearity among the individual predictor items was also examined to ensure that high correlations between indicators would not bias the model estimates. Variance inflation factor (VIF) and tolerance values were computed for all items measuring the independent constructs. As presented in Table 6, all VIF values range from 1.221 to 2.727, well below the conservative threshold of 3.3 recommended for PLS-SEM (Hair et al., 2019). Correspondingly, tolerance values are all above 0.30, further indicating that multicollinearity is not problematic. The significance values for all indicators are 0.00, confirming that the estimates are stable.

Table 6. VIF of the predictors

Variables	OPT	OVC	AVL	ANC	REP	RAV	FRM	MAC	HER	MKT	PTR
Sig.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tolerance	0.681	0.554	0.485	0.510	0.819	0.596	0.727	0.666	0.626	0.414	0.367
VIF	1,468	1,804	2,062	1,959	1,221	1,679	1,376	1,501	1,598	2,414	2,727

Note: VIF < 5 → Generally considered acceptable; multicollinearity is not a serious issue. VIF between 5 and 10 → Indicates moderate multicollinearity; may be tolerable depending on the context but should be checked carefully. VIF > 10 → Problematic; strong multicollinearity is present, and corrective measures (e.g., removing/reducing variables, combining predictors, or using techniques like ridge regression) are usually needed (Jeng, 2023).

These results demonstrate that both individual items and predictor constructs can be reliably included in the structural model without concern for inflated standard errors or unstable path coefficients. This supports the robustness of subsequent hypothesis testing and structural model evaluation.

Model fit assessment

To assess the overall adequacy of the proposed model, several global fit measures generated by SmartPLS were examined. As shown in Table 7, the SRMR value of 0.094 for both the saturated and estimated models indicates an acceptable level of fit, particularly in the context of PLS-SEM, which prioritizes prediction rather than exact model reproduction.

Table 7. Model fit

	Saturated model	Estimated model
SRMR	0.092	0.092
d_ULS	1.621	1.621
d_G	0.424	0.424
Chi-square	437.071	437.071
NFI	0.667	0.667

The d_ULS and d_G values are nearly identical across the two models, reflecting stable estimation and minimal discrepancy between the empirical and model-implied correlation matrices. Similarly, the Chi-square values show only negligible differences, further supporting model consistency. The NFI value of 0.891, although slightly below the conventional 0.90 threshold, is considered acceptable for PLS-SEM applications, especially in exploratory or complex models. Overall, these fit indices provide additional evidence that the proposed model demonstrates an acceptable fit to the observed data and is suitable for subsequent structural model evaluation.

Structural model assessment

After confirming the measurement model adequacy and acceptable model fit, the structural model was evaluated to examine the hypothesized relationships among the constructs. The assessment initially focused on the direct relationships (path coefficients) and their significance, along with the explanatory power (R^2) of the model.

Path coefficients and hypothesis testing (direct effects)

The direct effects of behavioral finance factors and PM2 adoption on perceived ethnic entrepreneurial investment success (EEIS) were assessed using Smart PLS. The results are presented in Table 8.

Table 8. Direct effects of behavioral finance factors and PM2 on perceived EEIS

Hypothesis	Path	β (Path Coefficient)	t-value	p-value	Decision
H1	Heuristics effects → Perceived EEIS	-0.419	6,213	0.000	supported
H2	Frame dependent biases → Perceived EEIS	-0.205	2.940	0.003	supported
H3	Market conditions → Perceived EEIS	0.048	0.733	0.464	N/A
H6	PM2 → Perceived EEIS	0.165	2.240	0.025	supported

Notes: β = standardized path coefficient; t-value and p-value were obtained using bootstrapping with 5,000 resamples in SmartPLS; positive β values indicate a direct positive relationship, while negative values indicate a direct negative relationship between the predictor and perceived EEIS.

Heuristic-driven biases were found to have a strong negative effect on perceived EEIS ($\beta = -0.419$, $t = 6.213$, $p < 0.001$), supporting H1. This indicates that investors' reliance on heuristics reduces their perception of investment success, suggesting that cognitive shortcuts significantly undermine perceived EEIS. Frame-dependent biases also negatively influenced perceived EEIS ($\beta = -0.205$, $t = 2.940$, $p = 0.003$), supporting H2. Although the effect is smaller than heuristics, it remains statistically significant, emphasizing that the framing of information shapes investors' evaluations.

Market conditions showed a minimal positive effect on perceived EEIS ($\beta = 0.048$, $t = 0.733$, $p = 0.464$), but this effect was not statistically significant, and H3 was therefore not supported. This suggests that external market factors do not play a substantial role in shaping investors' perceptions compared to cognitive factors.

PM2 adoption demonstrated a positive and significant effect on perceived EEIS ($\beta = 0.165$, $t = 2.240$, $p = 0.025$), supporting H6. This finding indicates that the implementation of structured project management practices enhances investors' perceptions of ethnic entrepreneurial investment success, potentially mitigating some of the negative influence of behavioral biases.

Overall, the analysis of direct effects shows that behavioral finance factors, particularly heuristics and frame-dependent biases, negatively affect perceived EEIS, while PM2 adoption contributes positively. Market conditions, in contrast, do not significantly influence perceived investment success, highlighting the dominant role of cognitive and organizational factors in investors' evaluations.

Coefficient of determination (R^2)

The explanatory power of the structural model was assessed using the coefficient of determination (R^2), which measures the proportion of variance in perceived ethnic entrepreneurial investment success (EEIS) explained by heuristic-driven biases, frame-dependent biases, market conditions, and PM2 adoption. The model yielded an R^2 value of 0.282 (Table 9), indicating that these predictors account for approximately 28% of the variance in perceived EEIS.

Table 9: Coefficient of determination (R^2) for perceived EEIS

Endogenous Construct	R^2	Interpretation
Perceived EEIS	0.282	Moderate

Note: R^2 = Coefficient of determination; values indicate the proportion of variance in the endogenous construct explained by the model's predictors. Interpretation follows conventional PLS-SEM guidelines.

It is meaningful in the context of behavioral finance and entrepreneurial investment research, where human decision-making is influenced by multiple cognitive, social, and environmental factors (Hair et al., 2019; Kahneman & Tversky, 1979). This R^2 demonstrates that the included behavioral and managerial factors significantly contribute to investors' perceptions of EEIS, providing a solid foundation for examining the specific effects of individual predictors and PM2 adoption in subsequent analyses.

Effect size (f^2)

The effect size (f^2) was calculated to evaluate the relative contribution of each predictor to the variance explained in perceived ethnic entrepreneurial investment success (EEIS). Table 10 presents the f^2 values for all predictors. Heuristic-driven biases have the largest effect on perceived EEIS ($f^2 = 0.231$), which falls between medium and large, indicating a substantial impact on investors' perceptions. Frame-dependent biases have a medium effect ($f^2 = 0.153$), showing that how information is presented moderately influences EEIS. PM2 adoption also has a medium effect ($f^2 = 0.136$), highlighting the importance of structured project management practices in enhancing perceived investment success. In contrast, market conditions exhibit a negligible effect ($f^2 = 0.003$), confirming their minimal contribution to EEIS in the model.

Table 10: Effect sizes (f^2) of predictors on perceived EEIS

Predictor	f^2	Effect size interpretation
Heuristic-driven biases	0.231	Medium–Large
Frame-dependent biases	0.153	Medium
Market conditions	0.003	Low
PM2 adoption	0.136	Medium

Note: f^2 = effect size; values indicate the relative contribution of each predictor to the variance explained in the endogenous construct (perceived EEIS). Interpretation follows Cohen's (1988) guidelines: small = 0.02, medium = 0.15, large = 0.35.

These results complement the direct effect and R^2 analyses. They demonstrate that heuristic-driven biases are the strongest determinant of perceived EEIS, followed by PM2 adoption and frame-dependent biases, while market conditions have virtually no influence. This highlights the dominant role of behavioral and managerial factors in shaping investors' perceptions.

Predictive relevance (Q^2)

The predictive relevance of the structural model was assessed using the blindfolding procedure in SmartPLS. The results show a Q^2 value of 0.151 for perceived ethnic entrepreneurial investment success (EEIS) (Table 11). This value exceeds the zero threshold and indicates moderate predictive relevance, suggesting that the model is capable of predicting investors' perceptions beyond mere sample fitting. In the context of behavioral finance and entrepreneurial investment research, where perceptions and decision-making are influenced by complex cognitive and contextual factors, this level of predictive relevance is considered meaningful.

Table 11: Predictive relevance (Q^2) for perceived EEIS

Endogenous Construct	Q^2	Interpretation
Perceived EEIS	0.158	Moderate predictive relevance

Note: Q^2 values greater than zero indicate that the model has predictive relevance for the endogenous construct (Hair et al., 2021).

Overall, the Q^2 result complements the R^2 and f^2 findings, demonstrating that the structural model not only explains a meaningful portion of variance in perceived EEIS but also possesses satisfactory predictive capability. This confirms the robustness and practical relevance of the proposed model.

Mediation analysis (PM2)

The mediating role of PM2 adoption in the relationship between behavioral finance factors and perceived ethnic entrepreneurial investment success (EEIS) was examined using the bootstrapping procedure in SmartPLS. Mediation was assessed based on the significance of specific indirect effects, with t-values and p-values obtained from 5,000 bootstrap samples.

The results indicate that PM2 adoption mediates the relationship between heuristic-driven biases and perceived EEIS (β = −0.084, t = 2.045, p = 0.040) (see Table 12). This finding suggests that heuristic-driven biases influence perceived investment success both directly and indirectly through the adoption of PM2 practices, highlighting the role of structured project management as an important transmission mechanism.

Table 12. Mediation effects of PM2 adoption

Path		Indirect effect (β)	t-value	p-value	Mediation type
H4	Heuristics → PM2 → EEIS	−0.084	2.045	0.040	Mediation
	Frame-dependent biases → PM2 → EEIS	-0.079	1.920	0.051	Partial mediation
	Market conditions→ PM2 → EEIS	0.011	0.688	0.357	No mediation
	BF → PM2 → EEIS	-0.085	2.210	0.027	Partial mediation

Note: Partial mediation occurs when both the direct and indirect effects are significant, whereas "No mediation" indicates that the indirect effect is not statistically significant at the 0.05 level. t-values and p-values are based on 5,000 bootstrap resamples.

PM2 adoption also demonstrates partial mediation in the relationship between frame-dependent biases and perceived EEIS (β = −0.079, t = 1.920, p = 0.061). Although the indirect effect is marginally significant, it suggests that structured project management practices can partially transmit the influence of framing biases on perceived investment success. In contrast, the indirect effect of market conditions through PM2 adoption is not statistically significant (β = 0.011, t = 0.688, p = 0.357), indicating no mediation. This result is consistent with the non-significant direct effect of market conditions observed in the structural model.

Importantly, to align with H4, we calculated the mediating effect of PM2 adoption for the combined behavioral finance construct. The results indicate significant partial mediation for the overall BF → PM2 → EEIS path (β = −0.085, t = 2.210, p = 0.027), confirming that PM2 mediates the relationship between behavioral finance as a whole and perceived investment success.

Overall, the findings suggest that PM2 adoption acts as a partial mediator for cognitive behavioral biases (heuristics and frame-dependent biases), while it does not mediate the effect of external market conditions on perceived EEIS.

Moderation analysis

The moderating role of PM2 adoption on the relationship between behavioral finance factors and perceived ethnic entrepreneurial investment success (EEIS) was examined using interaction terms in SmartPLS with 5,000 bootstrap resamples. The results are summarized in Table 13.

Table 13. Moderation effects of PM2 adoption

Interaction Path		β (Path coefficient)	t-value	p-value	Moderation effect
H5	Heuristics × PM2 → EEIS	-0.176	1.962	0.044	Significant moderation
	Frame-dependent × PM2 → EEIS	-0.167	1.821	0.070	Marginal moderation
	Market condition× PM2 → EEIS	0.008	0.130	0.897	No moderation
	BF × PM2 → EEIS				

Note: Moderation effects were tested using bootstrapping with 5,000 resamples. A negative interaction coefficient indicates that higher PM2 adoption mitigates the negative effect of the behavioral finance factor on perceived EEIS. "Marginal moderation" refers to p-values between 0.05 and 0.10.

The results indicate that PM2 adoption significantly moderates the relationship between heuristic-driven biases and perceived EEIS (β = −0.176, t = 1.962, p = 0.044). The negative interaction coefficient suggests that higher levels of PM2 adoption weaken the negative impact of heuristics, supporting the buffering role of structured project management

practices. In addition, the interaction between frame-dependent biases and PM2 adoption is marginally significant (β = −0.167, t = 1.821, p = 0.070), indicating a weaker but notable moderating effect. This finding suggests that PM2 adoption may partially reduce the adverse influence of framing biases on perceived EEIS, although the effect does not meet the conventional 0.05 significance threshold.

In contrast, the interaction between market conditions and PM2 adoption is not statistically significant (β = 0.008, t = 0.130, p = 0.897), indicating that PM2 adoption does not moderate the relationship between market conditions and perceived EEIS. This result is consistent with the non-significant direct and indirect effects of market conditions observed in earlier analyses. To align with H5 as formulated in the conceptual model, the moderation effect for the combined behavioral finance construct was calculated. The results indicate a significant interaction for the overall BF × PM2 → EEIS path (β = -0.140, t = 3.121, p = 0.044), confirming that PM2 adoption moderates the effect of behavioral finance on perceived investment success.

Overall, the moderation analysis demonstrates that PM2 adoption functions as a buffering mechanism primarily for cognitive behavioral biases, particularly heuristic-driven biases, while its moderating influence on external market-related factors is negligible in the context of small ethnic entrepreneurial businesses.

DISCUSSION

The results of this study provide important insights into the roles of behavioral and contextual factors in shaping ethnic entrepreneurs' perceived investment success. The structural model reveals that heuristic-driven biases and frame-dependent biases exert significant negative effects on perceived EEIS, confirming the dominant influence of cognitive limitations on entrepreneurial decision-making. In contrast, contextual market factors -comprising herding behavior, market information, and past trends- do not exhibit a significant direct effect on perceived EEIS, suggesting that external environmental cues play a relatively limited role when compared to internal cognitive processes.

Furthermore, the adoption of PM2 methodology demonstrates a positive and significant impact on perceived investment success and functions as both a partial mediator and moderator in the relationships between behavioral biases and EEIS. These findings indicate that structured project management practices can help mitigate the adverse effects of cognitive biases. Overall, the model explains a moderate proportion of variance in perceived EEIS (R^2 = 0.282) and demonstrates satisfactory predictive relevance, highlighting the combined importance of behavioral and managerial factors in ethnic entrepreneurial investment decisions.

The results indicate that heuristic-driven biases represent the most influential determinant of perceived ethnic entrepreneurial investment success. The strong and significant negative relationship between heuristics and EEIS (β = −0.419, p < 0.001), together with its medium-to-large effect size, suggests that cognitive shortcuts substantially distort investment evaluations among ethnic entrepreneurs. This finding implies that many investors rely on simplified judgment rules when assessing business opportunities, particularly in unfamiliar institutional and cultural environments. Rather than engaging in comprehensive financial and operational analysis, they tend to prioritize easily accessible information, prior assumptions, and intuitive judgments, which increases their vulnerability to systematic decision errors. This finding is consistent with prior behavioral finance research emphasizing that reliance on heuristics often leads to systematic judgment errors under uncertainty (Salehi et al., 2026; Spiliopoulos & Hertwig, 2024; Pompian, 2011; Belsky & Gilovich, 2010; Kahneman & Tversky, 1979). Similar patterns have been observed in entrepreneurial and small business contexts, where intuitive decision-making frequently substitutes for analytical reasoning, particularly in resource-constrained and information-poor environments (Taylor, 2024; Ogunlusi & Obademi, 2021; Guzavicius et al., 2014).

In the context of immigrant entrepreneurship, such reliance on heuristics may be intensified by limited access to formal advisory services, language barriers, and restricted knowledge of local regulations and market structures (Salehi, 2026; Kahneman & Tversky, 2013). Consequently, heuristic-based decision-making often substitutes for analytical reasoning, leading to overestimation of opportunities and underestimation of potential risks. The present findings therefore demonstrate that while heuristics may facilitate rapid decision-making, they are largely detrimental in complex entrepreneurial settings that require detailed planning and continuous adaptation. This reinforces the view that cognitive limitations constitute a major obstacle to sustainable investment success among ethnic entrepreneurs.

In addition to heuristic-driven biases, frame-dependent biases were found to exert a significant negative effect on perceived ethnic entrepreneurial investment success (β = −0.205, p = 0.003), although their impact is weaker than that of heuristics. This finding indicates that the manner in which information is presented, interpreted, and mentally categorized

plays an important role in shaping investment evaluations. Ethnic entrepreneurs who are influenced by framing effects, mental accounting, and regret aversion may assess identical business opportunities differently depending on contextual presentation, reference points, or previous experiences (Khalid & Riaz, 2026; Shalika & Buddhika, 2025). As a result, their judgments may deviate from objective performance indicators and long-term strategic considerations.

This pattern suggests that investment decisions are not solely determined by factual business information but are also shaped by subjective interpretations and emotional responses. In environments characterized by uncertainty and institutional complexity, such as those faced by many immigrant entrepreneurs, framing effects may become particularly salient (Bagozzi et al., 2016). Negative past experiences perceived social expectations, and community narratives can further intensify these biases, leading investors to prioritize short-term security over long-term growth (Serna-Zuluaga et al., 2024). Consequently, frame-dependent biases contribute to conservative or inconsistent decision-making patterns that may undermine sustained entrepreneurial performance.

This finding aligns with prior research on behavioral finance and entrepreneurial decision-making, which highlights that individuals' evaluation of gains and losses, reference dependence, and regret aversion can systematically influence choices under uncertainty (Cantarella et al., 2023; Thaler, 2008; Shefrin & Statman, 1985; Kahneman & Tversky, 1979). Studies in small business and entrepreneurial contexts (Ogunlusi & Obademi, 2021; Guzavicius et al., 2014; Shefrin, 2008) further confirm that framing effects, mental accounting, and loss aversion often lead investors to deviate from rational planning, particularly when facing incomplete information, resource constraints, and high uncertainty.

The findings further indicate that contextual market factors, comprising herding behavior, market information, and past trends, do not exert a significant direct influence on perceived ethnic entrepreneurial investment success ($\beta = 0.048$, $p = 0.464$). This result suggests that external environmental cues, while relevant to investment contexts, do not independently determine how ethnic entrepreneurs evaluate their business outcomes. Rather than functioning as direct behavioral drivers, these factors appear to operate as informational and situational inputs whose influence depends largely on individual cognitive processing and managerial practices. This pattern aligns with prior research emphasizing that environmental and market conditions often act as contextual antecedents rather than direct behavioral determinants (Cheng et al., 2025; Slomski et al., 2024; Simon et al., 2000; Shane & Venkataraman, 2000). In immigrant and small-business contexts, market trends, peer behavior, and informational cues primarily influence outcomes indirectly, through cognitive interpretation, social learning, and managerial action, rather than through direct causal effects on perceived success (Ogunlusi & Obademi, 2021; Guzavicius et al., 2014).

The non-significant relationship observed in this study reinforces the theoretical distinction between internal psychological mechanisms and external contextual conditions. While herding behavior reflects a socially driven tendency to follow others (Kumari et al., 2020), market information and past trends represent environmental signals that may be interpreted either rationally or irrationally. In the present context, ethnic entrepreneurs appear to filter these external cues through their cognitive biases and organizational practices. Consequently, contextual market factors serve primarily as background conditions that indirectly shape decision-making, underscoring that perceived investment success is predominantly determined by internal cognitive and managerial processes rather than the market environment alone.

The results further highlight the central role of PM2 methodology as both a mediating and moderating mechanism in the relationship between behavioral finance factors and perceived investment success. The mediation analysis shows that PM2 partially transmits the negative effects of heuristic-driven and frame-dependent biases to perceived EEIS, indicating that behavioral tendencies influence not only entrepreneurs' judgments but also how they structure, plan, and execute their investment projects. In this sense, cognitive biases shape the degree to which formal project management practices are adopted and effectively implemented, which in turn affects perceived outcomes. This finding supports the view of PM2 (European Commission, 2021; Kourounakis, & Maraslis, 2018) as an intermediate organizational mechanism through which psychological influences are translated into operational decisions and performance evaluations.

At the same time, the moderation analysis demonstrates that PM2 adoption weakens the negative impact of heuristic-driven biases and, to a lesser extent, frame-dependent biases on perceived EEIS. The significant and marginal interaction effects suggest that structured governance, systematic monitoring, and standardized decision procedures can buffer entrepreneurs against intuitive and emotionally driven judgment errors. By providing clear evaluation criteria, feedback mechanisms, and risk management tools (Mirbagheri & Rafiei Atani, 2025; European Commission, 2021), PM2 reduces excessive reliance on mental shortcuts and reframes decision-making toward more analytical and disciplined approaches. This dual function underscores that PM2 does not merely transmit behavioral effects but actively reshapes their influence, transforming potentially harmful cognitive tendencies into more controlled and strategically aligned investment practices.

Consequently, PM2 emerges as a critical capability that enables ethnic entrepreneurs to manage psychological constraints while enhancing adaptability and sustainability in uncertain business environments.

Taken together, the findings indicate that perceived ethnic entrepreneurial investment success is shaped primarily by internal cognitive processes and managerial capabilities rather than by external environmental conditions alone. The dominance of heuristic-driven and frame-dependent biases in explaining perceived EEIS, combined with the moderate explanatory and predictive power of the model, underscores the central role of psychological and organizational factors in entrepreneurial investment contexts. While contextual market factors provide important informational and environmental cues, their limited direct and indirect influence suggests that such signals affect outcomes mainly through entrepreneurs' cognitive interpretation and managerial responses. In this regard, investment success is not determined by market conditions per se, but by how entrepreneurs perceive, process, and operationalize market information within structured decision frameworks.

Furthermore, the integrated model demonstrates that PM2 methodology functions as a pivotal capability that connects behavioral tendencies with strategic execution. By simultaneously mediating and moderating the effects of cognitive biases, PM2 enables ethnic entrepreneurs to convert intuitive judgments into more systematic and controllable investment practices. This interaction between psychological predispositions and organizational structures reflects the dynamic nature of entrepreneurial decision-making in complex and uncertain environments. The model therefore advances behavioral finance research by illustrating how individual-level biases and project-level governance mechanisms jointly shape perceived investment outcomes. Overall, these results suggest that strengthening managerial systems and decision infrastructures may be as important as addressing cognitive biases themselves in enhancing the long-term performance, adaptability, and sustainability of ethnic entrepreneurial ventures.

Theoretical contributions

This study presents novel findings in certain areas that have not been explored in prior research. First, nearly all existing studies have examined the behavioral biases of financial market investors in decision-making. In contrast, this study focused on ethnic entrepreneurs, who primarily invest in real and tangible assets such as businesses and real estate. This represents a novel area of research, aiming to explore the impact of behavioral finance on the decision-making of ethnic entrepreneurs. Hence, it expands existing behavioral finance literature by applying psychological and decision-making biases (e.g., optimism, overconfidence, misjudgment, etc.) to the context of immigrant investors, a group often overlooked in mainstream research.

Moreover, the inclusion of PM2 methodologies is a novel approach, as these have seldom been examined as variables in existing research. In this study, we incorporated PM2 as both mediating and moderating variables within the conceptual model, yielding noteworthy results. It bridges the gap between project management theory and investment decision-making by examining the role of project management methodology (PM2) in shaping investor behavior, demonstrating that structured methods can influence financial behavior and decision-making quality. In addition, PM2 reduces the impact of behavioral biases by considering new roles and provides a new window for analyzing how structured systems affect investment outcomes in ethnic entrepreneurship contexts.

Ultimately, the findings contribute to ethnic entrepreneurship literature by showing how cultural, social, and psychological dimensions interact with formal systems like project management to influence the EEs' decisions.

Practical implications

The practical implications of this study are manifold. First, it provides valuable support to ethnic entrepreneurs and migrant investors in making informed and rational business decisions in the host country. In doing so, it enhances the success of ethnic entrepreneurship by helping investors recognize and avoid biases in their decision-making processes. This study specifically presents heuristics effects, frame dependent biases, contextual market factors, and behavioral biases -such as optimism, overconfidence, availability, anchoring, representativeness, regret aversion, framing, mental accounting, herding behavior, and reliance on past trends- and examines their impact on ethnic entrepreneurs' investment decisions, thereby raising awareness of potential biases. Additionally, the study enhances expatriates' understanding of investing in real assets such as land, housing, farms, shops, and various small businesses within their communities. In doing so, it opens a new avenue for expatriate investors beyond traditional financial markets.

Furthermore, an increase in the number of immigrant investors is likely to encourage other immigrants with entrepreneurial potential to invest or participate in some aspect of ethnic entrepreneurship. This, in turn, strengthens the ethnic economy within the community. It also positively impacts the economy of the ethnic group and immigrant population by facilitating easier job opportunities, improving communication among co-ethnics, and helping to overcome various social disadvantages.

Finally, these effects contribute positively to the broader regional economy. On the other hand, the results of this study indicate that immigrant investors should quickly adapt to the new business environment and effectively utilize project management methodologies. Understanding environmental factors and applying appropriate environmental analytics, along with possessing knowledge of agile management, portfolio management, and program management, can significantly increase the likelihood of success for ethnic entrepreneurs' projects or at least reduce the risk of failure.

Limitations and future studies

The current study offers valuable insights into ethnic entrepreneurship in the host country and its relationship with behavioral finance, considering the moderating and mediating roles of PM2. These represent the positive contributions of the research. Nonetheless, it has some limitations. First, based on the initial data, the sample was drawn from Quebec, specifically from Montreal and its surrounding suburbs. This selection is justified by the fact that different provinces and cities in Canada have varying conditions for accepting immigrants and investors. Additionally, ethnic entrepreneurs tend to have more investment opportunities in larger cities, while some prefer to operate in smaller cities due to certain restrictions. Moreover, the composition of immigrants varies across different cities and provinces and immigrants entering with an investment plan are often settled in smaller cities and provinces in accordance with government policy. Considering these cases, a larger sample size appears necessary to minimize potential biases in the results.

In addition, in this study, because of the small number of participants from some ethnicities, all entrepreneurs from different ethnic groups were analyzed together. However, if the sample sizes from different ethnic groups were sufficient, a comparative analysis of the relationships between variables and hypothesis testing could yield valuable insights. Future researchers conducting similar studies may take this into account. Furthermore, some factors were beyond the researchers' control, and it appears they may have influenced the results. Factors such as the entrepreneur's income, initial capital, and family income are important influences on investment decisions, particularly in ethnic entrepreneurship, as they can enhance investment resilience. However, due to respondents' sensitivity to these questions, such information was not collected. Moreover, the respondents' intellectual maturity and proficiency in French and English were beyond the researchers' control. However, the researcher simplified the questions at various stages to enhance their clarity and ease of understanding.

Another important limitation pertains to the combination of the variables. In this study, we focused on heuristics, framed dependent bias, and contextual market factors as behavioral finance factors; agile, portfolio, and program management as PM2 factors; and performance, sustainability, adaptability, satisfaction, and social effects as the EEs' decision factors. Nevertheless, many other factors -such as investor sentiment, ecology, moods, business environment, financial literacy, culture, education, and development etc. – can also be considered. These are variables that can interact with one another and ultimately influence the decisions and success of ethnic entrepreneurs. These can be interesting topics for future studies.

CONCLUSION

The findings of this study reveal that the success of ethnic entrepreneurial investments depends not only on external opportunities but fundamentally on the ways entrepreneurs perceive, interpret, and act on information within structured frameworks. Cognitive biases shape how entrepreneurs evaluate risks and opportunities, but their influence can be managed and transformed through disciplined project management practices. This highlights a broader principle: sustainable entrepreneurial performance arises from the alignment of human judgment with systematic processes, rather than from either factor in isolation. It suggests that interventions targeting decision-making quality, through training, tools, or structured methodologies, can meaningfully enhance investment outcomes in contexts characterized by uncertainty and limited resources.

More broadly, the research demonstrates that ethnic entrepreneurship is a dynamic interplay of psychological and managerial forces. Recognizing this complexity shifts the focus from simplistic measures of success or failure to understanding the mechanisms that drive effective decision-making and adaptability. By emphasizing the dual importance of behavioral and organizational factors, this study provides a lens for policymakers, educators, and support institutions to foster resilient entrepreneurial ecosystems. Ultimately, the conclusions point to a future where investment success is less a matter of chance or market conditions, and more the product of deliberate, informed, and well-structured decision-making.

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Author contribution statement

Ali Salehi: Conceptualization, Data Curation, Formal Analysis, Funding Acquisition, Investigation, Methodology, Resources, Software, Writing- Original Draft Preparation, Review & Editing. **Hamed Motaghi:** Project Administration, Supervision, Validation, Visualization, Writing – Review & Editing. **Manel Kammoun:** Project Administration, Supervision, Validation, Visualization, Writing – Review & Editing.

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The authors declare no conflicts of interest.

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Startup typologies in an emerging economy: Financial barriers, ecosystem support, and financing behavior

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Abstract

***PURPOSE**: This study examines whether ICT startups operating within a single emerging-economy ecosystem form distinct typologies based on perceived financial barriers and ecosystem support, and how these typologies relate to financing behavior, financing source composition, and firm characteristics. The study is framed as an exploratory, cross-sectional typology analysis of within-ecosystem heterogeneity. **METHODOLOGY**: The analysis is based on survey data collected from 111 ICT startups in Albania during March–May 2025. K-means clustering was applied using standardized scores of perceived financial barriers and ecosystem support. Differences across typologies were examined using ANOVA, Tukey post-hoc tests, Monte Carlo p-values for sparse financing-source tables, Cramer's V and financing-diversification checks. A parsimonious multinomial logistic regression model was used to profile typology membership. **FINDINGS**: Three typologies are identified: financially constrained, ecosystem-enabled, and ecosystem-disconnected startups. The typologies differ significantly in access to finance and startup performance. They also differ in selected financing sources, especially bootstrapping and crowdfunding. The total number of financing sources used does not differ significantly across groups, indicating differences in financing-source composition rather than overall diversification. Typology membership is profiled by prior startup experience, firm size, and lifecycle stage. **IMPLICATIONS:** The findings show that ecosystem support is not experienced uniformly by startups operating in the same setting. The study contributes to entrepreneurial ecosystem research by highlighting structured heterogeneity within a single ecosystem, and to entrepreneurial finance research by linking financing behavior to startups' perceived support-and-constraint profiles. For practice, the results suggest that startup support policies should be differentiated across financially constrained, ecosystem-enabled and ecosystem-disconnected firms. **ORIGINALITY & VALUE**: The study advances a typology-oriented perspective by showing that ICT startups within the same emerging-economy ecosystem may experience financial barriers and ecosystem support in different combinations. It also distinguishes financing-source composition from financing diversification, showing that startup groups may differ in the types of financing sources used even when the number of sources does not differ significantly. The study provides evidence from Albania, an underexplored small startup ecosystem where structural differentiation among startups is especially relevant.*

***Keywords:** entrepreneurial ecosystems, startup typologies, startup finance, financial constraints, ecosystem support, financing behavior, financing-source composition, digital entrepreneurship, ICT startups, emerging economies*

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INTRODUCTION

Entrepreneurial ecosystems are widely used to explain how startups access resources and develop over time, especially in settings marked by resource scarcity and institutional gaps (Spigel, 2017; Stam, 2015; Stam & van de Ven, 2021). Entrepreneurial activity depends both on firm-level capabilities and on the wider set of actors, institutions and support structures through which opportunities are identified and resources are accessed. Most of this evidence comes from advanced economies, where financing systems, support organizations and entrepreneurial infrastructures are more developed. Although this literature has advanced understanding of how ecosystem-level conditions are associated with entrepreneurial activity, it has also been criticized for treating ecosystems as relatively coherent environments and for paying insufficient attention to differences among firms operating within the same ecosystem (Wurth et al., 2022, 2023). This limitation is important because startups located in the same national or city-level ecosystem may not experience the same degree of support, network access or financing opportunity. In emerging economies, entrepreneurial ecosystems often operate under very different conditions. Startups in these contexts face institutional gaps, weak coordination, fragmented support structures and limited access to specialized finance, all of which can restrict their ability to scale and commercialize new ideas (Bruton et al., 2018; Qoriawan & Apriliyanti, 2023; Wurth et al., 2023). These challenges are particularly relevant for information and communication technology (ICT) startups, which depend on rapid scaling, specialized knowledge and financing arrangements suited to intangible assets and high uncertainty (Hall & Lerner, 2010; Ngoasong, 2018). ICT startups often need financing beyond conventional small-business credit because their assets are intangible, their revenues are uncertain, and their growth prospects are difficult to assess. Their financing conditions therefore depend not only on credit availability, but also on the suitability of seed capital, equity finance and ecosystem intermediation.

Albania provides a relevant setting because its startup ecosystem is expanding but remains structurally young. Recent assessments describe it as being in the early Activation Phase, with limited startup experience, resource constraints, and activity concentrated mainly in Tirana, while also noting stronger local connectedness, founder quality and growing international support through programs such as EU4Innovation and EBRD-backed initiatives (Startup Genome, 2025; StartupBlink, 2026).

This does not mean that finance is generally inaccessible across the Albanian economy. General access-to-finance conditions have improved in Albania (OECD, 2024). The constraint examined here is narrower: startup-oriented finance. Albanian startups still rely heavily on grants and bootstrapping, while angel investment and domestic venture-capital infrastructure remain limited, creating early-stage funding gaps between accelerator participation and follow-on investment (Startup Genome, 2025). This pattern is consistent with broader evidence from the Western Balkans, where startups' access to external finance remains constrained by weaker credit conditions, shallower venture capital markets, and less developed investor protection mechanisms (Kruja & Irimia-Diéguez, 2025). This makes Albania useful for examining how ICT startups in the same compact ecosystem occupy different perceived support-and-constraint positions.

Financial barriers remain a central challenge in these environments, including limited seed funding, weak venture capital markets, and restricted access to formal credit (Beck & Demirguc-Kunt, 2006; Samara & Terzian, 2021). In this study, financial barriers are examined as perceived financial barriers: founders' subjective assessments of the difficulty, suitability and accessibility of finance for their ventures, rather than direct measures of the objective supply of credit or investment. Recent studies on digital and ICT startup ecosystems in emerging regions consistently identify funding scarcity and uneven support as key obstacles, often compounded by regulatory frictions and weak coordination among ecosystem actors (Lee & Kim, 2025; Qoriawan & Apriliyanti, 2023). Moreover, ecosystem intermediaries such as incubators and accelerators do not necessarily provide financial resources directly; rather, they may indirectly facilitate startups' access to finance through networks, legitimacy, and brokerage functions (Wurth et al., 2022). Ecosystem support is not equally accessible to all startups and often depends on relationships, networks and intermediaries (Dourado Freire et al., 2023; Spigel & Harrison, 2018).

Most existing studies have analyzed these relationships through variable-centered approaches that estimate average associations between ecosystem conditions and startup outcomes (Stam & van de Ven, 2021). This has generated valuable insights, but it leaves limited room to understand how startups within the same ecosystem combine support and constraints in different ways, especially in relation to their financing behavior. Configurational perspectives offer a useful alternative because they show how different conditions combine to produce distinct organizational patterns rather than average effects (Fiss, 2011; Meyer et al., 1993). Typological and cluster-based approaches have been used in related firm-level research to capture heterogeneity that average-effect models may overlook. This study therefore uses K-means clustering as an

exploratory tool to identify coherent startup groups based on two theoretically central dimensions: perceived financial barriers and perceived ecosystem support. The aim is classification and interpretation, not causal estimation.

This issue is particularly relevant in emerging economies (Klein & Braido, 2024; Quinones et al., 2021). Startups operating in the same ecosystem may differ substantially in how they assemble financing portfolios, rely on different funding sources, and navigate constraints through alternative financing strategies. Such differences matter because financing choices are closely linked to how ventures sustain operations, manage risk and pursue growth under conditions of uncertainty. In this study, financing behavior refers to whether and how startups use particular funding sources, such as personal savings, bootstrapping, grants, bank loans, crowdfunding or investor capital. Financing portfolio composition refers to the overall combination of sources used by each firm. The distinction is important because two startups may both use external finance, yet differ substantially in the mix of informal, public, debt-based and equity-oriented sources that constitute their financing portfolios.

This study examines whether ICT startups operating within a single emerging-economy ecosystem form distinct groups based on different combinations of perceived financial barriers and ecosystem support and assesses how these groups differ in their financing behavior and financing portfolio composition. Typologies are defined here as internally coherent groups of startups that share similar combinations of perceived constraints and support conditions. The study uses a typology-oriented configurational perspective and does not focus on modeling direct or mediating effects among ecosystem conditions and startup outcomes. Here, a configurational perspective means examining how multiple conditions interact to form distinct startup profiles, rather than focusing on the separate effects of individual variables. This approach helps identify internally coherent startup groups and systematically examine differences in financing strategies and funding structures, while using performance only as a secondary validation measure. The practical relevance of this approach is that policies based on average ecosystem conditions may overlook firms that experience the same ecosystem in markedly different ways. Identifying typologies can therefore inform more targeted support instruments for startups that are financially constrained, ecosystem-enabled or weakly connected to formal support structures.

Using survey data from 111 ICT startups in Albania, an emerging economy, this study addresses the following research questions:

RQ1. What exploratory typologies can be identified among ICT startups operating within the same emerging-economy ecosystem based on perceived financial barriers and ecosystem support?
RQ2. How do these typologies differ in financing behavior and financing-source composition, and do they also differ in overall financing diversification?
RQ3. Which founder and firm-level characteristics are associated with typology membership?

The findings identify three startup typologies: financially constrained, ecosystem-enabled, and ecosystem-disconnected. Differences among these groups are most evident in access to finance, startup performance, and financing-source composition, rather than in the number of funding sources they use. Selected founder and firm characteristics, including prior startup experience, access to finance, firm size and lifecycle stage, are also associated with typology membership.

The study contributes to the literature in four ways. First, it advances entrepreneurial ecosystem research by showing that startups in the same ecosystem may access and use support conditions differently. Second, it brings a configurational perspective to the study of ICT startups in emerging economies by showing how distinct combinations of support and constraints correspond to distinct financing patterns. Third, it contributes to entrepreneurial finance research by showing that financing behavior and financing source composition are associated with startups' ecosystem position, not just firm-level financial choices. Fourth, it provides empirical evidence from an underexplored emerging economy, where ecosystem fragmentation and limited financial depth make such differentiation visible. The findings are not universally generalizable, but may be relevant to other small, concentrated and institutionally developing startup ecosystems. The remainder of the paper is organized as follows. The next section reviews the relevant literature and develops the hypotheses. The methodology section presents the research context, sample, measurement revision and analytical strategy. The results and discussion section reports and interprets the findings. The final section concludes by outlining contributions, implications, limitations, and directions for future research.

LITERATURE REVIEW

Ecosystem support in emerging economies

Entrepreneurial ecosystems are commonly conceptualized as interconnected constellations of actors, institutions, and resource associated with entrepreneurial activity and firm development (Autio et al., 2018; Stam, 2015). While this view has been largely developed in advanced economies, research increasingly shows that ecosystems in emerging economies operate under distinct structural and institutional constraints. Cao and Shi (2021) show that such ecosystems are often marked by resource scarcity, institutional voids, and fragmented support structures, which weaken coordination among actors and limit the development of specialized financial and innovation infrastructure. As result, ecosystem support tends to be less predictable and less evenly accessible than in more mature contexts. At the same time, the entrepreneurial ecosystem concept has been criticized for overstating coherence and underplaying variation among firms located in the same environment. Startups differ in visibility, legitimacy, founder networks, prior experience, and ability to use intermediaries. Ecosystem support should therefore be treated as unevenly perceived and unevenly accessed, especially where formal institutions and private finance markets remain incomplete. These conditions are especially relevant for ICT startups, which rely on rapid scaling, specialized knowledge and external networks to mobilize resources under uncertainty (Hall and Lerner, 2010; Ngoasong, 2018; Klein et al., 2019; Janeway, Nanda and Rhodes-Kropf, 2021). Their assets are often intangible, their early revenues are uncertain, and their growth prospects are difficult for conventional financiers to evaluate.

Evidence from startup financing and digital entrepreneurship research in emerging economies points to recurring funding gaps, regulatory frictions, weak investor networks,and infrastructural limitations (Ngoasong, 2018; Qoriawan & Apriliyanti, 2023; Samara & Terzian, 2021). Ecosystem support mechanisms such as incubators, accelerators, mentoring schemes, universities and public programs function less as direct funding providers. They function as intermediaries that may indirectly improve resource access by enhancing legitimacy, reducing information asymmetries, and connecting startups to investors and other institutional actors (Davalas & Angelaki, 2025; Dourado Freire et al., 2023; Kayser et al., 2023). Because support structures are often unevenly coordinated and used differently across firms, startups operating within the same ecosystem may still face different opportunities to access information, networks, and funding channels. Ecosystem support is therefore understood here not as a uniformly shared condition, but as a perceived and relational resource that shapes how startups engage with available financial resources.

Perceived financial barriers

Financial constraints have long been recognized as a major challenge for entrepreneurial ventures, especially in settings marked by underdeveloped capital markets, and institutional weaknesses (Beck & Demirguc-Kunt, 2006; Chundakkadan & Sasidharan, 2020; Hall & Lerner, 2010). In emerging economies, these constraints are often reinforced by limited risk capital, weak investor networks and regulatory uncertainty, which restrict startups' ability to secure external finance (Ferrucci et al., 2021).

These constraints are not only objective but also perceptual. Perceived financial barriers refer to entrepreneurs' subjective assessments of the difficulty, suitability or accessibility of external finance, including expectations of rejection, lack of information and perceived misalignment between financing instruments and business models (Cole & Sokolyk, 2016; Roper & Scott, 2009). Such perceptions may influence financing behavior independently of actual market conditions by affecting whether and how founders' approach external funding sources.

In ICT startup ecosystems, perceived financial barriers may be particularly pronounced due to valuation uncertainty, intangible assets and limited understanding of technology-based business models among investors and lenders (Quinones et al., 2021; Samara & Terzian, 2021). This is also consistent with recent review evidence showing that young and innovative startups often face financing difficulties because they lack historical data, proven performance metrics and transparency, which intensifies information asymmetry with external financiers (Kruja & Irimia-Diéguez, 2024). Under these conditions, founders may rely more heavily on internal or informal financing even when external options formally exist, which may, in turn, constrain growth. This makes perceived financial barriers relevant not only as constraints on resource acquisition, but also as factors that may generate different financing responses across ventures. In this study, perceived financial barriers are therefore treated as founder-level assessments of finance accessibility and suitability, not as direct measures of the objective supply of credit or investment.

Financing portfolios as behavioral expressions of positioning

Financing behavior can be observed through the financing portfolios that startups assemble over time. Financing portfolios provide a useful way to capture how startups navigate the constraints and opportunities of their ecosystem. They refer to the combination of funding sources used by firms, including internal funds, informal finance, public support and, where available, external equity (Block et al., 2018; Cassar, 2004; Berger & Udell, 2006). Prior research shows that these portfolios vary across stages of development and institutional contexts, reflecting not only funding needs, but also the structure of available opportunities.

In emerging economies, financing portfolios often reveal how startups adapt to constrained and uneven support environments. ICT startups may rely heavily on informal finance, bootstrapping, and public programs, particularly in the early stages, where formal capital remains limited. At the same time, ecosystem actors such as accelerators and innovation hubs can help ventures access early-stage support and partially bridge institutional gaps (Ngoasong, 2018; Quinones et al., 2021).

Entrepreneurial-finance theory provides a useful lens for interpreting these patterns. The pecking-order perspective suggests that firms tend to prioritize internal finance before moving toward external sources, largely because external capital is affected by information asymmetry and financing costs (Myers, 1984; Myers & Majluf, 1984). For young ventures, this logic is especially relevant because limited track records, intangible assets and uncertain revenues may increase dependence on founder resources, informal finance, or other accessible sources (Cassar, 2004). The financial-growth-cycle view further suggests that financing options should broaden as firms mature, accumulate credibility and become more visible to lenders or investors (Berger & Udell, 1998).

These pathways are not always stable. Limited investor availability, weak intermediation and scarce follow-on funding may disrupt financing trajectories and keep startups dependent on internal or contingent sources of finance (A. Z. Klein & Braido, 2024; M. Klein et al., 2019; Oladele et al., 2024). In small emerging ecosystems, this progression may be further constrained by thin domestic risk-capital markets and weak intermediation. For this reason, the present study distinguishes financing-source composition from financing diversification. Startups may differ in the types of financing sources they use, such as bootstrapping, grants, trade credit or crowdfunding, without necessarily relying on a larger number of sources. Financing portfolios are better understood not simply as technical funding choices, but as observable patterns reflecting how startups are positioned within their ecosystems and how effectively they mobilize available support and funding channels.

Toward a configurational and typological perspective

Research on ecosystem support, financial barriers and entrepreneurial finance consistently points to heterogeneity among startups operating within the same institutional context (Mason & Brown, 2014; Spigel & Harrison, 2018). Variable-centered approaches, which focus on average relationships between ecosystem conditions and firm-level outcomes, may obscure this within-ecosystem variation and offer limited insight into how multiple conditions combine within firms (Stam & van de Ven, 2021). Configurational perspectives offer an alternative by emphasizing that different outcomes may result from distinct combinations of conditions, rather than from single factors acting independently (Fiss, 2011; Misangyi et al., 2017). Typology-based approaches translate this logic into empirical analysis by identifying groups of firms with similar profiles that can be systematically compared (Ketchen & Shook, 1996; Meyer et al., 1993). This perspective is especially relevant in emerging-economy ecosystems, where fragmentation, institutional voids and uneven resource distribution are likely to generate diverse startup trajectories (Cao & Shi, 2021; Kayser et al., 2023; Qoriawan & Apriliyanti, 2023). It also aligns with research on digital entrepreneurship, which stresses the importance of context-specific resource mobilization and adaptive strategies in venture development (Klein & Braido, 2024; Ngoasong, 2018).

The literature suggests that startups operating within the same emerging-economy ecosystem are unlikely to experience financial barriers and ecosystem support in uniform ways. Different combinations of these two conditions may give rise to distinct startup typologies. These typologies are expected to differ in financing behavior and financing portfolio composition. Founder and firm level characteristics may also help profile differences in typology membership.

The conceptual argument is that perceived financial barriers capture information opacity and uncertainty surrounding young ICT ventures, while ecosystem support can reduce that opacity through signaling, network brokerage, legitimacy transfer and access to information channels. Where support is stronger, startups should be more visible to financiers and better positioned to use non-bank or investor-facing sources. Where support is weaker, startups are expected to remain

more dependent on internal, informal or transactional sources. These mechanisms link the typological classification to financing behavior without implying causal effects from cross-sectional data.

Accordingly, the following hypotheses are proposed:

H1: ICT startups operating within the same emerging-economy ecosystem can be grouped into exploratory typological profiles based on different combinations of perceived financial barriers and ecosystem support.
H2: The identified startup typologies are associated with systematic differences in financing behavior and financing portfolio composition, but not necessarily with overall financing diversification.
H3: Founder and firm level characteristics are associated with membership in different startup typologies.

METHODOLOGY

Research context

This study was conducted in Albania, a small, emerging economy in Southeast Europe characterized by a geographically concentrated, still-developing startup ecosystem. Recent ecosystem assessments estimate that Albania's broader startup ecosystem comprises approximately 400-420 companies, concentrated mainly in Tirana (Startup Genome, 2025). Building on this ecosystem-level context, the present study focuses more narrowly on independent ICT and ICT-enabled startups operating within this national startup ecosystem. Although the ICT sector has expanded steadily in recent years, early-stage financing channels remain underdeveloped. Entrepreneurial activity is primarily concentrated in Tirana, where incubators, accelerators, and donor-supported innovation programs operate. This setting provides a suitable context for examining within-ecosystem differentiation among ICT startups operating within the same institutional environment.

Research design and sample

This study adopts a cross-sectional survey design to identify structural heterogeneity among ICT startups. The design is exploratory and typology-oriented. It is not intended to estimate causal effects, but to identify whether startups can be grouped into internally coherent profiles based on perceived financial barriers and ecosystem support, and then to examine whether these profiles differ in financing behavior, portfolio composition, and firm characteristics.

The target population consisted exclusively of independent ICT startups operating in Albania. Firms were identified through multiple sources, including the national business registry using ICT-related activity codes, startup and innovation hubs in Tirana, accelerator and incubator participant lists, and professional ICT associations. To be eligible, firms had to be engaged in ICT-related activities and actively operating at the time of data collection. Founders and co-founders were selected as key informants because they are directly involved in financing decisions and strategic positioning. They were also appropriate respondents because the main constructs, perceived financial barriers and perceived ecosystem support, require respondents familiar with the venture's financing attempts and ecosystem interactions.

For this study, a startup was defined as an independent ICT or ICT-enabled venture founded within the previous ten years, actively operating in Albania, and pursuing an innovation-oriented or scalable business model in which digital technologies are central to the product, service delivery, or growth process. The sample excluded subsidiaries, branches of established corporations, public institutions, inactive firms and conventional SMEs that used ICT only for routine administration without a technology-based or scalable value proposition. ICT-enabled startups were included only when digital technology constituted a core element of the business model rather than a support function. This definition follows the logic of startup ecosystem assessments that distinguish technology-driven startups by age, independence, technology orientation and scalability, while adapting it to the Albanian registry and ecosystem context (Startup Genome, 2025).

The questionnaire was originally developed in English and translated into Albanian using a back-translation procedure. Two bilingual researchers independently translated and retranslated the instrument to ensure semantic equivalence. Minor discrepancies were resolved through discussion. A pilot test was conducted with ten ICT startup founders who were demographically similar to the final sample. The pilot resulted in minor wording and layout adjustments.

Data were collected online from March to May 2025. Invitation emails containing a survey link were sent directly to identified founders. Participation was voluntary and anonymous, and informed consent was obtained from all respondents. A total of 111 valid responses were retained for analysis. Because the sampling frame was compiled from overlapping

registry, ecosystem, and association sources, a precise, non-duplicated denominator could not be verified, and a formal response rate is therefore not reported. To assess potential non-response bias, early and late respondents were compared on key observable characteristics, including lifecycle stage, firm size and location. No substantively meaningful differences were observed.

The sample size is acceptable for an exploratory typology analysis with two clustering variables, where the solution is assessed through interpretability and stability checks rather than through population-level inference (Hair et al., 2019; Mooi & Sarstedt, 2014).

Sample characteristics

The sample reflects the characteristics of a young and knowledge-intensive startup population. Founders were relatively young, with the majority aged 25-44, and the gender distribution was balanced (55.9% male; 44.1% female).

In terms of firm development, startups were predominantly in early (58.6%) or growth (41.4%) stages. Market orientation was distributed across B2B, B2C and mixed strategies, while entrepreneurial activity was geographically concentrated in Tirana (61%), confirming its central role within the national ICT ecosystem. This geographic concentration is consistent with recent ecosystem assessments showing that Albanian startup activity remains strongly centered around Tirana and its surrounding support infrastructure.

Financing levels were generally modest, with most startups (80.2%) raising less than €50,000 and 19.8% securing larger investment rounds. Ownership structures were mainly sole proprietorships and limited liability companies, indicating relatively simple governance forms among ICT startups. These characteristics are consistent with an emerging startup ecosystem in which many ventures remain small, early-stage and dependent on founder resources, grants, informal finance, or limited external financing.

Conceptual and operational definitions of variables

The analysis focuses on four main constructs: perceived financial barriers (PFB), ecosystem support (ES), access to finance (AF) and startup performance (SP). All constructs were measured using multi-item Likert-type scales ranging from 1 (strongly disagree) to 5 (strongly agree) adapted from prior entrepreneurship and small business research.

Before calculating the composite scores, the items were screened for conceptual overlap with behavioral outcomes and financing-source measures. Items that captured behavior, funding outcomes or financing portfolio composition were excluded to avoid circularity between the clustering variables, comparison variables and financing-source outcomes.

Perceived Financial Barriers (PFB) were originally measured with eight items adapted from the entrepreneurial finance literature (Cowling & Sclip, 2023). The original item PFB2, "The requirements from financial institutions are not startup friendly," was excluded because it was conceptually broad and overlapped with general access-to-finance conditions rather than capturing a distinct perceived financial barrier. After this exclusion, the remaining seven items were renumbered sequentially as PFB1–PFB7 to avoid an item-numbering gap. Accordingly, the retained PFB2 in the final scale refers to the former PFB3 item, "Lack of collateral has prevented us from securing funding." The retained items capture founders' perceptions of difficulties in accessing external finance, collateral constraints, information asymmetry, application complexity, investor uncertainty, limited investor networks and perceived inaccessibility of external finance. Higher scores indicate stronger perceived financial barriers.

Ecosystem Support (ES) was measured with seven retained items adapted from entrepreneurial ecosystem research (Qian & Acs, 2023; Spigel & Harrison, 2018; Stam & van de Ven, 2021). The items assess perceived access to support programs, mentors, government initiatives, financial ecosystem actors, innovation culture, entrepreneurship events and university support. ES8 (participation in an incubator or accelerator) and ES9 (receipt of a public or donor grant) were excluded because they capture behavioral or funding outcomes rather than perceptions of ecosystem support. ES9 was also excluded because it overlaps with the financing-source indicator for grants or subsidies.

Access to Finance (AF) was measured with five retained items reflecting perceived ease of obtaining financing and satisfaction with financing conditions (M. Berger & Hottenrott, 2021; Block et al., 2018). AF6 was removed from the AF scale because it measures the use of multiple financing sources and therefore overlaps with financing diversification and portfolio composition.

Startup Performance (SP) was measured with nine self-reported items assessing revenue growth, customer expansion, team expansion, financial improvement and competitive progress over the previous twelve months (Chandler & Hanks, 1993; Dess & Robinson, 1984).

All constructs were operationalized as mean composite scores calculated from the retained items. The final measurement model contains 28 retained items: AF1-AF5, PFB1-PFB7, ES1-ES7 and SP1-SP9. Respondents also reported their use of specific financing sources through binary indicators, including personal savings, friends and family, retained earnings, bootstrapping, angel investors, venture capital, private equity, bank loans, trade credit, grants and crowdfunding. Financing diversification was calculated as the count of distinct sources used. Lifecycle stage was coded as a binary variable distinguishing early stage from growth stage firms.

Data analysis

The analysis proceeded in five stages. First, descriptive statistics were computed for the principal constructs, and the internal structure of the multi-item measures was assessed using principal component analysis (PCA) with varimax rotation, along with reliability analyses. The PCA was conducted on the 28 retained items. The Kaiser–Meyer–Olkin statistic, Bartlett's test of sphericity and Cronbach's alpha coefficients were used to examine measurement adequacy and internal consistency. These diagnostics are interpreted as evidence of internal consistency and an expected exploratory component structure, not as confirmatory validation.

Second, a K-means cluster analysis was conducted using standardized scores of perceived financial barriers and ecosystem support to identify internally coherent startup typologies. Standardization ensured equal weighting of the two clustering dimensions. Access to finance, startup performance, financing sources, financing diversification, lifecycle stage and other firm characteristics were not included in the clustering procedure. To select the retained cluster solution, the k = 2, k = 3, and k = 4 solutions were compared using silhouette coefficients, cluster-size balance, interpretability, and stability diagnostics. The K-means algorithm was run with 100 random initializations and a convergence tolerance of 0.000001 to reduce sensitivity to starting values. Outliers were assessed using the standardized PFB and ES scores before clustering. Cluster stability was further examined using bootstrap resampling and split-half validation, with the adjusted Rand index (ARI) used to assess the consistency of cluster assignments across repeated solutions.

Third, differences across the identified typologies were examined using variables that were not included in the clustering procedure. One-way analysis of variance (ANOVA), followed by Tukey post-hoc tests where appropriate, was used to assess differences in access to finance and startup performance. Differences in PFB and ES are not treated as independent evidence of cluster validity, as these variables define the clusters. Differences in specific financing sources were examined using contingency-table procedures. Because several financing-source categories contained small or zero cells, Monte Carlo p-values were calculated and Cramer's V was reported as an effect-size measure.

Fourth, financing diversification was examined separately using the count of distinct financing sources and tested using both ANOVA and the non-parametric Kruskal–Wallis test. This separate test is necessary because differences in financing-source composition do not automatically imply broader financing diversification.

Fifth, a multinomial logistic regression model was estimated to profile typology membership. The financially constrained typology served as the reference category. To avoid circularity, the clustering variables were excluded from the regression model. Access to finance, prior startup experience, firm size measured as the natural logarithm of employees and lifecycle stage were included as predictors. The model does not aim to estimate causal effects, but to identify how observable characteristics are associated with the likelihood of belonging to different startup typologies.

The probability of startup *i* belonging to typology *k* is specified as follows:

$$P(Y_i = k) = \frac{\exp(\beta_{0k} + X_i'\beta_k)}{\sum_{j=1}^{K} \exp(\beta_{0j} + X_i'\beta_j)}$$

Using typology 1 (financially constrained startups) as the reference category, the model is estimated as:

$$\log\left(\frac{P(Y_i=k)}{P(Y_i=1)}\right) = \beta_{0k} + \beta_{1k}AF_i + \beta_{2k}EXP_i + \beta_{3k}SIZE_i + \beta_{4k}STAGE_i, \quad k=2,3$$

where Y_i denotes typology membership, AF_i is access to finance, EXP_i is prior startup experience, $SIZE_i$ is the natural logarithm of employees, $STAGE_i$ is lifecycle stage. Estimated coefficients indicate associations with the relative odds of membership in each typology compared with the financially constrained reference group.

RESULTS AND DISCUSSION

Descriptive analysis and measurement quality

We first assessed the measurement structure and reliability of the multi-item constructs. The data showed satisfactory sampling adequacy, with a Kaiser–Meyer–Olkin value of 0.795, and Bartlett's test of sphericity was statistically significant ($\chi^2 = 3375.199$, df = 378, $p < 0.001$), supporting the factorability of the data. Principal component analysis (PCA) with varimax rotation and Kaiser normalization was conducted on the 28 retained items. Four components were extracted, corresponding to startup performance (SP), ecosystem support (ES), perceived financial barriers (PFB), and access to finance (AF). The four-component solution explained 73.566% of the total variance. The initial eigenvalues were 11.316, 4.615, 2.938, and 1.729. After rotation, the variance was redistributed across the four components, with rotated sums of squared loadings of 7.227, 5.133, 5.015 and 3.223, respectively. The rotated component loadings are presented in Table 1.

All scales showed strong internal consistency (Cronbach's α: PFB = 0.915; ES = 0.918; AF = 0.862; SP = 0.957). The rotated component pattern supports measurement adequacy and item-level construct distinctiveness. Given the exploratory and PCA-based nature of the assessment, however, these results are not interpreted as confirmatory evidence of discriminant validity. The reliability and component results therefore support the use of construct scores in the subsequent analyses.

Table 1. Rotated component matrix

	Component			
	SP	ES	PFB	AF
AF1. Our startup has been able to obtain the external financing it needs to grow				0.610
AF2. We have successfully accessed at least one form of external capital (loan or equity) in the last 12 months				0.722
AF3. It has been relatively easy to secure external financing from banks or investors				0.769
AF4. We did not face major delays in receiving the financing we applied for.				0.763
AF5. The terms (cost, interest rates, equity requirements) of financing were acceptable				0.623
PFB1. Accessing external financing has been a major challenge for our startup			0.803	
PFB2. Lack of collateral has prevented us from securing funding			0.721	
PFB3. The information asymmetry between our firm and financiers has been a barrier			0.774	
PFB4. Bureaucracy and application complexity have discouraged us from applying.			0.861	
PFB5. Investors perceive our revenue/growth as too uncertain			0.832	
PFB6. Insufficient networks with investors have negatively impacted my access to external funding			0.841	
PFB7. I perceive external financing sources (e.g., banks) as inaccessible for startups in my industry			0.773	
ES1. In our country, there are sufficient incubators, accelerators, or support programs for startups		0.822		
ES2. We have easy access to mentors, advisors, or experienced entrepreneurs who can support our startup		0.870		
ES3. Government programs (e.g., grants, incentives) effectively support startups like ours		0.618		
ES4. The local financial ecosystem (investors, venture capitalists, angel networks) is accessible to startups		0.820		
ES5. The regional entrepreneurial environment encourages innovation, collaboration, and new business creation		0.809		
ES6. There are frequent events (meetups, hackathons, competitions) promoting startups.		0.767		
ES7. Universities actively promote entrepreneurship		0.632		
SP1. Our startup has experienced positive revenue growth over the past 12 months.	0.793			
SP2. We have successfully achieved key product development or market milestones during the past year.	0.770			
SP3. Our team has expanded to support business growth and operations.	0.793			
SP4. Our customer base has grown steadily over the past 12 months.	0.845			
SP5. Our startup's financial performance has improved compared to the previous year.	0.883			
SP6. Our startup has made significant progress toward financial sustainability.	0.769			
SP7. Our competitive position in the market has improved relative to key competitors.	0.763			
SP8. We have successfully introduced new or improved products or services during the past year.	0.845			
SP9. Overall, our startup's performance has improved significantly over the past 12 months.	0.877			

Note: Extraction method: Principal component analysis. Rotation method: Varimax with Kaiser normalization. Loadings below 0.30 are suppressed. SP = startup performance; ES = ecosystem support; PFB = perceived financial barriers; AF = access to finance.

Descriptive statistics reported in Table 2 show variation across all four construct scores, with responses covering the full scale range from 1 to 5. Perceived financial barriers have the highest mean score, while ecosystem support and access to finance have lower mean scores. This indicates that respondents generally report stronger financial barriers than ecosystem support or financial access. The pattern is consistent with research on emerging-economy startup contexts, where finance-related constraints and uneven support structures often coexist (Cao & Shi, 2021; Samara & Terzian, 2021). The observed variation supports the use of a typology-oriented analysis, as startups differ meaningfully in their reported levels of financial barriers, ecosystem support, access to finance and performance.

Table 2. Descriptive statistics of construct scores

Construct	Mean	SD	Min	Max
Perceived Financial Barriers (PFB)	3.179	0.939	1.0	5.0
Ecosystem Support (ES)	2.759	0.909	1.0	5.0
Access to Finance (AF)	2.497	0.993	1.0	5.0
Startup Performance (SP)	3.078	0.970	1.0	5.0

Note: Values are construct means.

Correlations among the main constructs

Table 3 reports Pearson correlations among AF, PFB, ES, and SP. The coefficients follow the expected theoretical pattern: access to finance is positively associated with ecosystem support and startup performance, and negatively associated with perceived financial barriers. Perceived financial barriers show weaker negative associations with ecosystem support and performance. The matrix indicates theoretically meaningful associations without suggesting excessive overlap among the constructs. The association between ecosystem support and access to finance is therefore interpreted as expected construct convergence rather than as independent external validation of the ecosystem-enabled typology.

Table 3. Correlation matrix among the main constructs

Construct	AF	PFB	ES	SP
AF	1			
PFB	−0.343**	1		
ES	0.617**	−0.185	1	
SP	0.662**	−0.167	0.501**	1

Note: Pearson correlations are reported. **$p < 0.01$, two-tailed.

Cluster analysis: Identification of startup typologies

To examine whether startups form distinct profiles, K-means clustering was applied using standardized scores of perceived financial barriers and ecosystem support. Only these two variables were used in the clustering procedure. Access to finance, startup performance, financing sources, financing diversification and firm characteristics were reserved for external profiling and comparison. Alternative cluster solutions were compared before selecting the final model. As shown in Table 4, the two-cluster solution produced relatively broad groups and did not distinguish startups with low ecosystem support from those with high financial barriers. The four-cluster solution produced a marginally higher silhouette coefficient, but included a very small cluster, limiting its interpretability. The three-cluster solution provided the clearest balance between statistical adequacy, interpretability and usable group sizes.

Table 4. Alternative cluster solutions

Solution	Cluster sizes	Silhouette	Inertia
k = 2	64 / 47	0.341	139.962
k = 3	60 / 22 / 29	0.409	86.849
k = 4	45 / 39 / 21 / 6	0.410	64.443

The K-means algorithm was run with 100 random initializations and a convergence tolerance of 0.000001 to reduce sensitivity to starting values. Before clustering, standardized PFB and ES scores were screened to identify unusual values and possible data-entry errors. No cases were excluded, as the observed variation reflected meaningful differences in founders' perceptions. Stability checks further supported the retained three-cluster solution. Across 200 bootstrap resamples, the mean adjusted Rand index (ARI) was 0.704, while across 200 split-half samples, the mean ARI was 0.662. These values indicate moderate stability for an exploratory typology analysis and support the use of the three-cluster solution for descriptive profiling rather than causal inference.

Table 5. Final Cluster Centers

Cluster	n	PFB	PFB SD	ES	ES SD	Startup typology
Cluster 1	60	3.86	0.530	2.76	0.581	Financially constrained
Cluster 2	22	2.20	0.655	3.94	0.559	Ecosystem-enabled
Cluster 3	29	2.53	0.607	1.87	0.627	Ecosystem-disconnected

Note: PFB and ES are unstandardized cluster means. Clusters were estimated using standardized scores.

The three-cluster solution identifies three interpretable startup typologies. Cluster 1 (n = 60) combines high perceived financial barriers (PFB = 3.86) with moderate ecosystem support (ES = 2.76) and is labeled ‚financially constrained'. Cluster 2 (n = 22) combines low financial barriers (PFB = 2.20) with strong ecosystem support (ES = 3.94) and is labeled Ecosystem-enabled. Cluster 3 (n = 29) shows moderate financial barriers (PFB = 2.53) but weak ecosystem support (ES = 1.87) and is labeled Ecosystem-disconnected.

These findings provide partial support for H1 as an exploratory classification. ICT startups operating within the same ecosystem can be grouped into interpretable profiles defined by different combinations of barriers and support. The results should not be read as evidence of naturally occurring population types. They identify analytically useful patterns consistent with configurational approaches in entrepreneurship research, in which firm-level differences emerge from combinations of conditions rather than isolated factors (Fiss, 2011; Misangyi et al., 2017). The findings also support the view that ecosystem resources are not evenly available across ventures but are accessed and mobilized differently depending on firms' positions within the same environment (Wurth et al., 2023).

Because PFB and ES were used to form the clusters, differences on these dimensions are interpreted descriptively rather than as independent evidence of cluster validity. The retained solution is therefore assessed by comparing it with alternative k solutions, cluster sizes, interpretability, and stability checks. The label Ecosystem-disconnected should be understood specifically as weak connection to formal ecosystem support structures, not as a lack of all informal networks.

Differences in financing behavior and financing portfolio composition

Differences across typologies were examined using variables not included in the clustering procedure. Table 6 reports differences in access to finance and startup performance. The results show significant differences across typologies for both access to finance, $F(2,108) = 18.004$, $p < 0.001$, $\eta^2 = 0.250$, and startup performance, $F(2,108) = 10.127$, $p < .001$, $\eta^2 = 0.158$. Tukey post hoc tests indicate that ecosystem-enabled startups report significantly greater access to finance than both financially constrained and ecosystem-disconnected startups. A similar pattern is observed for startup performance, where the ecosystem-enabled group reports higher scores than the other two groups.

Table 6. External comparison of startup typologies

Variable	Cluster 1 Mean	Cluster 2 Mean	Cluster 3 Mean	F	p	η^2	Main post-hoc differences
Access to Finance	2.243	3.491	2.269	18.004	< 0.001	0.250	C2 > C1; C2 > C3
Startup Performance	2.994	3.808	2.697	10.127	< 0.001	0.158	C2 > C1; C2 > C3

Note: One-way ANOVA with Tukey post-hoc tests. AF and SP were not used in the clustering procedure.

These findings indicate that the typologies are associated with meaningful differences beyond the clustering variables. In particular, the ecosystem-enabled group reports stronger access to finance and higher performance. However, the AF difference is interpreted as expected construct convergence rather than as strong independent external validation, because access to finance is conceptually related to ecosystem support through signaling, brokerage, legitimacy transfer

and reduced information opacity (Dourado Freire et al., 2023; Ngoasong, 2018). The results should not be interpreted causally. The cross-sectional design shows an association between typology membership, reported AF, and reported SP, not whether ecosystem support produces better financing outcomes or performance.

Financing-source use was then examined using Monte Carlo p-values because several categories contained small or zero cell counts. Cramer's V is reported as an effect-size measure.

Table 7. Financing-source use by startup typology

Financing source	Cluster 1 n = 60	Cluster 2 n = 22	Cluster 3 n = 29	Monte Carlo p	Cramer's V
Personal savings	53 (88.3%)	16 (72.7%)	27 (93.1%)	0.088	0.208
Friends and family	26 (43.3%)	6 (27.3%)	11 (37.9%)	0.414	0.126
Retained earnings	13 (21.7%)	4 (18.2%)	9 (31.0%)	0.525	0.111
Bootstrapping	4 (6.7%)	8 (36.4%)	4 (13.8%)	0.004	0.322
Bank loans	9 (15.0%)	2 (9.1%)	0 (0.0%)	0.099	0.211
Investor equity	6 (10.0%)	6 (27.3%)	2 (6.9%)	0.059	0.223
Trade credit	0 (0.0%)	0 (0.0%)	3 (10.3%)	0.026	0.280
Public or donor grants	21 (35.0%)	10 (45.5%)	8 (27.6%)	0.441	0.126
Crowdfunding	0 (0.0%)	6 (27.3%)	0 (0.0%)	< 0.001	0.481

Note: Values are n (%). Monte Carlo p-values are reported because of sparse cells. Investor equity combines angel investors, venture capital, and private equity. Bank loans combine short- and long-term bank loans.

Table 7 shows that the typologies differ mainly in the composition of financing sources. Bootstrapping and crowdfunding are more common among ecosystem-enabled startups, suggesting that these firms are better positioned to use financing channels linked to visibility, networks and non-bank intermediation. By contrast, the trade-credit result should be interpreted cautiously because it is based on sparse cells and a small number of observations. Its presence among ecosystem-disconnected firms may indicate reliance on transactional relationships where formal ecosystem support is weaker.

Several non-significant and borderline findings are also informative. Personal savings are common across all groups, which is expected in an early-stage ecosystem where founder finance remains central. Public or donor grants do not differ significantly across typologies, indicating that grant use alone does not distinguish ecosystem position. Investor equity is more common among ecosystem-enabled startups, but the association is only borderline ($p = 0.059$). This is consistent with the limited depth of angel and venture-capital markets in this context. Bank loans also show only a weak association ($p = 0.099$), suggesting that conventional debt finance is not the primary basis for differences among these startup typologies. Financing diversification was tested separately from financing-source composition. As shown in Table 8, ecosystem-enabled startups report a somewhat higher mean number of financing sources, but the difference is not statistically significant using either ANOVA, $F(2,108) = 2.739$, $p = 0.069$, $\eta^2 = 0.048$, or the Kruskal–Wallis test, $H = 3.992$, $p = 0.136$. These findings provide partial support for H2: the typologies differ in financing-source composition, but not in overall financing diversification.

Table 8. Financing diversification by startup typology

Cluster	Mean	SD	Median	Min	Max
Cluster 1: Financially constrained	2.23	0.95	2	1	5
Cluster 2: Ecosystem-enabled	2.82	1.37	3	1	5
Cluster 3: Ecosystem-disconnected	2.21	1.05	2	1	4

Note: Financing diversification is the count of distinct financing sources used. ANOVA: $F = 2.739$, $p = 0.069$, $\eta^2 = 0.048$. Kruskal–Wallis: $H = 3.992$, $p = 0.136$.

These results clarify the interpretation of financing behavior. The typologies differ more clearly in the types of financing sources used than in the number of sources. Therefore, the findings should be described as differences in financing-source composition rather than as evidence that one typology has a significantly broader or more diversified financing portfolio.

Profiling typology membership

A multinomial logistic regression model was estimated to profile typology membership, using the financially constrained group as the reference category. Perceived financial barriers and ecosystem support were excluded from the model because they were used to form the clusters. Founder age and education were also excluded because sparse categories produced unstable estimates. The model is therefore parsimonious and is interpreted as a profiling model rather than a causal model. It is statistically significant, LR χ^2 (8) = 46.481, $p < 0.001$, with McFadden $R^2 = 0.209$. Results are reported in Table 9.

Table 9. Multinomial logistic regression

Predictor	C2 vs C1 OR	95% CI	p	C3 vs C1 OR	95% CI	p
Access to Finance	4.923	[2.180–11.114]	< 0.001	0.970	[0.509–1.841]	0.926
Previous startup experience	1.364	[0.304–6.114]	0.686	3.998	[1.199–13.329]	0.024
Firm size (log employees)	0.849	[0.363–1.984]	0.707	0.220	[0.079–0.611]	0.004
Early stage (vs. growth)	1.263	[0.258–6.188]	0.773	0.205	[0.061–0.687]	0.010

Note: C1 = financially constrained; C2 = ecosystem-enabled; C3 = ecosystem-disconnected. OR = exp(B). Reference category: C1. Model fit: LR χ^2 (8) = 46.481, $p < 0.001$; McFadden $R^2 = 0.209$; N = 111.

The regression results provide partial support for H3. Access to finance is positively associated with membership in the ecosystem-enabled group relative to the financially constrained group. Because access to finance was not used to form the clusters, this result is treated as an adjusted profiling association and as expected construct convergence, not as evidence of a causal effect. This pattern is consistent with ecosystem research showing that support structures may improve startups' visibility, legitimacy and access to resource channels, particularly through networks and intermediary organizations (Spigel & Harrison, 2018; Wurth et al., 2023). Prior startup experience is associated with higher odds of membership in the ecosystem-disconnected group, suggesting that experienced founders may be better able to continue operating even when formal ecosystem support is weaker. This interpretation is consistent with research showing that founder experience and learning shape how young ventures mobilize resources and navigate financing constraints under uncertainty (Cassar, 2014; Ngoasong, 2018). Firm size is negatively associated with membership in the ecosystem-disconnected group, suggesting that smaller firms are more likely to exhibit this profile. Early-stage status is also negatively associated with membership in the ecosystem-disconnected group, relative to growth-stage status, after controlling for the other predictors. This lifecycle result is interpreted cautiously. It suggests that lifecycle stage helps profile membership rather than serving as a standalone explanation of the typologies.

CONCLUSION

This study examined whether ICT startups in Albania form distinct typologies based on founders' perceptions of financial barriers and ecosystem support, and whether these typologies differ in financing behavior and firm characteristics. Using survey data from 111 startups, the analysis identified three exploratory typological profiles: financially constrained, ecosystem-enabled and ecosystem-disconnected startups.

The findings provide partial support for H1. Startups operating within the same ecosystem do not report the same combination of perceived financial barriers and ecosystem support. The financially constrained typology combines high perceived financial barriers with moderate ecosystem support. The ecosystem-enabled typology is characterized by stronger support and lower barriers, whereas the ecosystem-disconnected typology is weakly connected to formal ecosystem-support structures. These results suggest that entrepreneurial ecosystems should not be examined only at the aggregate level, but also through the uneven ways in which startups perceive, access and use support conditions.

H2 is partially supported. The typologies differ in financing-source composition, especially bootstrapping and crowdfunding. The trade-credit finding should be interpreted cautiously because it is based on sparse cells and a small number of observations. Ecosystem-enabled startups appear better placed to use sources linked to visibility, networks and non-bank intermediation. Ecosystem-disconnected startups show weaker engagement with formal support channels and some reliance on more transactional financing arrangements. However, the number of financing sources used does not differ significantly across typologies. The findings therefore indicate differences in financing-source composition, but not in overall financing diversification.

H3 is also partially supported. Access to finance, prior startup experience, firm size and lifecycle stage help profile typology membership. Given the exploratory and cross-sectional design, these findings should be interpreted as adjusted associations rather than causal effects.

The study contributes to entrepreneurial ecosystem research by showing that support structures are not experienced evenly by startups operating in the same setting. It also contributes to entrepreneurial finance research by distinguishing financing-source composition from financing diversification. Startups may differ in the kinds of funding sources they use even when they do not differ in the number of sources used. This distinction helps explain financing behavior as part of a startup's position within ecosystem and financial channels, rather than only as an isolated firm-level funding decision.

The findings also point to differentiated support needs. Financially constrained startups may benefit from assistance with funding readiness, investor communication and navigation of available instruments. Ecosystem-enabled startups may need follow-on finance, investor-readiness support and stronger links to regional or international funding networks. Ecosystem-disconnected startups require more active outreach, mentoring and brokerage to connect them with formal support structures. A uniform support model is therefore unlikely to address the needs of all startup profiles.

The findings should be interpreted within the Albanian context and should not be assumed to generalize directly to larger or more mature startup ecosystems. The three profiles identified here may not appear in the same form in other countries. Nevertheless, similar internal differentiation may also exist in other small or institutionally developing startup ecosystems.

The study has several limitations. It uses self-reported, cross-sectional data, which limits causal inference and may not fully capture objective financing conditions. The sample is limited to ICT startups in Albania, and the modest sample size requires caution when interpreting regression results and less frequently used financing sources. The cluster solution should be treated as exploratory, typology-oriented and context-sensitive, although its interpretability and stability checks support its use for descriptive profiling.

Future research could examine whether startups move between typologies over time and how such transitions relate to financing trajectories, growth and survival. Comparative studies across emerging economies would help assess whether similar patterns appear in other small ecosystems. Combining survey data with objective financing records and qualitative interviews with founders, investors and ecosystem intermediaries would also help explain how signaling, brokerage, legitimacy transfer and information opacity shape financing behavior.

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Author contribution statement

Iris Kruja: Conceptualization, Methodology, Data Curation, Formal Analysis, Investigation, Visualization, Writing – Original Draft Preparation, Writing – Review & Editing. **Ana I. Irimia-Diéguez**: Conceptualization, Methodology, Supervision, Writing – Review & Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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Patterns of cybersecurity performance in corporations: International evidence*

***Anna Doś*[1], *Elisa Flori*[2], *Piotr Łasak*[3], *Francesco Pattarin*[4]**

Abstract

PURPOSE: *The primary objective of this study is to identify institutional environments (institutional-level factors) and corporate characteristics (organizational-level factors) associated with cybersecurity performance, and to assess their importance in explaining differences in cybersecurity performance across organizations.* ***METHODOLOGY:*** *We apply binary logistic regression to firm-level data from the Orbis database to examine how institutional- and organizational-level factors are associated with cybersecurity performance. The dataset covers companies operating in the United States, Europe, and China in 2022, comprising 1,211 observations.* ***FINDINGS:*** *Companies in China, Northern Europe and Southern Europe underperform those in the United States in terms of cybersecurity performance. Firms in the financial and healthcare sectors exhibit stronger cybersecurity performance, while higher financial leverage, larger firm size, and greater profitability (ROE) are associated with lower cybersecurity performance levels.* ***IMPLICATIONS:*** *From a theoretical perspective, our study supports the usefulness of an institutional approach to cyber risk, complementing and extending the investment-oriented perspective that currently dominates the literature. Our findings also offer insights for investors seeking to reassess asset allocation strategies in light of cybersecurity-related risk exposure. They inform managers aiming to identify best practices for safeguarding corporate value against cyber threats, and support policymakers in identifying where voluntary business cybersecurity practices underperform and may require complementary regulatory or policy measures.* ***ORIGINALITY & VALUE:*** *This study is the first to analyze multi-level patterns of cybersecurity performance on an international scale. It contributes to the existing literature by revealing the regional and sectoral distribution of cybersecurity performance and demonstrating that firms with greater financial risk exposure may also be more susceptible to cyber risks, thereby amplifying potential adverse outcomes.*

Keywords: *cybersecurity performance, corporate cybersecurity, cyber risk, cyber risk management, cybersecurity ratings, institutional theory, institutional determinants, firm-level determinants, financial leverage, operational risk*

INTRODUCTION

Corporations around the world are facing the need to reconsider their production, investment, and innovation strategies due to the rapid advancement of technology. The evolution of traditional industrial and manufacturing methods, propelled by sophisticated digital technologies, connectivity, and automation, has led to a growing reliance on digital systems and networks within business operations. While these innovative solutions bring about opportunities, they also introduce new risks, with cyber threats emerging as a major concern for both managers and investors. Cyber risk commonly refers to the risk of financial loss, disruption or reputational damage to an organization resulting from the failure of its IT systems

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(Aldasoro et al. 2020; Biliavska et al., 2025; Ruan, 2017). Sometimes cyber risk is treated as a form of operational risk (Curti et al., 2023). A more detailed taxonomy of cyber risk is provided by Rabitti et al. (2025). As businesses become increasingly dependent on IT products and services, cyber risk becomes more widespread. Moreover, in today's landscape, organizations are increasingly vulnerable to cyber risks due to ongoing geopolitical tensions, particularly as these tensions affect supply chains, physical infrastructure, and external networks. The World Economic Forum ranks the prevalence of cybercrime and cyber insecurity as the eighth most severe global risk over a two-year horizon. (WEF, 2023). According to Cybersecurity Ventures, the global cost of cybercrime was estimated at USD 9.5 trillion in 2024 and could reach USD 10.5 trillion per year by 2025 (CV, 2023; Sharif & Mohammed, 2022). IBM estimates that the average cost of a data breach reached an all-time high of USD 4.45 million in 2023 (IBM, 2023). Taking a long-term view, the average cost has increased 15.3% from USD 3.86 million in the 2020 report. Kazim and Shanshul (2024) provide estimates indicating that the costs of cybercrime are increasing by 15% per year. According to them, the British companies lost an estimated $55 billion between 2018 and 2023 due to cyberattacks.

Unfortunately, organizations are failing to keep pace with the scope and scale of cyber risk (Accenture, 2023). The considerable expense of a cyber-attack includes reputational, legal, and cyber-protection costs to the firm. These costs can affect the evaluation of a firm's risk and value. Accordingly, there is extensive evidence that financial markets react negatively to announcements of cyber-attacks suffered by companies (Kammoun et al., 2019; Arcuri et al., 2020; Smith et al., 2023).

Interestingly, academic literature appears to lag behind the growing practical concerns surrounding cyber risk. Thus far, only a limited number of papers have been published to investigate the factors that differentiate the levels of cyber risk across business organizations. Nevertheless, it's been established that the effects of cyber risk exposure as well as the effects of cyber events are serious and diverse. Jamilov et al. (2021) show a sizable effect of cyber exposure on the return on assets of firms, cash flows, and equity option valuation. It is also confirmed that cybersecurity risk negatively affects corporate innovation and supply chains (Wang et al. 2024; Crosignani et al. 2023). Evans et al. (2023) and Huang and Wang (2021) show that severe data breaches increase the cost of debt. A few authors report negative equity market returns following cyber events (Kammoun et al., 2019; Arcuri et al., 2020; Smith et al., 2023). Overall, these consequences provide a compelling rationale for managers to seek methods to safeguard corporate value against cyber threats and for investors to reassess their asset allocation strategies. Investors have an interest in understanding patterns of cyber-risk exposure across asset classes. Policymakers likewise aim to understand where and why voluntary business practices to enhance cybersecurity performance fall short. These concerns necessitate both an in-depth understanding of an organization's cyber risk exposure and an understanding of the distribution of cyber risk across businesses.

This study focuses on the latter issue, which is of paramount importance for large-scale screening by global investors and policymakers. Knowledge of differences in cyber risk exposure across company categories is scarce. Aldasoro et al. (2022), focusing on USA evidence, found that larger firms and firms operating in the financial sector experience greater levels and numbers of cyber risk-related losses. Palsson et al. (2020) provide evidence that, in the USA, the number of cyber incidents is highest in the financial sector, followed by the Information Technology (IT) sector, healthcare, retail, and education. Concurrently, IBM (2023) has demonstrated that the average cost of a data breach in the USA is twice that in European countries. Despite these contributions, prior research has predominantly focused on U.S. firms, offering limited insight into how cyber risk levels in the United States compare with those in other regions or how industry-level sensitivity to cyber threats varies globally. Moreover, apart from firm size, other key organizational characteristics have rarely been examined as determinants of cyber risk exposure. Overall, the literature on the determinants of cyber risk remains at a nascent stage, providing only fragmented evidence on the firm-level and contextual factors associated with cyber risk. Moreover, a critical factor of cybersecurity problems is the response of corporations to cyber risk. Once cyber risk is recognized and assessed, a company can introduce diverse risk mitigation measures to improve its cybersecurity (Kosub, 2015). This aspect is presently gaining scholars' attention (Lee, 2020; Romanosky and Sayers, 2024). In particular, Li et al. (2019) call for including both the internal and external environments of organizations in cybersecurity research.

In response to the urgent need to enhance understanding of the patterns of distribution of cyber risk among businesses, this study focuses on a selected aspect of cyber risk exposure, which is companies' cybersecurity performance, combining two critical elements of cyber risk: level of external threat and organizational response to exposure. Rather than providing an in-depth explanation of the mechanisms underlying the level of corporate cybersecurity, this study aims to identify factors specific to the business environment (institutional-level factors) as well as company-specific factors (organizational-level factors) that are associated with patterns of corporate cybersecurity performance across companies.

This knowledge is crucial for investors and policymakers, as it helps them identify high- and low-risk companies and recognize the most vulnerable business organizations. It also provides a key insight for future studies exploring the complex processes involved in cyber risk management decision-making and assessing the effectiveness of corporate responses to cyber threats. We measure organizations' cybersecurity performance with a cyber risk rating by Bitsight. It is a well-established rating, as it is provided by one of the first external rating organizations and – importantly – it isn't a prescriptive security framework but an external rating that monitors cybersecurity performance (Choi et al. 2021). The rating encompasses the organization's security practices, compromised systems, and cyber incidents. It is developed based on monitoring external network activity worldwide to detect cyber events, such as communication with command-and-control servers, malware activity, and participation in DDoS attacks. It exhibits a data-driven, outside-in approach (with no required participation by the rated organization) to rate an organization's cybersecurity performance. Therefore, it is not exposed to self-reporting bias. In addition, Bitsight's rating provides cyber risk scores comparable to those of other cyber risk rating agencies (Keskin et al. 2021).

BitSight's rating classifies organizations into three categories: *basic* (low cybersecurity performance), *intermediate* (average performance), and *advanced* (superior performance). Given the very small number of firms classified as low performers in the regions we focus on, the analysis focuses on two categories—*advanced* and *intermediate*—to capture meaningful variation in cybersecurity performance across organizations. Consequently, we use binary logistic regression analysis to examine the determinants of achieving an advanced level of cybersecurity performance. Our dataset covers companies operating in the USA, Europe, or China in 2022, with 1,211 data points. The independent variables are derived from the Orbis database. They include corporate characteristics that indicate organization-level as well as institutional-level factors.

We show that both institutional- and organizational-level factors significantly influence cybersecurity performance and cyber risk exposure. Companies in China, Northern Europe, and Southern Europe underperform those in the United States in cybersecurity performance, suggesting potential structural gaps in these regulatory frameworks. Firms in the financial and healthcare sectors tend to perform better than those in the "other industries" category, with the financial sector emerging as a benchmark among vulnerable sectors. Moreover, higher financial leverage, stronger financial performance, and larger firm size are associated with weaker cybersecurity performance, suggesting that leverage may amplify overall risk exposure.

Our findings provide valuable insights for investors on potential screening criteria to help construct a portfolio that accounts for a firm's effectiveness in managing cyber risk. Furthermore, our results offer policymakers guidance for identifying concentrations of cyber risk and emphasize the urgent need to implement safety measures to enhance sectoral and market resilience.

The manuscript is structured as follows. It begins with a review of cybersecurity as a strategic issue for companies, followed by the development of a theoretical framework and hypotheses, first focusing on institutional-level factors and then on organizational-level factors influencing cybersecurity performance. The subsequent sections present the variables, research methodology (binary logistic regression), and sample characteristics. The paper then reports and discusses the empirical results, and concludes with key findings, implications, and directions for future research.

LITERATURE REVIEW

Cyber risk and cybersecurity

The rapid digitalization of current economies and financial markets presents significant opportunities on the one hand, but introduces new and serious threats on the other (Agosto & Giudici, 2023). As Romanosky and Sayers (2024) note, today's cyber risk is among the gravest facing organizations. Such risk encompasses a range of phenomena that damage or otherwise negatively affect a firm's IT-related assets (Oltramari & Kott, 2018). Moreover, risks related to IT, often referred to as cyber risk, overlap with and contribute to other business risks, creating a novel challenge for companies, investors, and policymakers. And although a precise understanding of cyber risk is key to designing security-enhancing measures, today's literature falls short of providing a clear, unified, and broadly accepted definition of this phenomenon (Cains et al., 2022; Strupczewski, 2021). As Cremer et al. (2022) argue, research on cyber risk is still in its infancy due to its dynamic, emerging nature.

Aldasoro et al. (2020) associate cyber risk with the risk of financial loss, disruption, or reputational damage to an organization resulting from failures in its IT systems. Cebula et al. (2014), Curti et al. (2023), and Romanosky and Sayers (2024) define cybersecurity risks as operational risks to information and technology assets that affect the confidentiality, availability, or integrity of information or information systems. Strupczewski (2021) defines cyber risk as an operational risk associated with the performance of activities in cyberspace, threatening information assets, ICT resources, and technological assets, and may cause material damage to an organization's tangible and intangible assets, business interruption, or reputational harm. More specifically, cyber risk encompasses non-financial operational risks arising from the use of advanced technologies in business activities (Ramakrishna, 2023). This definition also embraces physical threats to the ICT resources within the organization (Table 1). The above-mentioned definitions highlight diverse sources, occurrences, and consequences of cyber risk that deserve further discussion.

Eling and Wirfs (2019) propose a classification of cyber risk based on its sources. Following a well-established definition of operational risk, they divide cyber risk into four main categories: threats caused by people, threats caused by systems and technical failures, failed internal processes, and external events. A deeper insight into cyber risk occurrences across these four categories is presented in Table 1.

Table 1. Classification of cyber threats and their causes

Endangered area	Activity causing the threat	Description
Privacy	Unauthorized contact or disclosure	Personal information is used in an unauthorized manner to contact or publicize information about an individual or organization.
Privacy	Unauthorized data collection	Information about the users of electronic services, such as social media, cell phones, websites, etc. is captured and stored without their knowledge or consent, or when prohibited information is collected.
Data	Physically lost or stolen	Personal confidential information or digital assets have been stored on, or may have been stored on, computers, peripheral equipment, data storage, or printouts that have been lost, stolen, or improperly disposed of.
Data	Malicious breach	Personal confidential information or digital assets have been or may have been exposed or stolen by unauthorized internal or external actors whose intent appears to have been acquiring such information.
Data	Unintentional disclosure	Personal confidential information or digital assets have either been exposed or may have been exposed to unauthorized viewers due to an unintentional or inadvertent accident or error.
Identity	Fraudulent use/ account access	Identity theft is the fraudulent use of confidential personal information or account access to steal money, establish credit, or access account information.
Industrial	Industrial controls and operations	Losses involving disruption or attempted disruption to "connected" physical assets such as factories, automobiles, power plants, electrical grids, and similar.
Network/ website disruption	N/A	Unauthorized use of or access to a computer or network, or interference with the operation of the same, including viruses, worms, malware, digital denial of service (DDOS), system intrusions, and similar.
Phishing, spoofing, social engineering	N/A	Attempts to get individuals to voluntarily provide information which could then be used illicitly.
Skimming, physical tampering	N/A	Use of physical devices to illegally capture electronic information, such as bank account or credit card numbers, for individual transactions, or to install software on point-of-sale devices to accomplish the same goal.
IT	Configuration/ implementation errors	Losses resulting from errors or mistakes which are made in maintaining, upgrading, replacing, or operating the hardware and software IT infrastructure of an organization, typically resulting in system, network, or web outages or disruptions.
IT	Processing errors	Losses resulting from internal errors in electronically processing orders, purchases, registrations, and similar, usually due to a security or authorization inadequacy, software bug, hardware malfunction, or user error.
Cyber extortion	N/A	Threats to lock access to devices or files, fraudulently transfer funds, destroy data, interfere with the operation of a system/network/site, or disclose confidential digital information such as identities of customers/employees, unless payments are made.

Source: Own elaboration based on Malavasi et al. (2022).

It should be stressed that cyber risk can arise from more than one category of sources. Another distinctive aspect of cyber risk is that it primarily arises from criminal activities. Crotty and Daniel (2022) highlight that while cyber threat agents range from nation-states to script kiddies, by far the most active are cybercriminals accounting for over 80% of cyber incidents. Internet connection is a key channel for cybercrime (Radwan, 2023; Stevens, 2023). Significantly, new types of cybercrime are not always covered by existing law, which is one factor enabling their commission.

Cyber risk occurrence can have diverse results. Agrafiotis et al. (2018) note that the consequences of cyber risk can be suffered by businesses as well as their environments, and thus, negative externalities should be taken into consideration when identifying the consequences of cyber risk. Finally, Agrafiotis et al. (2018) distinguish five types of cyber risk consequences:

- physical/digital - harm related to physical or digital negative effects on someone or something (abuse, identity theft, reduced performance);
- economic - harm that relates to negative financial or economic consequences (reduced profits, investments, fall in stock price);
- psychological - harm which focuses on an individual and their mental well-being (discomfort, low satisfaction, negative changes in perception);
- reputational - harm pertaining to the general opinion held about an entity (damaged relationships with customers, reduced corporate goodwill, reduced credit scores);
- social/societal - capture of harms that may result in a social context or society more broadly (disruption in daily life activities, negative changes in public perception).

Focusing on economic harms, Jamilov et al. (2023) highlight that cyber risk consequences can be observed as:

- firms' balance sheet effects - it has negative and significant effects on future ROA, cash flow, and valuation;
- firms' stock market performance – negative and significant effect on stock returns, large and significant positive effect on realized volatility. An example is the negative market returns that follow announcements of cyber-attacks suffered by hospitality companies (Arcuri et al, 2020).

All of these categories of costs are financially material. The experts estimate that the cost of global losses from cybercrime amounted to USD 8.15 trillion in 2022, and predict that this figure will reach USD 13.82 trillion in 2028 (Fleck, 2024). The dynamics of losses from 2018 to 2028 are presented in Figure 1.

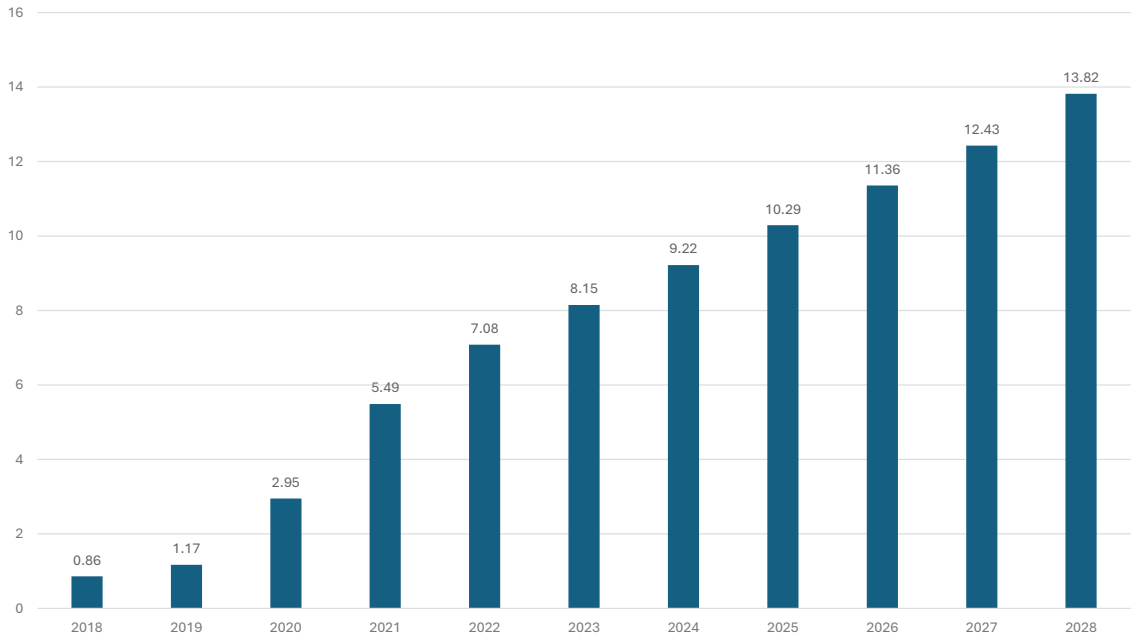

Figure 1. The estimated annual cost of cybercrime worldwide in the period of 2018-2028 (trillion USD)

Source: own elaboration based on Statista.

The most important category of cyber costs is data breach costs. According to Statista (2023), the global average cost of a data breach between March 2021 and March 2022 was USD 4.35 million. Notably, the most targeted are enterprises in finance, information, professional services, healthcare, manufacturing, public administration, education, and other branches (Kuzior et al., 2023).

Risk-averse decision-makers aim to decrease cyber risk exposure and attain cybersecurity. Craigen et al. (2014) propose that 'cybersecurity is the organization and collection of resources, processes, and structures, used to protect cyberspace and cyberspace-enabled systems from occurrences that misalign de jure from de facto property rights'. Cains et al. (2022) argue that the term cybersecurity has a broader, interdisciplinary perspective and encompasses fields such as sociology, psychology, risk, decision science, and many others. They conclude, however, that because cybersecurity is multidisciplinary, no standardized terminology exists across disciplines. In this research, we adopt a broad definition of cybersecurity as the collection of tools, techniques, policies, security measures, security guidelines, risk mitigation strategies, actions, training, good practices, security reassurance, and latest technologies that may be used to protect cyberspace and the assets of users (Humayun et al. 2020). The main security objectives are confidentiality, integrity, and availability (Gunduz et al., 2020).

In the past, business cybersecurity efforts have predominantly focused on technical controls, such as firewalls, intrusion prevention/detection systems, and encryption mechanisms (Cremer et al., 2022; Haner & Knake, 2021; Kuzior et al., 2023; Valkenburg & Bongiovanni, 2024). Presently, more sophisticated approaches are used, including quantitative methods and models (Dacorogna & Cratz, 2023; Bentley et al., 2020) as well as practices focused on organizational, human, and governance dimensions (Savas & Caratas, 2022; Valkenburg & Bongiovanni, 2024; Zängerle et al., 2023). Although there is considerable variation in the approach and sophistication of practices related to the management of cyber risk (Romanosky & Sayers 2024), cybersecurity practices focus on the business's internal and external environment and its effect on cyber risk as well as on business financial performance and the connection between financial and operating outcomes (Orlando, 2021).

Cybersecurity can be improved by cyber risk management (Bentley et al., 2020; Dacorogna and Cratz, 2023; Giudici & Raffinetti, 2021; Orlando, 2021; Reanud et al., 2020). This process involves identifying and analyzing cyber risks, followed by decisions on risk avoidance, mitigation, and financing (Eling et al. 2021). Financing options may include transferring the risk, for example, through insurance, or retaining it. Cyber incidents trigger financial losses, but also reputational and trust losses. Thus, risk prevention and mitigation measures are of paramount importance (Valkenburg & Bongiovanni, 2024). Focal points of cyber risk management include (Orlando, 2021):

- pursuing research on the inclusion of cyber risk considerations in board and top management decision-making and overall corporate governance;
- implementing technical cybersecurity solutions;
- applying a suitable cyber risk policy, embracing risk transfer, risk mitigation, and risk retention to reach the desired level of residual risk.

Regardless of the type of cyber risk, the literature emphasizes that prevention and early detection are strategically significant for combating this category of risk (Kuzior et al., 2022; Hariharan, 2020). In addition, human factors and proper risk awareness and communication are key (Gatzeert and Schubert, 2020; Björck et al, 2024; Ulrich et al., 2021). While not all risks can be avoided, their negative consequences can be reduced through careful risk mitigation planning.

The complexity of cyber risk and its financial significance are paramount challenges from an investor's perspective. Global investors must understand the levels of risk across sectors, countries, and other categories of companies, primarily to efficiently diversify risk and assess which companies offer the most attractive returns for an acceptable level of risk. Additionally, investors need to identify systemic risks, such as regulatory changes or geopolitical events, that could impact entire sectors or other groups of companies. Therefore, it is essential for investors to recognize which observable characteristics can serve as signals for cyber risk. These characteristics can be used to screen the entire universe of companies raising funds, helping investors select those that align with their risk appetite and financial goals, as well as to plan risk management and hedging strategies.

Because cyber risk creates negative externalities and is closely linked to criminal activity, there's a strong rationale for government intervention in business cybersecurity practices. Policymakers adopt an international perspective on cyber risk, considering cyber espionage and industrial espionage (Agosto & Guidici, 2023; Demertzis & Wolff, 2020). A good example of the international complexity of cyber risk is the EU market, where there are significant gaps between national

regulatory and supervisory architectures designed to safeguard business activity and the international nature of cyber risk. One good example of such a mismatch is the financial sector, where the digitalization of financial services and the increasing use of third-party service providers trigger concerns about financial stability (Vucinić & Luburić, 2022). There is an urgent need for improved, integrated cybersecurity policies globally, as research indicates that the growth of cyber risk may lead to systemic risk (Głogowski, 2023; Jamilov, 2021). Knowledge of patterns in the distribution of cyber risk is crucial for understanding the collective risk of groups of companies. It is also essential for implementing regulations or interventions, ensuring fair and stable markets, and coordinating policy responses between countries. As a result, policymakers are another key stakeholder group that requires knowledge of corporate cyber risk distribution patterns.

Therefore, in the subsequent sections, this study develops a framework to identify factors associated with cyber risk performance across companies, and consequently, with corporate cyber risk exposure. It focuses on factors at both the institutional level (related to the business environment) and the organizational level (specific to a company), which are easily observable and can serve as an initial screen for large-scale screening purposes.

Institutional factors of cybersecurity

In this section of the paper, we explore the role of institutional-level factors in understanding cybersecurity distribution patterns. Institutional theory proposes that the primary goal of organizational decisions is to enhance legitimacy among stakeholders within its environment. This legitimacy is achieved by adopting processes, structures, and strategies that align with institutions, that is, the rules of the game within a specified environment (Dacin et al. 2007). To structure the analysis of institutions potentially relevant for cybersecurity, we follow Williamson (2000), who proposes four levels of institutions: (1) social embeddedness, (2) institutional environment, (3) governance, and (4) resource allocation and employment.

The first level represents informal institutions, customs, traditions, social norms, and behaviours. It can be used to study cybersecurity from a cultural and social-behavioural perspective. The second level represents the formal rules of the game. It embraces the executive, legislative, judicial, and bureaucratic powers. Here, the crucial aspect is domestic cybersecurity law. The third level represents the governance structures designed by partners to mediate economic relationships (Klein, 1998). The fourth level allows for framing the cybersecurity issue from the perspective of an individual entity – the possessed infrastructure, programmes, and internal policies related to cybersecurity, as well as the human factors (Björck et al., 2024).

The second level can be operationalized by focusing on countries/regions with diverse regulatory solutions that create unique institutional environments. Countries exhibit different levels of digitalisation encompassing (Digital Progress and Trends Report 2023, World Bank Group):

- digital adoption (individuals using the internet, fixed broadband, access to digital payments);
- digital sector (value added in ICT manufacturing and ICT services, ICT patent publications, etc.);
- digital infrastructure (broadband infrastructure and data infrastructure).

Three regions exhibit notably distinct differences in terms of cybersecurity: the United States, the European Union, and China. These are the markets with the most advanced technology. On the one hand, technology determines the level of cyber risk. On the other hand, the risk is influenced by regulations governing the use of information technologies. Each of these three markets has different regulations related to the development of new technology, which, in turn, affects the level of cyber risk. The US market is called a *market-driven regulatory model*, where the government is advocating for an open, unregulated, and private sector-led digital economy. It promotes "internet freedom agenda", according to which innovation is free from government regulation or censorship (Bradford, 2023). The EU market is called the *rights-driven regulatory model*, where tech companies must follow rules established by governments. The EU rules are drafted to specifically reflect European values that call for human dignity, data privacy, democratic discourse, or other core rights of European digital citizens. It is a human-centric and rights-driven approach to digital regulation. The Chinese *state-driven regulatory model* seeks to harness technology to strengthen government control as opposed to protecting individual freedom. It is a command-and-control system. The Chinese government seeks to leverage technology to fuel the country's economic growth and development while maintaining social harmony and control over its citizens' communications (Bradford, 2023). The features of the three markets lead to the conclusion that the US market is the most open, the Chinese one is the most closed and the EU market is featured by a middle level of freedom for private business activity in the high-tech sector. Greater openness seems more harmful to businesses in terms of cyber risk, as rapid technology adoption

creates vulnerabilities, system inconsistencies create weak points, cybercriminals can target less-regulated systems, and cyberattacks originating in one part of the world can quickly spread across open networks.

The three regulatory models are connected with the approaches to cybersecurity. The European Union initiated the regulation of cybersecurity in 2013 with the First European Union (EU) Cybersecurity Strategy. It was dedicated to three key areas: (1) network and information security measures dedicated to operators of essential services, and providers of critical and digital infrastructures; (2) electronic communications, including privacy and data protection issues; (3) cybercrime (Fuster and Jesmontaite, 2020). The strategy had five priorities: (1) achieving cyber resilience; (2) drastically reducing cybercrime; (3) developing cyber-de fence policy and capabilities related to the Common Security and Defence Policy (CSDP); (4) developing the industrial and technological resources for cybersecurity; and (5) establish a coherent international cyberspace policy (Bederna and Rajnai, 2022). The strategy was the starting point and triggered a regulatory wave. In consequence, the current European regulatory landscape for ICT and cyber risk for business activity is multilayered and complex. There is no single major European cybersecurity legislation; rather, there is a multitude of European and national regulations and sector-specific standards. Despite such a status quo, decision-makers continue their efforts to unify the legislation. In 2016, two of the most important and far-reaching pieces of legislation were implemented – the Directive on Security of Network and Information Systems (NIS Directive) and the General Data Protection Regulation (GDPR). Moreover, until 2020, eight other legislations were introduced with ICT and cybersecurity relevance (Krüger & Brauchle, 2021). In 2020, the European Commission launched the Digital Europe Programme, which is part of the Multiannual Financial Framework (MFF), intended to shape the digital transformation of Europe's society and economy (Ghiretti, 2021). Apart from other goals, one is to enable widespread use of digital technologies across the economy and society and to improve cybersecurity (European Commission, 2021). Currently, the EU's approach to cybersecurity policy is based on three crucial pillars: (1) an institutional perspective, (2) as a values-based actor, (3) a realpolitik dimension (Hasmath & Berzina-Cerenkova, 2022). All three pillars play a significant role in defining the specific nature of EU cybersecurity policy.

In the Chinese case, the cybersecurity issues relate to the transformation of the economy. The last step in the transition of the Chinese economy began in 2015, when the CCP initiated the national strategic plan Made in China 2025 (MIC). It was oriented on transforming this country from a manufacturing giant into a world manufacturing power with a key focus on technological development. The development is strictly interconnected with the processes of digitalisation of the economy. Like other countries, the Chinese leadership treats cybersecurity as one of the most important security issues to address in the 21st century. China's approach to cybersecurity is driven by the central objective of establishing cyber sovereignty within China and ensuring that the respect of national sovereignty becomes one of the guiding principles governing global cyberspace. In the Chinese approach, security and control are prioritized over rights, openness, and freedom on the Internet. Moreover, the Chinese agenda on cybersecurity is divided into four main dimensions, which are not only oriented toward economic protection and technical aspects but also related to ideological and social issues, as well as military aspects. They embrace (Bersick et al., 2016): capability building (focused on the technical aspects of cybersecurity), stability and domestic security, with a special focus on content and public opinion, the military dimension, and the international governance of global cyberspace. These areas show that the Chinese approach implies China's "own control" over the enumerated processes. In such an approach, not only the common benefits, but also the conflictual nature and competitive partnership prevent far-reaching cooperation with other countries on cybersecurity issues. In addition, China implemented data protection law, consumer protection law, cybercrime law, and some other regulations (Jiang, 2020). It should be noted that while China, on the one hand, has strengthened its policies on personal data protection and consumer protection, it has also placed significant emphasis on and allocated resources to cybercrime, public order, and cyber defense.

The US market-driven regulatory model is characterized by greater tolerance for new technologies. Nevertheless, it quickly became apparent that control over IT infrastructure had deteriorated due to technological advances and increasingly sophisticated cyber-attacks. It caused concern for the White House administration. Its representatives also recognized that many other countries' governments were giving greater attention to cybersecurity issues. Consequently, the US began actively pursuing numerous actions and industrial policy initiatives. The time frames for cybersecurity policy in the US are similar to those in the EU. They were implemented since the beginning of the 21st century (Aggarwal & Reddie, 2018). Here might be included the creation of the Office of Homeland Security, the President's orders dedicated to cybersecurity issues, the Federal Information Security Management Act of 2002 (FISMA), the Comprehensive National Cybersecurity Initiative (CNCI), Commission on Cybersecurity for the 44th Presidency, Critical Infrastructure Security

and Resilience, and many more. In December 2014, the U.S. Congress passed five major legislative proposals aimed at enhancing U.S. cybersecurity. The authors of the law were convinced that the focus on cyber risk is crucial, as cybersecurity challenges constitute the greatest long-term threat to national security (Trautman, 2015). The key strategic plans in this area include National Strategy to Secure Cyberspace (2003), Cybersecurity Review (2009), the National Cyber Strategy (2018), and the National Cybersecurity Strategy published by the White House on March 2, 2023. All of these strategies were dedicated to the most significant dangers, and they consequently encompassed an increasing number of issues. Among others, there was the vulnerability of critical infrastructure and the importance of fighting cybercrime. There was also sharing information about breaches and security gaps, and engaging with the private sector.

Cybersecurity from the US perspective also has an international dimension. The concern about China's efforts to promote advanced technology through its Made in China 2025 policy has taken on a larger role in the policy addressing global competition in high technology. Together with other initiatives, the US government faces a delicate balancing act to create an effective and usable information-sharing regime, foster a duty of care toward cybersecurity by private actors, oversee the nascent cyber insurance system, devote public resources to cybersecurity education, and engage with the transnational aspects of cybersecurity. Despite many threats, the industrial policies favored by Washington are also likely to reflect existing power dynamics in the US domestic marketplace. The current 'winners' in the internet marketplace – IT companies – appear to have significant lobbying advantages with attendant consequences upon the US government's market facilitation and regulatory roles. This means that the cybersecurity policy remains in its infancy in the US (Aggarwal & Reddie, 2018). US-EU relations regarding cybersecurity issues are closer. The EU and the US share common threat perceptions and interests; they converge around several cybersecurity principles and norms, and they coordinate their actions in practice. It means that the EU-US cybersecurity relationship has taken the form of functional cooperation, aimed at safeguarding common interests and avoiding the costs and vulnerabilities arising from EU-US interdependencies in the cyber realm. At the same time, both markets have different priorities in cybersecurity areas (Anagnostakis, 2021).

The literature-based analysis of cybersecurity levels in the USA, the EU, and China indicates significant variation across these markets and their businesses. In areas such as online banking, identity theft, and encryption, the United States leads, whereas the European Union excels in data security, privacy, smart grids, and cybercrime policies. China, in turn, performs better in network policy. Mishra et al. (2022) suggest that the United States and the European Union are somewhat more effective in addressing emerging cybersecurity threats than China. It should be emphasized that the highest levels of cybersecurity are currently observed in the USA and leading EU countries, attributable to advanced regulations, infrastructure, and international cooperation (Fahey, 2024; Jacuch, 2021). Despite rapid technological development, China remains comparatively more exposed to digital threats and is often perceived as a source of risk. Nevertheless, the country is quickly advancing its cyber capabilities by investing in new technologies, developing its own regulatory framework, and dynamically building its cybersecurity industry. China is implementing testing and training solutions and introducing educational programs focused on cybersecurity (Creemers, 2023; Yang et al., 2025). The government is centralizing management and promoting "cyber sovereignty," which enhances system control and resilience. The literature emphasizes that China's cybersecurity level is still lower than in the USA or leading EU countries, though the gap is gradually narrowing. The rapid development of advanced digital technologies in China is contributing to the country's growing sophistication in digital security. The state of digital security in China continues to evolve rapidly (Putri et al., 2024). It is important to note, however, that comparative analyses of cybersecurity across these regions remain relatively underexplored. Given the significance of this issue and the highly dynamic processes of economic digitalization, further research in this area is warranted. Therefore, based on the previous literature, we hypothesize that:

H1: Corporations with headquarters located in China or Europe have lower levels of cybersecurity performance than corporations with headquarters located in the US.

The third level of institutions proposed by Williamson (2000) is governance. DiMaggio and Powell (1983, p. 143) delve deeper into this level and define "organizational field" as comprising a population of organizations operating in the same domain, defined by the similarity of their services or products. DiMaggio and Powell (1983) stress that organizations that, in the aggregate, constitute a recognized area of institutional life become increasingly similar due to institutional processes that take place in that field. Therefore, institutional factors can be attributed to organizational fields. Therefore, attention should be paid to sectors that are the primary organizational field.

Industry-specific dynamics largely shape the processes of digitalization. This mechanism is precisely explained by the dynamics of change in organizational fields, which are referred to as isomorphic processes. Isomorphic processes encompass coercive, mimetic, and normative isomorphism, with all three evidenced as affecting organizational cybersecurity (Jeyaraj & Zadeh, 2020; Hu et al., 2005). A coercive isomorphism of cybersecurity practices can be observed at the level of supply chain networks (Creazza et al., 2022). The participating entities implement uniform mechanisms for combating cyber risk. Mimetic isomorphism can be observed at the level of digital platforms. In this case, some platforms imitate the methods of operation of others, especially those that are perceived as successful. Normative isomorphism can be observed in cybersecurity standards, such as SANS Institute, the Information Systems Audit and Control Association (ISACA), and the Software Engineering Institute (SEI) are promoted by sectoral associations (Cavusoglu et al. 2015).

While there may be discrepancies among industry rankings of cyber risks, certain industries are believed to be particularly risky (Shevchenko et al., 2022). According to Statista (2023), the greatest cyberattack risks challenge industries that handle vast amounts of sensitive data, such as education, law firms, marketing agencies, consulting services, and the healthcare industry, which relies on interconnected medical devices and extensive health record databases. The financial sector has also become a battleground for cyberattacks due to the large volume of sensitive data it stores. Conversely, criminals target the energy and utility sector because it controls critical infrastructure essential for social resilience. The reports from the IBM 'Cost of a Data Breach Report' for 2019 and 2023 present the distribution of data breach costs across industries (Table 2). Still, there is a need to better understand the distribution of cyber risk across sectors. Our research focuses on four industries: energy and finance, which are significant for economies and businesses, and healthcare and education, which are important for society. All these industries are characterized by a high level of technology integration in their activities.

Table 2. Cost of data breach by industry in the period of 2019-2023 (in millions USD)

Industry	2019	2020	2021	2022	2023
Healthcare	6.45	7.13	9.23	10.10	10.93
Financial	5.86	5.85	5.72	5.97	5.90
Pharmaceuticals	5.20	5.06	5.04	5.01	4.82
Energy	5.60	6.39	NA	4.72	4.78
Industrial	5.20	4.99	4.24	4.47	4.73
Technology	5.05	5.04	4.88	4.97	4.66
Professional services	4.62	4.23	4.65	4.70	4.47
Transportation	3.77	3.58	3.75	3.59	4.18
Communications	3.45	3.01	3.63	3.62	3.90
Consumer	2.59	2.59	3.70	3.86	3.80
Education	4.77	3.90	3.79	3.86	3.65
Research	1.65	1.53	3.60	3.88	3.63
Entertainment	4.32	NA	3.80	3.83	3.62
Media	2.24	1.65	3.17	3.15	3.58
Hospitality	1.99	1.72	3.03	2.94	3.36
Retail	1.84	2.01	3.27	3.28	2.96
Public sector	1.29	1.08	1.93	2.07	2.60

Source: Cost of a Data Breach Reports (2019, 2023).

The energy sector is a cornerstone of every economy and is typically classified as part of the state's critical infrastructure. Many other industries rely on the delivery of energy services, heightening the importance of cybersecurity threats within this sector (Kelic, 2019; Venkatachary et al., 2017). Given its significance to society, a cyber-attack on the energy sector could have catastrophic consequences, potentially disrupting gas and electricity supplies for millions of individuals and businesses (Livingston et al., 2019). It is highlighted that the probability of cyberattacks in the energy sector increases tremendously due to the complex infrastructure involved in smart grids as well as new geopolitical conflicts (Priyadarshini et al., 2021; Simons et al., 2020; Willett, 2023).

Turning to the finance sector (encompassing banking, insurance, and capital markets), cyber risk assumes paramount importance for several reasons. Firstly, financial institutions hold sensitive data, rendering them prime targets for cyber threats (Gatzert & Shubert, 2022; Varga et al., 2021). Secondly, the finance sector heavily relies on cutting-edge technologies, making it an attractive target for cyber breaches compared to non-financial entities (Eling & Wirfs, 2019). Thirdly, the finance sector generates systemic risk, wherein cyber threats can have a disproportionately large impact on society due to the pivotal role of financial institutions as universal intermediaries. Moreover, financial institutions are interconnected internationally, meaning that local problems at one institution can threaten many others in the network, with far-reaching negative consequences (Corbet & Gurdgiev, 2017; Curran, 2020; Gatzert & Shubert, 2022). All these reasons, along with the growing scale and intensity of cyber threats and risks in the financial sector, led us to include the financial sector in our study.

Another sector where cybersecurity plays a crucial role is healthcare. Malavasi et al. (2022) point out that the financial and health sectors face similar risks related to privacy data, and these industries are more exposed to unintentional data disclosure than other business sectors. It stores a wealth of information with significant monetary and intelligence value to cyber criminals and nation-state actors (Cartwright, 2023; Coventry & Branley, 2018). Over the last decades, the sector has improved service capacity, efficiency, and overall performance by leveraging digital technologies such as AI, IoT, user response data, digitalization, machine learning, human psychology, augmented reality (AR), big data mining, etc. At the same time, the positive processes raise the level of cyber risk. As Wasserman and Wasserman (2022) highlight, cyberattacks in healthcare are growing exponentially. By 2019, 24% of cyberattacks were in the healthcare industry. In 2014, 90% of hospitals and clinics experienced at least one data breach, and 45% experienced at least 5. The number of healthcare breaches filed in the US per year has more than tripled in the past decade. Compared to other sectors, cyber risks in healthcare have many dimensions. There are threats to personal data security, as well as other threats associated with the application of advanced technology in medical treatment. Moreover, the expansion of portable devices such as smartphones and USB devices, as well as the enormous number of connected medical devices, is widening the attack surface (Anand & Leonova, 2023). As Paul et al. (2023) point out, the healthcare sector in 2021 faced the most ransomware attacks. The proliferation of portable devices like smartphones and USB devices, as well as the growing number of connected medical devices, is widening the attack surface. In recent years, especially after the COVID-19 pandemic, education has also been among the sectors most endangered by cyber threats. Nevertheless, practices in the sector seem to be advancing rapidly, with considerable investment in resources and governance of cyber risk (Javaid et al. 2023, Garcia-Perez et al. 2023).

The contemporary teaching process is based on online services that support teaching and learning activities. Higher education institutions make full use of ITC and the Internet in nearly all of their operations (Kilag et al., 2023; Rahim, 2021). At the same time, cyberspace in this sector remains insecure. Educational institutions encounter diverse cybersecurity threats, including data breaches, ransomware attacks, phishing, and others. Educational organizations hold immense amounts of personal data, which can ultimately cause serious damage to these entities. As Liluashvili (2021) highlights, the cyberattack damage to higher education can include reputational, financial, and even national security, as some higher education entities are involved in defense research projects. Cyber risk exposure in education is driven by the volume of data, the importance of trust, and universities' culture of openness (Li et al., 2023; Ulven & Wangen, 2021). It is reported that sector regulators lag in establishing minimum cybersecurity requirements for education providers (Chapman, 2019).

Overall, there can be sectoral variations in the probability of cyber events as well as in the level of losses that such events can trigger. Sector-specific cybersecurity vulnerabilities shape the experience as well as the approach to cybersecurity management practices prevalent in the sector. These include sector-specific regulations, collaboration among sector stakeholders, the role of various regulatory/supervisory bodies, the impact of industry associations and networks, and more (Calliess & Baumgarten, 2020; Hasan et al., 2023). Sometimes, country governments establish specialized agencies to address specific problems (Srinivas et al., 2019). This leads us to the formulation of the research hypothesis:

H2: Operating in the energy, financial, healthcare, and education sectors is associated with a higher likelihood of superior cybersecurity performance.

Organizational drivers of cybersecurity

In this section of the paper, we explore organizational-level factors (elements within a company) that may help to explain the distribution of cyber risk performance across organizations. Firms accept cyber risk as part of their overall operational risk

to leverage a competitive edge in technology, distribution, or information. The neo-classical finance theory postulates that any attempt to manage unsystematic risk is of no value to the firms. Nevertheless, industry practitioners routinely allocate resources to risk management activities, signaling the value and relevance of prudent risk management in a real business context where market imperfections exist (Lin et al., 2012; Bogodistov & Wohlgemuth, 2017). Still, the implementation of cyber risk management practices has been found to be diverse (Accenture, 2023), and thus, organizational factors associated with improvements in cybersecurity performance need to be explored. The literature predominantly views allocating resources to cybersecurity as an investment decision and consequently adopts investment-related theoretical frameworks, such as real options theory and learning models, to identify the factors driving cybersecurity investment levels (Xu et al. 2019; Weishäupl et al. 2018; Shaikh & Siponen, 2023). This study takes a risk management perspective. In this vein, committing resources to cybersecurity is perceived to reduce earnings and cash flow volatilities, facilitating evaluation and monitoring of firm performance by investors rather than another positive NPV project. Consequently, in this section, we build on the risk management literature to identify groups of organizational factors we expect to be associated with cybersecurity performance.

The role of firm size for cybersecurity performance appears to be a perplexing issue. The cyber risk literature provides extensive evidence that firm size predicts both cyber risk exposure and the level of cyber risk-related losses (Jamilov et al. 2023; Aldasoro et al. 2022; Kamiya et al. 2021; Biener et al. 2015; Jiang et al. 2024). Indeed, larger firms are often targeted for cyberattacks (Gatzert & Shubert, 2022). However, much less is known about the extent to which firm size influences overall corporate cybersecurity performance—a construct shaped by organizational processes and resource allocation dilemmas, and managerial priorities. The processes-related framing of the issue emphasizes that, while larger firms possess the resources needed to acquire and implement cybersecurity-enhancing measures, they also face organizational inertia (Audretsch & Elston, 2002; Colombo & Delmastro, 2002). Organizational inertia broadly refers to an established organization's inability to enact sufficient internal change in the face of environmental shifts (König et al. 2021). Larger organisations must rely on established hierarchies and routines, which lead to inertia (Ozawa, 2023). They must also coordinate across multiple units, so changes in one area often trigger costly adjustments elsewhere, resulting in slow, fragmented responses to new threats (Zhou et al. 2017). Overall, organisational inertia hampers the corporate agility required to adapt to a rapidly evolving digital environment (Zhen et al. 2021; Kaganer et al. 2023). Another mechanism underlying the relationship between firm size and cybersecurity performance is the resource-allocation dilemma, in which investments in cybersecurity must be carefully weighed against their expected benefits to the firm. While firm size is proportionally related to the costs of improving cybersecurity performance—such as expenditures on systems, software, and employee training—the benefits of such investments may not scale proportionally with size. Aldasoro et al. (2022) note that a significant proportion of losses resulting from cyber incidents are reputational in nature. Interestingly, the risk management literature suggests that for larger firms, declines in market valuation following reputational incidents tend to be relatively smaller (Murphy et al., 2009; Sturm, 2013; Carberry et al., 2018). The remediation of reputational incidents typically involves fixed costs that larger companies can more easily absorb (Zaby and Pohl, 2019). Moreover, firms with stronger brands may be better equipped to counter reputational damage, thereby reducing the overall impact of such incidents (Murphy et al., 2009; Greyser, 2009). In contrast, reputational risk imposes a greater burden on smaller firms, as it exacerbates information asymmetry and increases both the cost and difficulty of accessing equity and debt financing (Cao et al., 2012; 2015; Kölbel et al., 2017). Consequently, costly improvements in cybersecurity may yield diminishing marginal benefits for larger firms. Therefore, based on these process- and resource-allocation-related considerations, we hypothesize that:

H3: Larger companies are more likely to exhibit lower levels of cybersecurity performance than smaller companies.

Cyber risk constitutes an integral component of operational risk, and cyber-related losses can be regarded as fixed costs that contribute to a firm's operating leverage. Traditional financial literature has long examined the relationship between operating leverage and financial leverage (or gearing), generally suggesting that these two forms of leverage behave as substitutes (Li & Henderson, 1991; Trezevant, 1992). Within this framework, firms with higher financial leverage possess stronger incentives to mitigate operational risks to avoid amplifying overall earnings volatility (Purnanandam, 2008).

However, subsequent research in finance highlights that the interplay between financial and operational risks is complex. Empirical evidence indicates that the relationship between operating and financial leverage may at times be positive rather than substitutive (Ho et al., 2004; Chiou & Su, 2007; Sarkar, 2020). This complexity becomes particularly relevant when considering firms' decisions regarding cybersecurity investment and performance.

Improving cybersecurity performance is characterized by a high degree of investment specificity. Such improvements often require a considerable, intangible, multi-year investment with option-like payoffs. From a corporate finance perspective, this raises the issue of *debt overhang*—the well-documented phenomenon in which equity holders underinvest in positive net present value (NPV) projects when the expected gains primarily accrue to debtholders (Myers, 1977; Aivazian et al., 2005; Iqbal et al., 2022). Evidence shows that investment in cybersecurity performance reduces the benefits to equity holders by negatively affecting the firm's dividend policy (Hoang, 2025). Conversely, enhanced cybersecurity performance primarily benefits debtholders by reducing the firm's credit risk exposure (Sheneman, 2025). Consequently, equity holders bear the cost of enhanced cybersecurity, while the benefits accrue disproportionately to debt providers, weakening shareholders' incentives to finance such initiatives. Furthermore, the literature on corporate investment under financial constraints demonstrates that senior claims—such as mandatory debt-service payments—can crowd out otherwise positive-NPV investments (Rauh, 2006; Deng & Fang, 2022). The distortion is particularly severe for projects with long gestation periods or delayed payoffs, as these investments are typically financed through equity rather than debt (Hennessy, 2004; Grundy & Verwijmeren, 2020). Given that cybersecurity investments often possess long-term, intangible, and uncertain returns, they are especially vulnerable to such financing frictions. Therefore, after considering cybersecurity investment-specificity – capital structure link, we hypothesize that:

H4: Companies with higher financial leverage are more likely to exhibit lower levels of cybersecurity performance.

Cyber risk is frequently discussed in the context of financial performance. The prevailing view is that profitable companies possess greater capacity to allocate resources toward cybersecurity, thereby strengthening their digital resilience. In line with this argument, Makridis and Liu (2021) find that more productive firms tend to exhibit fewer cybersecurity vulnerabilities and have access to superior human capital, which enhances their ability to mitigate cyber threats. However, Anderson and Choobineh (2008) emphasize that decisions regarding the allocation of available budgets to cybersecurity are also shaped by a firm's risk tolerance. This insight introduces an important nuance: financial performance does not translate automatically into stronger cybersecurity, as firms' risk attitudes and managerial behaviors mediate how resources are deployed.

Two key mechanisms help explain the relationship between financial performance and cybersecurity investment decisions. The first pertains to the availability of slack resources and their usefulness in absorbing risk, while the second concerns the behavioral dynamics of managerial decision-making.

Firms with higher financial performance can build a resource cushion—commonly referred to as organizational slack—that allows discretionary allocation of funds to address emerging threats or pursue new opportunities (Bourgeois, 1981; Cyert & March, 2015). Slack serves as a buffer that enhances resilience by enabling the absorption of shocks during adverse events (Conz et al., 2023; Tognazzo et al., 2016). Yet, the availability of such resources can also encourage greater risk-taking. Empirical studies demonstrate that increases in slack are associated with the adoption of riskier strategies and practices (Voss et al., 2008; Moses, 1992). Moreover, this effect tends to be amplified in deregulated or high-uncertainty environments (Martinez & Artz, 2006), such as cybersecurity, where governance and risk standards are less formalized.

A complementary perspective arises from the managerial risk-taking literature, which focuses on decision-makers' behavior rather than organizational characteristics. From an agency theory standpoint, managers in well-performing firms are often subject to weaker shareholder scrutiny, thereby granting them greater discretion to pursue risky strategies (Jensen, 1986; Hoskisson et al., 2017). Empirical evidence suggests that monitoring intensity tends to concentrate on underperforming firms (Brav et al., 2022), implying that financially successful firms may neglect in certain domains—such as cybersecurity—where risks are less immediately visible.

A behavioral finance perspective further enriches this argument, showcasing that past financial performance can stimulate overconfidence (Puetz & Ruenzi, 2011; O'Connell & Teo, 2009). Financial success breeds overconfidence, as decision-makers take too much credit for good outcomes (Ben David et al., 2007; Gervais & Odean, 2001). Overconfidence, in turn, has been shown to negatively affect a wide range of corporate decisions, including mergers and acquisitions, financing policies, and risk management practices (Brahma et al., 2023; Malmendier et al., 2011; Adam et al., 2015). Within the context of digital transformation, overconfidence can undermine adaptive routines essential to organizational resilience (Kunz & Sonnenholzner, 2023) and lead to strategic errors in digital initiatives due to overly optimistic assessments of technological or market conditions (Qi et al., 2021).

Taken together, these strands of evidence suggest that high financial performance can have ambivalent implications for cybersecurity. On the one hand, greater resources could enable stronger protective investments; on the other hand, financial success may create slack and foster managerial overconfidence, both of which can reduce attention to cybersecurity risks. Accordingly, we hypothesize the following:

H5: Companies with higher financial performance are more likely to exhibit lower levels of cybersecurity performance than companies with lower financial performance.

METHODOLOGY

We developed a unique dataset, including data from the Orbis database, on corporate characteristics, industry and country of headquarters, and cyber risk performance. The sample size consists of 1,211 companies headquartered in the USA, China, or Europe. Our dataset covers one year: 2022. Aiming to uncover patterns of cybersecurity across organizations, we investigate the associations between institutional-level factors, organizational-level factors, and corporate cyber risk performance.

The information on cybersecurity performance is obtained from the Orbis database, based on the rating provided by BitSight, one of the first external cyber risk rating organizations. Importantly, it isn't a prescriptive security framework, but an external rating that monitors cybersecurity performance (Choi et al., 2021). Although it cannot capture all nuances of cybersecurity performance, BitSight's rating provides cyber risk scores similar to those of other cyber risk rating agencies (Keskin et al. 2021). This feature enhances the credibility of a rating (Berg et al., 2022). The rating is a measure of an organization's security performance and, accordingly, its level of cybersecurity risk. The cyber risk rating uses a data-driven, outside-in approach (with no required participation by the rated organization) to assess an organization's security effectiveness. This results in an objective assessment of an organization's security posture. Unlike other security ratings, BitSight's rating has been proven by third parties to correlate with the likelihood of a breach or ransomware attack. Four categories of risk vectors are included in the rating:

- Diligence: These risk vectors assess the steps an organisation has taken to prevent attacks, their best practice implementation, and risk mitigation (e.g., server configurations) to determine if their security practices are on par with industry-wide best practices;
- Compromised Systems: These risk vectors indicate the presence of malware or unwanted software, which is evidence of security controls failing to prevent malicious or unwanted software from running within an organization;
- User Behaviour: These risk vectors reflect employee activities, such as file sharing and password re-use, that can introduce malware to an organisation or result in a data breach;
- Public Disclosures: These risk vectors indicate publicly disclosed events of unauthorised access, often involving data loss or theft.

Risk vectors are weighted based on importance. According to the rating methodology, the rating ranges from 250 to 900. The provider proposes three categories of organizations based on their cyber risk ratings (Table 3).

Table 3. Categories of companies based on their level of cyber risk rating

Category	Rating Range	Description	Distribution
Advanced	740-900	Strong security performance and lower risk	50% of entities
Intermediate	640-730	Fair security performance and moderate risk	45% of entities
Basic	250-630	Poor security performance and high-risk	5% of entities

Source: Orbis database.

Given the very small number of companies in the "Basic" category in the database, we exclude this group from our analysis and focus instead on the "Intermediate" and "Advanced" categories, where meaningful differences can be observed. Accordingly, we treat our dependent variable as a binary variable, taking the value of 1 if a company exhibits an "Advanced" level of cybersecurity performance, and 0 otherwise (i.e., for companies classified as having an "Intermediate" level of cybersecurity performance).

Independent variables related to organizational-level factors are quantitative, and those related to institutional factors are qualitative: binary variables indicating whether a company operates in a given industry or is headquartered in a given country (the full country–region classification used to construct these dummies is provided in Table A1 in the Appendix). European countries were grouped into four regions—Northern, Southern, Western, and Eastern Europe (see Table A1 in the Appendix). This classification reflects well-documented differences across these regions in terms of digitalization, regulatory capacity, and corporate risk management practices. Northern Europe (Denmark, Finland, Ireland, Sweden) is characterized by advanced digital infrastructure and high levels of e-government adoption. Western Europe (Austria, Belgium, France, Germany, Luxembourg, Netherlands) comprises economies with strong regulatory capacity and long-standing traditions of corporate risk management. Southern Europe (Cyprus, Greece, Malta, Italy, Portugal, Spain) is distinguished by comparatively weaker enforcement capacity and lower average levels of digital maturity among firms. Eastern Europe (Bulgaria, Croatia, Hungary, Poland, Romania, Slovenia) consists largely of post-transition economies with more recent integration into EU regulatory and governance frameworks. In addition, we adopted control variables. Description of variables is provided in Table 4.

Table 4. Description of independent variables

Variables		**Explanation and measurement**
Dependent variable		
CyberRisk_AdvPerformance		• 1: Advanced security performance and lower risk • 0: Intermediate security performance and moderate risk
Independent variables		
Quantitative independent variables representing organisational-level factors	*Leverage*	An independent variable measuring the degree of financial leverage is calculated as the Debt to Equity (D/E) ratio, representing the relationship between debt and equity. Leverage was obtained from the Orbis database.
	ROE	An independent variable used to approximate a company's profitability. ROE (return on equity) is calculated as a relation of net profit to equity. ROE was obtained from the Orbis database.
	LogTA	An independent variable used to approximate a company's size. TA stands for Total assets. TA was obtained from the Orbis database. For modeling purposes, we used the natural logarithm of TA.
	Employees	An independent variable used to approximate a company's size. The number of employees was obtained from the Orbis database.
Qualitative variables representing institutional-level factors	*Region*	• China • North Europe • South Europe • West Europe • East Europe • United States
	Industry	• Education • Energy • Financial • Healthcare • Other

We encoded qualitative variables as binary, dropping the first level to avoid linear dependencies in the model matrix. Therefore, in interpreting regressions, coefficients for qualitative variables shall be interpreted as differential effects relative to the baseline reference.

Categorizing dependent variables into two groups allows the use of binary logistic regression models (Böhning, 1992). Logistic regression models a relationship between predictor variables and a categorical response variable. Binary logistic regression treats the outcome variable as a dichotomous variable. In our case, we compare the Intermediate categories to the Advanced category. We estimate three models. Model 1 includes only Leverage and its squared term, in order to capture potential nonlinear effects. Model 2 expands the specification by adding ROE, its squared term, and the number of Employees, thus incorporating all quantitative organizational-level factors. Model 3 further augments the model by adding Region and Industry, thereby including also qualitative institutional-level factors.

Model 1

$$CyberRisk_AdvPerformance = \beta_0 + \beta_1 Leverage + \beta_2 Leverage^2 + \epsilon$$

Model 2

$$CyberRisk_AdvPerformance = \beta_0 + \beta_1 Leverage + \beta_2 Leverage^2 + \beta_3 ROE + \beta_4 ROE^2 + \beta_5 Employees + \epsilon$$

Model 3

$$CyberRisk_AdvPerformance = \beta_0 + \beta_1 Leverage + \beta_2 Leverage^2 + \beta_3 ROE + \beta_4 ROE^2 + \beta_5 Employees + \beta_6 Region + \beta_7 Industry + \epsilon$$

Sample characteristics

This section presents the descriptive statistics and correlation analysis for the variables included in the study. It provides an overview of the sample composition, detailing the number of companies observed across regions and industries, and examines the relationships among key firm-level and institutional-level variables used in the regression models. Descriptive statistics for dependent and independent variables are presented in Table 5.

Table 5. Descriptive statistics for dependent and independent variables

Variable	Min	Q1	Median	Mean	Q3	Max
Leverage	0	15.39	56.88	95.94	122.08	972.78
ROE (in %)	-906.9	-36.64	5.52	-23.84	21.76	311.42
N_employees	1	114	1034	9545	6575	440000
TA	663000	1.39E+08	7.02E+08	5.93E+09	3.51E+09	2.17E+11
CyberRisk_AdvPerformance	0	0	0	0.4443	1	1

This study focuses on developed economies with advanced levels of digitalization and economic complexity, specifically the United States, China, and European countries. While a country-level analysis was initially considered, the number of observable firms across several European countries proved too small to support reliable econometric inference. Consequently, we adopt a regional classification within Europe that reflects well-established institutional differences in regulatory traditions, approaches to risk, and innovation systems, and that represents a common approach in comparative institutional research. As shown in Table 6, companies are unevenly distributed across regions, reflecting differences in regional economic size and capacity. Nevertheless, the number of observations within each region remains sufficient to ensure the reliability and robustness of the regression analysis. Table 7 presents the distribution of companies by sector.

Table 6. Companies' distribution by region

Region	Intermediate cybersecurity performance	Share (%)	Advanced cybersecurity performance	Share (%)	Total	Share (%)
China	41	3.39	5	0.41	46	3.80
EastEU	14	1.16	4	0.33	18	1.49
NorthEU	54	4.46	38	3.14	92	7.60
SouthEU	42	3.47	11	0.91	53	4.38
UnitedStates	446	36.83	428	35.34	874	72.17
WestEU	76	6.28	52	4.29	128	10.57
Total	673	55.57	538	44.43	1,211	100.00

Table 7. Companies' distribution by industry

Region	Intermediate cybersecurity performance	Share (%)	Advanced cybersecurity performance	Share (%)	Total	Share (%)
Education	5	0.41	8	0.66	13	1.07
Energy	37	3.06	26	2.15	63	5.20
Financial	35	2.89	41	3.39	76	6.28
Healthcare	191	15.77	268	22.13	459	37.90
Other	405	33.44	195	16.10	600	49.55
Total	673	55.57	538	44.43	1,211	100.00

The distribution of companies across sectors reflects the sample's structural characteristics, with the financial and energy sectors dominated by large, well-established firms. Conversely, the relatively small representation of the education sector is consistent with its composition of predominantly small and private institutions, many of which are not covered by commercial databases.

The regional and sectoral composition of the sample is determined by data availability in the Orbis database and the coverage of external cybersecurity ratings; as a result, U.S.-based firms and highly digitalized sectors such as healthcare are overrepresented, a limitation that is explicitly accounted for through the inclusion of region and industry controls in the empirical models. While this uneven representation may limit the generalizability of the results, it does not affect the internal validity of the estimated relationships, which are identified through within-sample variation conditional on institutional and organizational controls.

To address the influence of outliers, Leverage was winsorized at the 5th and 95th percentile thresholds, while ROE and Employees were winsorized at the 2.5th and 97.5th percentile thresholds (Table A2 in the Appendix reports the pre-winsorization percentile cut-offs computed from the raw data). Total Assets (TA) were transformed using the natural logarithm and subsequently scaled. All continuous variables were mean-centered (but not standardized) to facilitate the interpretation of both main and squared effects. Table 8 presents the correlation matrix for variables after the transformations.

Table 8. Correlation matrix for variables after the transformations

Variable	Leverage	ROE	LogTA	Employees
Leverage	1.000			
ROE	0.060*	1.000		
LogTA	0.369***	0.500***	1.000	
Employees	0.272***	0.262***	0.566***	1.000

Note: The table reports pairwise Pearson correlation coefficients among continuous variables after transformations. Significance levels: $p < 0.1$, $p < 0.05$, $p < 0.01$.

Based on the correlation analysis, the transformed variable LogTA, representing company size, exhibited high correlations with several other independent variables. Consequently, it was excluded from the regression models to avoid multicollinearity, with Employees retained as the preferred proxy for firm size. We argue that the number of employees more accurately captures organizational inertia, as it directly reflects the scale and diversity of organizational structures, procedures, and routines, and thus better represents the overall complexity of the firm.

RESULTS AND DISCUSSION

Results from binary logistic regressions – including Model 1, 2, and 3 – are presented in Table 9. In the regression models, RegionChina, RegionEastEU, RegionNorthEU, RegionSouthEU, and RegionWestEU are interpreted relative to the omitted reference category RegionUSA, while IndustryEducation, IndustryEnergy, IndustryFinancial, and IndustryHealthcare are interpreted relative to the omitted reference category IndustryOther. Average Marginal Effects (AMEs) for all models are reported in Table A3 (see Appendix), providing a summary of the estimated effects in terms of changes in predicted probabilities. For Model 3, Table A4 presents a robustness check comparing standard logistic

estimates with Firth penalized estimates, showing that the results remain consistent in terms of coefficient signs, magnitudes, and significance levels. Predicted-probability plots and Generalized Variance Inflation Factors (GVIFs) for Model 3 are also provided in the Appendix (specifically, Figure A1 and Table A5), offering additional insights into model fit and potential multicollinearity.

Table 9. Results from the binary logistic regressions

Variable	(1)	(2)	(3)
Leverage	-0.007***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)
Leverage²	0.00003***	0.00001	0.00001
	(0.00001)	(0.00001)	(0.00001)
ROE		-0.009***	-0.008***
		(0.002)	(0.002)
ROE²		-0.00002***	-0.00002***
		(0.00001)	(0.00001)
Employees		-0.00002***	-0.00002***
		(0.00001)	(0.00001)
RegionChina			-1.943***
			(0.500)
RegionEastEU			-0.815
			(0.555)
RegionNorthEU			-0.459**
			(0.232)
RegionSouthEU			-1.143***
			(0.369)
RegionWestEU			-0.151
			(0.217)
IndustryEducation			0.799
			(0.587)
IndustryEnergy			0.496
			(0.290)
IndustryFinancial			0.771***
			(0.261)
IndustryHealthcare			0.313*
			(0.162)
Constant	-0.439***	-0.205**	-0.248*
	(0.083)	(0.097)	(0.133)
Observations	1,211	1,211	1,211
Log Likelihood	-804.224	-758.992	-731.909
Akaike Information Criterion (AIC)	1,614.448	1,529.984	1,493.818
McFadden Pseudo R2	0.033	0.088	0.120
Adjusted McFadden Pseudo R2	0.030	0.080	0.102

Note: Robust standard errors (HC1) are reported in parentheses. Significance levels: $p < 0.1$, $p < 0.05$, $p < 0.01$.

Institutional- and organizational-level independent variables show a significant association with the dependent variable across both models. The steady improvement in model fit across models 1, 2, and 3 (lower AIC, higher log-likelihood) indicates that both firm-level and institutional-level factors improve the explanatory power of cybersecurity performance.

The main model demonstrates that being located in China or Southern Europe reduces the log-odds by more than 1, corresponding to a drop in the predicted probability of achieving an advanced level of cybersecurity of around 20–30 percentage points, depending on baseline probabilities. Thus, firms in China are significantly less likely to achieve an advanced level of cybersecurity performance than those in the United States. Within Europe, firms in Southern Europe also exhibit a substantially lower probability of achieving advanced cybersecurity performance than U.S. firms. Companies in Northern Europe perform moderately worse than their U.S. counterparts. At the same time, the coefficient for Western Europe and Eastern Europe is negative but statistically insignificant, indicating that cybersecurity performance in these

regions is broadly comparable to that observed in the United States. Although Western Europe is generally characterized by higher levels of economic and institutional development, the relatively strong performance observed in Eastern Europe (not different from that observed in the U.S.) may stem from specific characteristics of the sample composition.

Overall, these results indicate that U.S. firms outperform those in China and most European regions in terms of cybersecurity performance, with the weakest outcomes observed in China and Southern Europe. This evidence provides important insights for investors regarding geographic screening of cybersecurity risk exposure, which appears to be lowest in the United States. The findings also carry policy implications for Europe, suggesting that cybersecurity practices in Southern Europe should be urgently improved. The current "two-speed" model of cybersecurity performance risks undermining confidence in the European market as a whole. Similarly, policymakers in China may need to reconsider existing approaches, as current strategies appear insufficient to foster high levels of corporate cybersecurity resilience.

A coefficient of 0.771 for the Financial sector corresponds roughly to a 15–20 percentage point increase in the predicted probability of attaining advanced cybersecurity performance relative to firms in category "Other industries" for the total sample. This result is consistent with the sector's strict regulatory environment and its high exposure to cyber threats, both of which incentivize continuous investment in cyber resilience. Similarly, the Healthcare sector coefficient (0.313) implies an approximate 7–10 percentage point higher probability of achieving an advanced cybersecurity level. Healthcare firms demonstrate a significantly higher likelihood of advanced cybersecurity performance, potentially due to the sensitivity of personal data and stringent sector-specific compliance requirements.

Firms in the Energy sector are not significantly more likely to attain advanced cybersecurity performance. Therefore, although the sector is vulnerable to cybersecurity risks, its performance remains similar to that of the "Other industries" category. Although the coefficient for the education sector is positive, it is not statistically significant, suggesting no clear difference in cybersecurity performance relative to the "Other industries" category. Consequently, two industries emerge as leaders in cybersecurity performance: financial services and healthcare. This finding is particularly noteworthy as it contrasts with earlier evidence indicating that cyber losses were concentrated in the financial and healthcare sectors (Pálsson et al., 2020). Our results may suggest that the historically high exposure and accumulated experience with cyber incidents in these sectors have led to improved preparedness and more mature cyber-risk management practices. In other words, what was once a vulnerability has now become a source of comparative advantage.

From an investment perspective, this finding implies that cyber risk may now be more concentrated outside these two well-prepared sectors, offering valuable guidance for portfolio-level risk screening.

From a policy standpoint, regulators should investigate the factors underlying the superior cybersecurity performance observed in the financial and healthcare sectors. Understanding whether this advantage stems primarily from regulatory enforcement or economies of scale is crucial. If regulatory pressure has been the driving force, similar oversight should be extended to other sectors where data sensitivity and potential spillover effects pose systemic risks. Conversely, if economies of scale are the primary determinant, policymakers should design mechanisms that facilitate collaborative cybersecurity solutions and resource sharing among smaller firms and sectors. Moreover, the findings suggest that the energy sector—as a provider of critical infrastructure—may warrant greater regulatory oversight and enhanced technical support, given its exposure to cyber threats and a relatively moderate level of cybersecurity performance, which could lead to significant societal vulnerabilities. The results presented in Table 8 reveal several robust and statistically significant relationships between firm-level characteristics and the likelihood of achieving an advanced level of cybersecurity performance. Although the coefficients are modest in magnitude, their signs are consistently negative across model specifications.

Firm size, measured by the number of employees (*Employees*), is negatively associated with cybersecurity performance. The coefficient for *Employees* is consistently negative and significant, reinforcing the notion that firm size is inversely related to cybersecurity effectiveness. Despite the higher cyber-related losses typically observed among large companies (Aldasoro et al., 2020), our findings indicate that these firms also tend to underperform in terms of cybersecurity management relative to smaller firms. This suggests that greater organizational complexity and coordination costs may hinder the effective implementation of cybersecurity measures.

This finding carries important implications for both investors and managers. Investors often associate firm size with lower overall risk; however, our results provide novel evidence that investing in larger companies may actually entail greater exposure to cyber risk, which may not align with low-risk investment strategies. For managers of large corporations, the results highlight the disadvantages of organizational inertia. Although larger firms face heightened exposure due to their visibility and extensive use of IT systems (Dinkova et al., 2023), their structural rigidity may limit their capacity to adapt

to the increasingly dynamic cyber threat environment. Managers should therefore seek ways to enhance organizational agility by continuously updating systems, routines, and response mechanisms to strengthen cyber resilience.

From a policy perspective, these findings underscore the need for targeted initiatives aimed at improving cybersecurity performance among large firms. Given their systemic importance, cyberattacks in this segment can produce disproportionate, economy-wide consequences. Policymakers should therefore design incentives or regulatory mechanisms that promote greater cybersecurity preparedness and resilience among large organizations.

The inclusion of quadratic terms allows for potential nonlinearities in the relationship between financial characteristics and cybersecurity performance. However, for the variable leverage, the implied turning point lies at the extreme upper bound of the empirically observed data range (see Figure A1 in the Appendix). As a result, within the support of the data, the marginal effects of leverage on the probability of attaining advanced cybersecurity performance remain monotonic. Specifically, increases in financial leverage are consistently associated with a lower likelihood of achieving advanced cybersecurity performance across the vast majority of firms in the sample. Accordingly, the quadratic specification should not be interpreted as reflecting a substantively meaningful threshold or reversal in the effect of leverage, but rather as a flexible functional form that confirms the robustness of the negative marginal effects within the relevant range of observations.

Financial leverage exhibits a consistently negative and statistically significant association across all model specifications, indicating that firms with higher leverage are less likely to achieve advanced levels of cybersecurity performance. One plausible explanation is that equity holders may be reluctant to invest in projects where the benefits of improved risk management would accrue primarily to debt holders. This finding may also indicate that companies with a higher tolerance for financial risk are inclined to take on more operational risk associated with cyber events. It aligns with the leverage ratchet effect, as potential losses from cyber risks may prompt a further increase in the level of financial leverage in favour of shareholders. It is also possible that financial leverage reduces firms' financial flexibility, limiting the resources available for non-core investments such as cybersecurity enhancement. Resource constraints, therefore, may drive the lower likelihood of achieving advanced cybersecurity performance among leveraged firms. This finding serves as a crucial alert for corporate stakeholders, indicating that an easily observable proxy for risk (leverage) can signify a company's exposure to additional, less visible risks. Importantly, this finding potentially indicates a moral hazard problem, as there is an information asymmetry concerning cybersecurity performance between companies and their external stakeholders.

Profitability (ROE) also displays a strong negative relationship with cybersecurity performance. However, the plots (Figure A1 in the Appendix) reveal a clear nonlinear pattern. At low to moderate ROE levels, higher profitability is associated with a greater likelihood of advanced cybersecurity performance, suggesting that some degree of financial slack may support investments in cybersecurity capabilities. However, beyond a certain ROE threshold, further increases in profitability are associated with a declining probability of advanced cybersecurity performance. This downward slope at higher ROE levels implies that highly profitable firms either become complacent regarding cyber risk mitigation or prioritize short-term financial gains over long-term resilience investments. This suggests that high profitability, rather than being treated as a source of funding for cybersecurity measures, is associated with a higher cyber risk tolerance among highly profitable corporations across regions and sectors. This finding appears to confirm that companies with greater slack resources are more inclined to take on risks, as any resulting consequences can be readily absorbed by an abundance of resources (Moses, 1992). Another explanation is that some companies are highly focused on financial performance and may be willing to reduce or postpone cybersecurity investments to lower costs and thereby increase profitability. This finding carries important implications for shareholders, as it highlights a potential trade-off between their interests, such as receiving dividends and reinvesting profits, and utilizing profitability to offset any cyber losses that may occur. Thus, shareholders should be aware of the nonlinear relation between ROE and cybersecurity. Our result also aligns with studies indicating that decision-makers achieving higher financial performance tend to exhibit greater risk-taking behavior (Puetz & Ruenzi, 2011; O'Connell & Teo, 2009). Finally, the enhanced availability of affordable cybersecurity solutions could potentially reverse the relationship between Return on Equity (ROE) and cybersecurity performance.

In addition, we estimate binary logit models separately for five industry subsamples (Education, Energy, Financial, Healthcare, and "Other industries"), with **advanced cybersecurity performance** as the dependent variable. The results (Table 10) reveal substantial **heterogeneity across industries**, indicating that the correlates of cybersecurity performance are strongly sector-specific.

Table 10. Results from industry-specific binary logistic regressions

Variable	Education	Energy	Financial	Healthcare	Other
Leverage	-2.959***	0.002	-0.010*	-0.004*	-0.003
	(0.167)	(0.009)	(0.006)	(0.002)	(0.002)
Leverage²	0.031***	-0.00001	0.00005	0.00001	-0.00000
	(0.002)	(0.00004)	(0.00003)	(0.00002)	(0.00001)
ROE	-3.065***	-0.115**	-0.009	-0.008***	-0.007**
	(0.168)	(0.054)	(0.009)	(0.003)	(0.003)
ROE²	-0.011***	0.001**	0.0002	-0.00003**	0.00000
	(0.001)	(0.001)	(0.0002)	(0.00001)	(0.00002)
Employees	-0.051***	-0.0001	-0.00001	-0.0001	-0.00001*
	(0.002)	(0.0001)	(0.00002)	(0.00003)	(0.00001)
RegionChina			-15.340***	-1.007	-2.436***
			(1.351)	(0.800)	(0.742)
RegionEastEU		-14.933***		-0.341	-0.721*
		(1.450)		(0.341)	(0.414)
RegionNorthEU	-276.516***		-0.148	-0.629	-0.653
	(15.890)		(0.826)	(1.059)	(0.652)
RegionSouthEU		-0.138	-0.868	-1.903*	-1.007**
		(1.421)	(1.181)	(1.113)	(0.449)
RegionWestEU	-448.893***	18.224***	1.306*	-0.644	-0.193
	(23.659)	(1.194)	(0.764)	(0.491)	(0.272)
Constant	-263.851***	1.533	-0.366	-0.041	-0.246
	(12.587)	(1.137)	(0.615)	(0.235)	(0.171)
Observations	13	63	76	459	600
Log Likelihood	-0.000	-35.521	-44.637	-277.023	-351.849
Akaike Information Criterion (AIC)	16.000	89.043	109.274	576.045	725.698
McFadden Pseudo R^2	1.000	0.168	0.149	0.111	0.070
Adjusted McFadden Pseudo R^2	0.076	-0.043	-0.042	0.076	0.041

Note: Robust standard errors (HC1) are reported in parentheses.
Significance levels: $p < 0.1$, $p < 0.05$, $p < 0.01$.

Importantly, the results for subsamples show that regional coefficients vary strongly across sectors, underscoring the importance of industry–region interactions. In the Financial sector, firms headquartered in China are significantly less likely to exhibit advanced cybersecurity performance compared to U.S.-based financial firms. No statistically significant differences are observed between U.S. firms and those located in European regions, suggesting that regulatory and supervisory convergence in Financial sector may limit cross-regional variation within this sector. This suggests that the financial sector in China is more vulnerable to cyber threats than financial sector companies in the United States and Europe.

In the Energy sector, firms headquartered in Eastern Europe exhibit significantly lower cybersecurity performance than U.S. firms, whereas firms in Western Europe show significantly higher performance. This contrast highlights the uneven institutional and regulatory environments affecting cybersecurity preparedness within the same high-risk industry.

The Education sector shows extremely large and negative coefficients for European regions; however, given the very small sample size in this subsample (N=13), these estimates should be interpreted with caution.

Across most sectors, financial leverage is negatively associated with advanced cybersecurity performance. This relationship is particularly strong in the Education, Financial, and Healthcare sectors. No significant effect of financial leverage was found in Energy, suggesting that cybersecurity in Energy sector is a priority regardless of distribution of benefits between shareholders and debt providers.

Similarly, profitability (ROE) is negatively related to cybersecurity performance across all sectors, except the Financial sector, where higher profitability is correlated with improved cybersecurity performance.

Firm size, measured by the number of employees, shows a negative, statistically significant association with cybersecurity performance in Education and in the residual category "Other industries", whereas it is insignificant in Energy, Financial, and Healthcare. Given the small size of the Education subsample and the marginal significance of the coefficient for the "Other industries" category, the subsample analysis casts doubt on the robustness of the correlation between scale-related complexity and cybersecurity performance.

In addition, we conducted robustness checks by excluding U.S. firms from the sample and re-estimated three models using only non-U.S. companies. These results are now reported in Table A6 in the Appendix. The non-U.S. subsample analysis shows that, relative to firms headquartered in China, companies in Northern and Western Europe are significantly more likely to exhibit advanced cybersecurity performance, whereas differences in Eastern and Southern Europe are not statistically significant. Consistent with the full-sample results, higher ROE is associated with lower cybersecurity performance, whereas leverage and firm size do not exhibit robust effects within the non-U.S. subsample.

CONCLUSION

This study investigates patterns of cybersecurity performance across organizations, with a focus on institutional- and organizational-level factors that differentiate them. Using binary logistic regression, we analyzed a sample of 1,211 companies from the USA, Europe, and China in 2022.

Firms in China are significantly less likely to achieve an advanced level of cybersecurity performance than those in the United States. Within Europe, firms in Southern and Northern Europe also exhibit a substantially lower probability of achieving advanced cybersecurity performance than U.S. firms. Cybersecurity performance in Western Europe is broadly comparable to that observed in the United States. Overall, the non-U.S. robustness checks confirm that regional heterogeneity in cybersecurity performance persists beyond comparisons with U.S. firms, particularly highlighting the stronger performance of Northern and Western European companies relative to China. Next, we demonstrate that companies operating in the Financial and Healthcare sectors are significantly more likely to exhibit advanced cybersecurity performance than companies in the "Other industries" category, which are deemed less prepared to manage cyber risks. Consequently, our results highlight unequal progression and robustness of cybersecurity norms and regulations across sectors, including vulnerable sectors, and significant differences in sector exposure to cybersecurity.

Our findings reveal previously unidentified correlations between organizational factors and cybersecurity performance. Specifically, companies with higher Debt-to-Equity ratios exhibit lower cybersecurity performance. In addition, at low to moderate ROE levels, increases in profitability are associated with an improved cybersecurity performance, however, beyond a certain ROE threshold, further increases in profitability are associated with a declining probability of advanced cybersecurity performance. Overall, these findings suggest that businesses adjust their cybersecurity management to align with their overall risk tolerance, which is influenced by available resources and/or shareholders' risk preferences. Building on these results, we underscore the trade-offs between shareholder returns and the necessity to allocate resources for potential losses. Additionally, we draw attention to the potential moral hazard issue stemming from diminished cybersecurity performance among leveraged companies.

The subsample analyses reveal substantial heterogeneity across industries, highlighting the importance of industry–region interactions in explaining cybersecurity performance. Regional effects vary markedly by sector. Importantly, in finance, firms headquartered in China exhibit significantly weaker cybersecurity performance than U.S.-based firms, while no significant differences are observed between U.S. and European financial firms. Across most sectors, higher financial leverage is associated with lower cybersecurity performance; this relationship is not observed in energy. Profitability is generally negatively related to cybersecurity performance, except in the financial sector, where higher profitability is associated with stronger cybersecurity outcomes. Finally, firm size shows limited and inconsistent effects across subsamples, casting doubt on the robustness of a general relationship between scale-related complexity and cybersecurity performance.

Overall, our results support the identification of vulnerable groups using information easily accessible to managers, policymakers, and investors. Our models do not fully explain the variability in cybersecurity performance because numerous hidden factors (e.g., psychological propensities of decision-makers, complex network relationships, or organizational and governance deficiencies) can significantly contribute to the level of cybersecurity performance. However, these potential factors – although conceivably informative - cannot be directly observed by stakeholders.

The study carries both theoretical and practical implications. The primary theoretical implication is the establishment of the crucial role of country-level and industry-level institutions in shaping corporate cybersecurity performance, thereby supporting the notion that cyber risk management is institutionally anchored. Prior studies on cyber risk and cybersecurity have largely overlooked the institutional perspective. Our results highlight institutional theory as a promising approach for further investigating cybersecurity disparities across organizations. The second theoretical implication stems from the confirmation of all three hypotheses related to organizational factors. This confirms our assertion that cybersecurity practices are better understood through a risk management perspective rather than an investment decision perspective.

Our study holds significant practical implications for investors, managers, and policymakers alike. By elucidating the institutional and organizational factors that differentiate organizations' cybersecurity performance, we help investors understand variations in cyber risk exposure across entities. This understanding is crucial for constructing and managing global, multi-sector investment portfolios. Additionally, our findings can assist managers in benchmarking their organization's cybersecurity performance and identifying efficient cybersecurity practices beyond their sector.

The implications for policymakers are particularly noteworthy, given the substantial negative externalities associated with cyber risk. We highlight the superiority of Chinese and European norms over American ones, signaling to policymakers worldwide that, despite the USA's leading position in the tech sector and status as the most advanced economy, more effective cybersecurity solutions may be found in China or Europe. We alert policymakers and regulatory authorities focused on the education sector to the urgent need for intervention to ensure basic cyber safety. Based on our findings, regulators and policymakers in education should consider implementing measures already in place in healthcare and finance sectors.

Our study is subject to several limitations. Firstly, due to data constraints, we restrict our investigation to regions comprising China, Europe, and the USA. Consequently, there may be country-level solutions that surpass those identified in our study yet remain unexplored. Secondly, we did not have access to the continuous variable representing cybersecurity performance. As a result, our findings may lack some nuance that could be captured through more granular data. Nevertheless, we believe the results remain informative, as the study adopts the perspective of external stakeholders for whom categorical assessments are often more intuitive and actionable than continuous numerical scales. Thirdly, we do not incorporate human factors into our analysis of cybersecurity management. Given their recognized significance (Henshel et al. 2015; Corradini & Nardelli, 2019), our depiction of organizational-level factors in cybersecurity is thus incomplete. Fourthly: sectoral effects—particularly for Healthcare firms—may partly reflect sample composition and differences in the baseline category rather than purely underlying sectoral characteristics. Lastly, our study covers only a single year due to data availability, thereby failing to capture longitudinal patterns in the evolution of cybersecurity performance across diverse organizations.

We advocate that future research adopt an integrated behavioral and risk-management perspective to better understand the organizational-level factors that influence cybersecurity performance. We encourage researchers to disentangle cybersecurity performance by distinguishing between human resource preparedness, technical solutions, and procedural mechanisms to identify which components contribute most significantly to overall cybersecurity effectiveness. Future studies should also examine how cyber risk clusters with other forms of organizational risk, such as financial or operational risk, reveal potential interdependencies and compounding effects.

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Appendix

Table A1. Classification of countries by region

Region	Countries
North Europe	Denmark, Finland, Ireland, Sweden
South Europe	Cyprus, Greece, Malta, Italy, Portugal, Spain
West Europe	Austria, Belgium, France, Germany, Luxembourg, Netherlands
East Europe	Bulgaria, Croatia, Hungary, Poland, Romania, Slovenia

Table A2. Raw-data percentiles used to define winsorization thresholds

Variable	Percentile	Value
Leverage	5^{th}	0.85
	95^{th}	320.28
ROE	2.5^{th}	-309.16
	97.5^{th}	73.30
Employees	2.5^{th}	7.00
	97.5^{th}	73,650.00

Table A3. Average Marginal Effects (AMEs) – All models

Model	Variable	AME	Std. Error	z	p-value
1	Leverage	-0.002	0.000	-7.416	0.000
	$Leverage^2$	0.000	0.000	3.737	0.000
2	Leverage	-0.001	0.000	-3.435	0.001
	$Leverage^2$	0.000	0.000	1.225	0.220
	Employees	0.000	0.000	-3.813	0.000
	ROE	-0.002	0.000	-6.475	0.000
	ROE^2	0.000	0.000	-3.318	0.001
3	IndustryEducation	0.171	0.124	1.378	0.168
	IndustryEnergy	0.106	0.062	1.705	0.088
	IndustryFinancial	0.165	0.055	2.983	0.003
	IndustryHealthcare	0.067	0.035	1.888	0.059
	Leverage	-0.001	0.000	-3.336	0.001
	$Leverage^2$	0.000	0.000	1.005	0.315
	Employees	0.000	0.000	-3.551	0.000
	RegionChina	-0.344	0.056	-6.118	0.000

Model	Variable	AME	Std. Error	z	p-value
	RegionEastEU	-0.171	0.113	-1.512	0.131
	RegionNorthEU	-0.099	0.050	-1.978	0.048
	RegionSouthEU	-0.231	0.062	-3.696	0.000
	RegionWestEU	-0.033	0.045	-0.733	0.463
	ROE	-0.002	0.000	-4.669	0.000
	ROE^2	0.000	0.000	-2.829	0.005

Table A4. Robustness check: Comparison of standard logit and Firth penalized estimates – Model 3

Model	Variable	Odds Ratio	95% CI Lower	95% CI Upper	p-value
Penalized logit (Firth)	(Intercept)	0.782	0.603	1.013	0.063
Standard logit (BL)	(Intercept)	0.780	0.600	1.013	0.063
Penalized logit (Firth)	IndustryEducation	2.138	0.718	6.902	0.172
Standard logit (BL)	IndustryEducation	2.224	0.716	7.597	0.174
Penalized logit (Firth)	IndustryEnergy	1.641	0.927	2.876	0.088
Standard logit (BL)	IndustryEnergy	1.642	0.923	2.895	0.088
Penalized logit (Firth)	IndustryFinancial	2.139	1.290	3.567	0.003
Standard logit (BL)	IndustryFinancial	2.162	1.297	3.624	0.003
Penalized logit (Firth)	IndustryHealthcare	1.369	0.997	1.877	0.052
Standard logit (BL)	IndustryHealthcare	1.368	0.994	1.879	0.054
Penalized logit (Firth)	Leverage	0.996	0.993	0.998	0.001
Standard logit (BL)	Leverage	0.996	0.993	0.998	0.001
Penalized logit (Firth)	$Leverage^2$	1.000	1.000	1.000	0.305
Standard logit (BL)	$Leverage^2$	1.000	1.000	1.000	0.316
Penalized logit (Firth)	Employees	1.000	1.000	1.000	0.000
Standard logit (BL)	Employees	1.000	1.000	1.000	0.000
Penalized logit (Firth)	ROE	0.992	0.989	0.996	0.000
Standard logit (BL)	ROE	0.992	0.989	0.996	0.000
Penalized logit (Firth)	ROE^2	1.000	1.000	1.000	0.005
Standard logit (BL)	ROE^2	1.000	1.000	1.000	0.005
Penalized logit (Firth)	RegionChina	0.156	0.056	0.359	0.000
Standard logit (BL)	RegionChina	0.143	0.049	0.339	0.000
Penalized logit (Firth)	RegionEastEU	0.481	0.143	1.338	0.167
Standard logit (BL)	RegionEastEU	0.443	0.122	1.286	0.163
Penalized logit (Firth)	RegionNorthEU	0.637	0.399	1.008	0.054
Standard logit (BL)	RegionNorthEU	0.632	0.394	1.004	0.054
Penalized logit (Firth)	RegionSouthEU	0.331	0.159	0.639	0.001
Standard logit (BL)	RegionSouthEU	0.319	0.151	0.622	0.001
Penalized logit (Firth)	RegionWestEU	0.862	0.574	1.287	0.469
Standard logit (BL)	RegionWestEU	0.859	0.571	1.287	0.464

Figure A1. Predicted-probability plots – Model 3

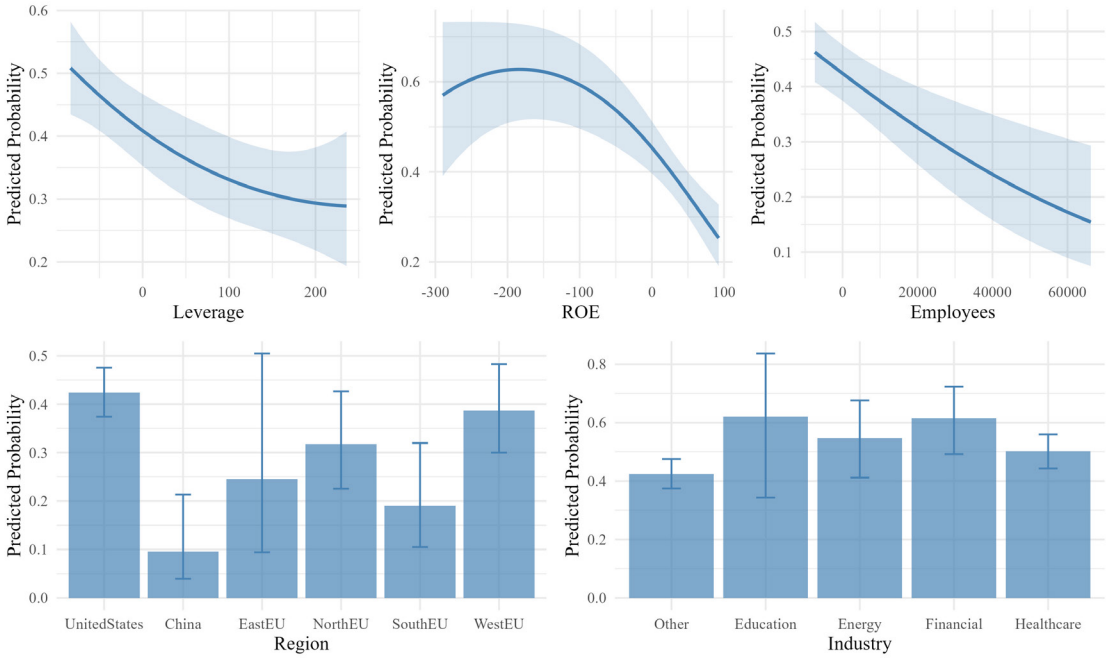

Table A5. Generalized Variance Inflation Factors (GVIFs) – Model 3

Variable	GVIF	Degrees of freedom (Df)	$GVIF^{1/(2*Df)}$
ROE	4.238	1	2.059
ROE^2	3.471	1	1.863
Leverage	2.947	1	1.717
$Leverage^2$	2.611	1	1.616
Employees	1.192	1	1.092
Industry	1.678	4	1.067
Region	1.122	5	1.012

Table A6. Results from the binary logistic regressions excluding U.S. firms

Variable	(1)	(2)	(3)
Leverage	-0.002	-0.001	-0.001
	(0.002)	(0.002)	(0.003)
$Leverage^2$	0.00001	0.00000	0.00001
	(0.00002)	(0.00002)	(0.00002)
ROE		-0.009**	-0.007*
		(0.004)	(0.004)
ROE^2		0.00003	-0.00003
		(0.00003)	(0.00003)
Employees		-0.00000	-0.00000
		(0.00001)	(0.00001)
RegionEastEU			0.898
			(0.804)
RegionNorthEU			1.267**
			(0.570)
RegionSouthEU			0.621
			(0.638)

Variable	(1)	(2)	(3)
RegionWestEU			1.597***
			(0.534)
IndustryEducation			1.864
			(1.267)
IndustryEnergy			0.620
			(0.856)
IndustryFinancial			1.313***
			(0.387)
IndustryHealthcare			0.315
			(0.327)
Constant	-0.810***	-0.665***	-2.135***
	(0.159)	(0.208)	(0.538)
Observations	337	337	337
Log Likelihood	-212.353	-204.326	-187.433
Akaike Information Criterion (AIC)	430.707	420.652	402.867
McFadden Pseudo R^2	0.002	0.040	0.119
Adjusted McFadden Pseudo R^2	-0.012	0.012	0.054

Biographical notes

Anna Doś (Ph.D., Hab.) is an Associate Professor at the Kraków University of Economics, within the Department of Financial Markets. Her research interests revolve around finance for sustainable development, with a particular emphasis on incorporating ESG factors into risk and profitability assessments in investments. Additionally, she explores strategies to enhance enterprise value aligned with sustainable development goals. Anna Doś has undertaken research internships at Sacred Heart University in Milan and the University of Modena and Reggio Emilia. Furthermore, she has collaborated on a scientific project with John Moores University in Liverpool.

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Anna Doś: Conceptualization, Formal Analysis, Literature Investigation, Data Curation, Resources, Writing – Original Draft, Writing – Review & Editing. **Elisa Flori:** Conceptualization, Methodology, Formal Analysis, Validation, Data

Curation, Visualization, Literature Investigation, Writing – Review & Editing, Supervision. **Piotr Łasak:** Literature Investigation, Data Curation, Writing – Original Draft, Writing – Review & Editing. **Francesco Pattarin**: Conceptualization, Methodology, Formal Analysis, Data Curation, Writing – Original Draft.

Conflicts of interest

The authors declare no competing interests. Piotr Łasak serves as an Associate Editor of JEMI and was not involved in the peer review process, editorial handling, or decision-making for this manuscript.

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