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The impact of Generative Artificial Intelligence on the strategic practices of small and medium-sized enterprises: evidence from Portuguese SMEs

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Resumo

A Inteligência Artificial Generativa (GenAI) influencia crescentemente as atividades organizacionais, apoiando o processamento de informação, criação de conteúdo, tomada de decisão e inovação. À medida que estas ferramentas se tornam mais acessíveis, as pequenas e médias empresas (PMEs) enfrentam tanto oportunidades para melhorar a eficiência e análise estratégica, como desafios de integração, fiabilidade e adoção responsável.

Esta tese examina o impacto estratégico percebido da inteligência artificial generativa neste contexto. Com base na Visão Baseada em Recursos e na teoria das Capacidades Dinâmicas, não se assume que a GenAI crie valor estratégico automaticamente. Pelo contrário, a sua relevância deverá depender da forma como é usada e integrada nas organizações e apoiada pela gestão.

Metodologicamente, o estudo adota um desenho predominantemente quantitativo e transversal, baseado num questionário online estruturado, complementado por uma análise exploratória das respostas abertas. A análise empírica incide sobre PMEs portuguesas que reportaram utilizar GenAI, resultando numa amostra final de 84 respostas válidas após critérios de elegibilidade e qualidade. A análise inclui estatística descritiva, fiabilidade, correlações, regressões OLS, diagnósticos, robustez, mediação e análises exploratórias.

Os resultados mostram que a GenAI é utilizada entre as PME respondentes, sobretudo para fins operacionais e de eficiência. Contudo, a integração estratégica permanece menos desenvolvida, sugerindo que muitas empresas ainda se encontram no processo de incorporar esta ferramenta em rotinas de gestão e práticas estratégicas. As regressões indicam que a utilização estratégica da GenAI, a sua integração e o apoio da gestão de topo são preditores positivos e significativos do impacto estratégico percebido. As capacidades dinâmicas não surgiram como preditor direto ou mediador, embora análises complementares sugiram associação com inovação. No geral, os resultados sugerem que o valor estratégico da GenAI nas PMEs depende menos da adoção ou frequência de utilização, isoladamente, e mais da aplicação estratégica, integração organizacional e apoio da gestão.

Palavras-chave: Inteligência Artificial Generativa; Pequenas e Médias Empresas; Gestão Estratégica; Visão Baseada em Recursos; Capacidades Dinâmicas; Impacto Estratégico Percebido

Abstract

Generative Artificial Intelligence (GenAI) is increasingly influencing organizational activities by supporting information processing, content generation, knowledge work, decision-making and innovation-related tasks. As these tools become more accessible, small and medium-sized enterprises face both opportunities to improve efficiency and strategic analysis and challenges related to integration, managerial use, reliability and responsible adoption.

This thesis examines the perceived strategic impact of GenAI in this context. Grounded in the Resource-Based View and Dynamic Capabilities perspectives, GenAI is not assumed to create strategic value automatically. Rather, its potential strategic relevance is expected to depend on how it is used and integrated into organizational routines and supported by managerial action.

Methodologically, the study adopts a predominantly quantitative and cross-sectional research design, based on a structured online questionnaire and complemented by an exploratory qualitative analysis of open-ended responses. The empirical analysis focuses on Portuguese SMEs that reported using GenAI, resulting in a final sample of 84 valid responses after eligibility and response-quality screening. The analysis includes descriptive statistics, reliability assessment, correlation analysis, OLS regression models, diagnostic and robustness tests, mediation analysis and complementary exploratory analyses.

The results show that GenAI is already used extensively among responding SMEs for operational and efficiency-oriented purposes. However, strategic integration remains less developed, suggesting that many firms are still in the process of embedding this tool into managerial routines and strategic practices. Regression results indicate that strategic use of GenAI, GenAI integration and Top Management Support are positive and statistically significant predictors of perceived Strategic Impact. By contrast, Dynamic Capabilities did not emerge as a significant direct predictor or mediator, although complementary analyses suggest their association with broader Innovation Capability. Overall, the findings suggest that GenAI's strategic value in SMEs depends less on adoption or frequent use alone and more on its strategic application, organizational integration and managerial support.

Keywords: Generative Artificial Intelligence; Small and Medium-Sized Enterprises; Strategic Management; Resource-Based View; Dynamic Capabilities; Perceived Strategic Impact

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$PSI_i = \beta_0 + \beta_1 SU_i + \beta_2 SI_i + \beta_3 TMS_i + \beta_4 DC_i + \gamma X_i + \varepsilon_i$ (3.1) 19

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1. Introduction

1.1 Context and Motivation

Generative Artificial Intelligence (GenAI) has become one of the most visible developments in artificial intelligence and is increasingly influencing organizational activities. By supporting content creation, information processing, knowledge work and decision-making, GenAI may improve the speed and quality of certain knowledge-intensive tasks while contributing to innovation-driven processes (Mariani et al., 2023; Noy & Zhang, 2023; Brynjolfsson et al., 2025).

These developments are relevant not only because GenAI can support operational efficiency, but because it may influence managerial and strategic practices. For instance, in organizational contexts, GenAI can assist with activities such as analysing information, generating alternatives, supporting decision-making, exploring market trends and contributing to innovation-related processes. As a result, the strategic relevance of GenAI may depend on how it is used, integrated into organizational routines and combined with existing resources, knowledge and managerial capabilities.

This issue is of particular importance in the context of SMEs, which play a central role in economic activity, employment and innovation, but often differ from larger firms in terms of resources, structures and strategic processes. For instance, they may face financial and managerial constraints, limited access to specialized technological expertise and lower levels of formalized strategic planning, while also benefiting from flexibility, shorter communication channels and more centralized decision-making (Julien, 1993; Levy & Powell, 2004; Thong, 1999).

The motivation for this dissertation therefore lies in understanding how Portuguese SMEs are using GenAI and whether this use is associated with perceived strategic value.

1.2 Problem Statement

Despite the growing relevance of GenAI in organizational contexts, its strategic implications at the firm level remain insufficiently understood. Existing research has shown that AI and GenAI can support productivity, knowledge-intensive work and innovation-related activities, particularly by improving the speed, quality and efficiency of specific tasks (Noy & Zhang, 2023; Brynjolfsson et al., 2025; Mariani et al., 2023). However, much of this evidence remains focused on task-level outcomes, technical capabilities or broad innovation processes, rather than on how GenAI is incorporated into strategic practices within firms.

This distinction is important because the use of GenAI does not necessarily imply strategic impact. For instance, firms may rely on it for routine activities, like drafting content, summarizing information or supporting everyday productivity, without integrating it into strategic decision-making, planning, market analysis, innovation processes or organizational adaptation. Therefore, the central problem addressed in this thesis is not simply whether SMEs use GenAI, but whether and how this use becomes strategically meaningful.

This problem is particularly relevant in the context of Portuguese SMEs, where accessible GenAI tools may create opportunities for experimentation, but where limited resources, uneven digital maturity and less formalized managerial processes may constrain deeper organizational integration. As a result, there remains limited empirical evidence on whether GenAI use and integration are associated with perceived strategic impact in this context.

Accordingly, this study addresses the following research problem: while GenAI is increasingly available to SMEs, it remains unclear whether it is being used mainly as an operational efficiency tool or whether it is becoming integrated into strategic practices capable of impacting decision-making, innovation, responsiveness and competitive positioning.

1.3 Research Objectives and Research Questions

In order to address this main objective, the study pursues the following specific objectives: 1) To describe how Portuguese SMEs are currently using GenAI in organizational contexts; 2) To distinguish between operational use, strategic use and organizational integration of GenAI; 3) To examine whether the strategic use of GenAI is associated with perceived strategic impact; 4) To assess whether GenAI integration into organizational routines and managerial processes is associated with perceived strategic impact; 5) To analyse the role of top management support in explaining perceived strategic impact; 6) To examine whether dynamic capabilities help explain the relationship between GenAI-related practices and perceived strategic impact; 7) To explore complementary dimensions related to GenAI use, including perceived opportunities and risks, innovation capability, responsible AI concerns, explainability, sustainability and future orientation. Based on these objectives, the dissertation is guided by the following research questions:

i. RQ1: How are Portuguese SMEs currently using GenAI, and to what extent is this use operational or strategic in nature?
ii. RQ2: Is the strategic use of GenAI associated with perceived strategic impact in Portuguese SMEs?

iii. RQ3: Is the integration of GenAI into organizational routines and managerial processes associated with perceived strategic impact?
iv. RQ4: What role does top management support play in explaining the perceived strategic impact of GenAI?
v. RQ5: Do dynamic capabilities help explain the relationship between GenAI-related practices and perceived strategic impact?
vi. RQ6: How do Portuguese SMEs perceive the main opportunities and risks associated with GenAI use, including responsible and future-oriented dimensions such as ethics, explainability, sustainability and future investment intentions?

1.4 Thesis Structure

The thesis is organized into six chapters. Following the introduction, Chapter 2 presents the literature review and theoretical framework of the dissertation, mainly discussing GenAI in organizational contexts, the characteristics of SMEs, the Resource-Based View and Dynamic Capabilities perspectives, and the research gap that supports the conceptual model.

Chapter 3 describes the methodology adopted in the study. Concretely, it presents the research design, the target population and sampling strategy, the data collection method and the main variables and constructs used in the empirical analysis. It also explains the data preparation and screening procedures, the quantitative and qualitative analysis techniques, the reliability and validity procedures, and the ethical considerations followed throughout the research process. Following Chapter 3, Chapter 4 reports the empirical results, starting by presenting the data screening process and the final analytical sample, followed by the sample description and descriptive statistics of the main constructs. The chapter then presents the reliability analysis, correlation analysis, multicollinearity assessment, regression models, diagnostic and robustness checks, mediation analysis and complementary exploratory analyses.

Chapter 5 discusses the main findings in light of the literature and theoretical framework, focusing on the distinction between operational and strategic GenAI use, the roles of integration and top management support, dynamic capabilities, responsible use and the practical implications for SMEs.

Finally, Chapter 6 concludes the thesis by summarizing the main contributions of the study, acknowledging its limitations and suggesting possible directions for future research.

2. Literature Review

This chapter reviews the main theoretical and empirical contributions relevant to the study of generative artificial intelligence in Portuguese SMEs, being organized into seven sections. The first introduces the concept of GenAI, discussing its technical foundations, organizational applications and main limitations. The second turns to the specific characteristics of small and medium-sized enterprises and their strategic management practices, setting out why SMEs constitute a particularly relevant context for studying the adoption and use of emerging digital technologies. The third lays out the thesis' theoretical foundations, centred on the Resource-Based View and Dynamic Capabilities theory as complementary lenses for understanding how technologies may generate strategic value.

The chapter goes on to discuss how GenAI can contribute to strategic value creation, particularly through decision support, innovation-related activities and organizational adaptation, before focusing on the benefits and risks of GenAI adoption as well as ethical and responsible use. It closes by identifying the research gap that the study addresses and setting out the conceptual logic that guides the empirical analysis.

2.1 Generative Artificial Intelligence in Organizations

Generative Artificial Intelligence (GenAI) refers to a class of machine learning systems designed to produce new, original content across various modalities, namely text, images, and other complex data, by learning statistical patterns from large datasets. These systems are distinguished from traditional AI approaches by their generative capabilities, which enable them to synthesize new outputs rather than simply classifying or predicting existing data structures (Sengar et al., 2025).

From a technical perspective, Generative AI is grounded in deep learning architectures which learn underlying data distributions to subsequently produce statistically consistent outputs. Key approaches include transformer-based models, whose self-attention mechanisms excel at capturing sequential dependencies and contextual relationships in complex data (Sengar et al., 2025; Vaswani et al., 2017).

Recent advances in GenAI have been driven by developments in deep learning methodologies (Mienye & Swart, 2024), increased computational capacity with its respective downside in energy consumption (Strubell et al., 2019) and the availability of large and diverse datasets. In particular, transformer-based models have played a central role in the development of contemporary language-based and multimodal GenAI systems while other

generative architectures, such as GANs and diffusion models, have contributed significantly to image synthesis and other forms of content generation (Zhang et al., 2025).

Beyond their technical foundations, GenAI systems are being increasingly applied to organizational activities such as content generation, information processing, knowledge-intensive work and innovation-related tasks. Moreover, emerging empirical evidence further indicates that these tools may augment productivity in certain forms of cognitive work (Brynjolfsson et al., 2025; Mariani et al., 2023; Noy & Zhang, 2023), providing the groundwork for understanding GenAI from a strategic management perspective. At the same time, the literature acknowledges important concerns related to reliability, bias and responsible deployment, issues discussed in greater detail in Section 2.5.

2.2 Small and Medium-Sized Enterprises and Strategic Management

Small and medium-sized enterprises (SMEs) constitute a major form of business organization in the European economy and play a crucial role in employment and value creation (Lagüera González et al., 2026). Beyond their economic weight, SMEs are likewise relevant in entrepreneurship and innovation research, which highlights the role of smaller firms and entrepreneurial activity in innovation, regional development and economic dynamism (Acs & Audretsch, 1990; Audretsch & Keilbach, 2004).

Despite their importance, SMEs differ from larger organizations in terms of structure, resource endowments and managerial processes. They typically face resource and financial constraints (Wiklund & Shepherd, 2005; Rosenbusch et al., 2011), limited managerial expertise and restricted access to specialized technological knowledge (Thong, 1999), although strategic orientation may mitigate these limitations (Wiklund & Shepherd, 2005; Aragón-Sánchez & Sánchez-Marín, 2005). These constraints may limit the extent to which SMEs can engage in formalized strategic planning or invest in technological innovation (Levy & Powell, 2004). At the same time, SMEs benefit from the flexibility, short communication channels and quicker decision-making process that their smaller more agile structure allows, which may enable them to respond quicker to environmental changes and emerging opportunities than larger firms (Julien, 1993; Levy & Powell, 2004).

Strategic management practices within SMEs also differ from those typically observed in larger organizations, given that their strategy is often less formal, more closely embedded in everyday managerial activity, and shaped by incremental decision-making, learning and adaptation over time (Mintzberg & Waters, 1985; Mintzberg, 1994). In addition, in

many cases, strategic direction is also strongly influenced by the owner-manager, whose personal vision and commitment shape organizational priorities and actions (Gibb & Scott, 1985). This is particularly relevant as managerial capabilities influence how resources are orchestrated and deployed within the organization (Andersén, 2021). At the same time, empirical evidence suggests that greater formalization of strategic planning may be associated with improved performance (Kraus et al., 2006).

These characteristics may facilitate faster action once the potential value of a technology is recognized, although the evidence for consistently greater experimentation and implementation speed remains more suggestive than conclusive (Levy & Powell, 1998; Ghobakhloo et al., 2011). In addition, Thong's model of information systems adoption in small businesses shows that decision-maker characteristics and perceived IS attributes are central determinants of adoption (Thong, 1999) and more broadly, studies on IT innovation adoption identify top management support as one of the most consistent predictors of technology endorsement and implementation (Jeyaraj et al., 2006). This reinforces the relevance of managerial support in SMEs, where owners, founders and senior managers concentrate technology-related decisions (Martin et al., 2016).

Consequently, understanding how SMEs integrate emerging technologies such as GenAI into their managerial and strategic practices, as well as the role played by top management, represents an important area of investigation.

2.3 Resource-Based View and Dynamic Capabilities as Theoretical Foundations

This study is grounded primarily in the Resource-Based View (RBV) and Dynamic Capabilities theory, two complementary perspectives within strategic management that are particularly suitable for understanding how firms derive value from emerging technologies. While several theoretical lenses have been used in prior research on digital technologies and artificial intelligence, including adoption-oriented frameworks, the present study focuses on the strategic implications of GenAI once it is already in use within firms. Consequently, theories concerned with resource development, organizational adaptation and value creation provide a more adequate analytical basis for this work.

The Resource-Based View explains firm performance in terms of internal resources and capabilities. Barney (1991) argues that resources can become sources of sustained competitive advantage when they are valuable, rare, imperfectly imitable and non-substitutable (VRIN). Later developments of this perspective further emphasize that firms must also be

organized in ways that allow them to exploit those resources effectively. Peteraf (1993) develops this logic further by identifying the conditions under which resources can generate superior performance, stressing that not all resources automatically lead to competitive advantage. More concretely, the author makes the economic mechanisms explicit, separates clearly product-market competition (ex post limits) from factor-market competition (ex-ante limits) and emphasises imperfect resource mobility and heterogeneous resources, which clarifies why some resources produce firm-level advantages.

This perspective is particularly pertinent for the study of digital technologies. Bharadwaj (2000), for example, applies RBV to information technology and argues that the strategic value of IT depends not merely on the possession of technological assets, but on the way firms develop and deploy IT capability in combination with organizational resources. His argument is consistent with earlier RBV-supported information systems research that suggests that IT does not usually generate sustained competitive advantage through technical resources alone but through complementary human, managerial and organizational resources which are harder to imitate (Mata et al., 1995). Moreover, it is also coherent with RBV evidence linking resource value and competitive advantage to performance outcomes (Newbert, 2008).

However, while RBV is useful for explaining where strategic value may come from, it is less explicit about how firms transform resources into adaptive advantage under dynamic or turbulent conditions. This is where the Dynamic Capabilities theory becomes particularly relevant. Teece et al. (1997) define dynamic capabilities as the firm's ability to integrate, build, and reconfigure internal and external competences in response to changing environments. Eisenhardt and Martin (2000) refine this argument by suggesting that dynamic capabilities are specific, identifiable organizational and strategic processes that help firms reconfigure resources and adapt in changing markets, such as product development, strategic decision-making, and resource reallocation. Teece (2007) later elaborates this perspective by emphasizing the micro foundations of dynamic capabilities, particularly the ability to sense opportunities and threats, seize opportunities, and reconfigure resources and routines. Firms that can systematically sense, seize and reconfigure are better at creating and protecting intangible assets that underpin superior returns over time.

Pavlou and El Sawy (2011) add to these contributions, aiming to conceptualize and operationalize dynamic capabilities as a set of concrete capabilities. Their paper offers a clear structural view, whereby dynamic capabilities are shown to reconfigure operational

capabilities, driving performance, as turbulence shapes these effects. This theory is therefore especially suitable for this study because the potential value of GenAI may lie not specifically in its technical functionality, but in its possible contribution to organizational adaptation. If GenAI supports firms in scanning the environment, identifying opportunities, structuring decisions, and redesigning processes, then its strategic relevance may be reflected in stronger sensing, seizing, and reconfiguring capabilities. In a nutshell, dynamic capabilities are often understood as influencing performance indirectly, by renewing the operational capabilities that produce efficient processes and effective new products.

Taken together, RBV and Dynamic Capabilities provide a coherent foundation for examining the strategic impact of Generative AI in SMEs. Concretely, RBV helps explain why technologies become strategically meaningful only when they are organized and combined with firm-specific resources (Barney, 1991; Bharadwaj, 2000), while Dynamic Capabilities theory explains how firms mobilize and reconfigure those resources in order to adapt and create value in changing environments (Teece et al., 1997; Teece, 2007). In this sense, the two perspectives are complementary: RBV addresses the potential source of value, whereas Dynamic Capabilities addresses the organizational processes through which that value is realized.

2.4 GenAI and Strategic Value Creation

Building upon RBV and dynamic capabilities literature, one area in which GenAI might contribute to strategic value is in managerial decision making, inasmuch as strategic decisions often require the collection and analysis of substantial information, the evaluation of multiple alternatives, and the interpretation of environmental conditions and market developments (Eisenhardt, 1989; Dean & Sharfman, 1996). Prior research suggests that AI systems may support these processes by improving information processing, pattern recognition and the evaluation of alternatives while requiring human judgement and contextual interpretation (Duan et al., 2019; Jarrahi, 2018; Shrestha et al., 2019). Concretely, recent evidence on GenAI indicates that it may contribute to strategic decision-making by supporting the evaluation of strategic alternatives (Doshi et al., 2025).

Even though much of the empirical GenAI evidence does not examine strategic decision-making directly, it suggests that GenAI can support forms of analysis, synthesis, problem structuring and alternative evaluation that are relevant to managerial work (Brynjolfsson et al., 2025; Noy & Zhang, 2023).

In addition to supporting decision-making, broader AI and innovation management research increasingly argues that the technology can affect innovation processes themselves. Cockburn et al. (2019) distinguish automation-oriented AI and AI as a method of invention, where tools such as deep learning and prediction algorithms become core instruments scientists and engineers use to discover patterns, generate hypotheses and design new products. They argue that this second role could have a larger long-run impact because it changes how innovation is done. Mariani et al. (2023), in their systematic review of AI in innovation research, highlight AI-enabled activities such as idea generation, experimentation and the recombination of knowledge as important ways through which AI supports innovation processes. What is more, Haefner et al. (2021) argue that AI reshapes innovation management by transforming information processing and research, enabling new forms of experimentation and reconfiguring key organizational processes involved in innovation. Together, these contributions provide a theoretical basis for the expectation that GenAI may support strategic value creation by accelerating ideation, broadening the search for alternatives and reducing the time and cognitive effort required for certain innovation-related activities.

Essentially, these contributions act as a cornerstone for examining whether the strategic use of GenAI is associated with perceived strategic outcomes and if GenAI-related practices are linked to broader innovation capability, an issue that is becoming increasingly relevant in emerging research on GenAI and innovation management (Mariani & Dwivedi, 2024).

2.5 Ethical and Responsible Use of Generative AI

The growing use of GenAI raises important ethical, regulatory and governance concerns, as their outputs may not always be reliable, unbiased or transparent. Prior research on AI ethics shows that principles like transparency, fairness, responsibility, privacy and non-maleficence have become centrepieces in the discussion of AI's trustworthiness. Furthermore, these principles require organizational mechanisms in order to be effectively translated into practice (Jobin et al., 2019; Mittelstadt, 2019).

Concretely, in the European context, these concerns have also become increasingly relevant from a regulatory perspective and the EU has reflected them in the EU Artificial Intelligence Act (European Parliament and Council of the European Union, 2024), establishing a harmonized legal framework for artificial intelligence in the European Union, following a risk-based approach and imposing strict requirements on AI systems which may

pose threats to health, safety and fundamental human rights. Although this thesis does not aim to assess legal compliance with the AI Act, the regulation reinforces the importance of issues like transparency, risk management, human oversight, data governance, robustness and accountability in the organisational use of AI.

One important concern relates to bias, discrimination and misinformation, as large language models are trained on extensive datasets that may unknowingly contain social biases, stereotypes or problematic representations, which can consequently be reproduced or amplified in generated outputs (Bender et al., 2021; Sheng et al., 2019). In addition, language generation systems may produce outputs that are fluent and convincing at first glance but are factually incorrect, a phenomenon commonly known in the literature as hallucinations (Ji et al., 2023). These risks are especially relevant when GenAI is used to support business analysis, strategic interpretation or decision-making, since AI-supported decision processes rely on information processing, alternative evaluation and human interpretation. Consequently, inaccurate or biased outputs may warp users' assessment of problems, option comparison processes and the way they justify decisions (Duan et al., 2019; Jarrahi, 2018; Shrestha et al., 2019).

Hence, these issues reinforce the importance and need of human oversight, explainability and responsible organizational use. GenAI systems should be understood as a tool whose outputs require interpretation, validation and contextual judgment by human users. In this sense, explainability can be understood as an important organizational requirement: Managers need to understand, question and justify the use of AI-generated outputs before incorporating them into their decisions. This is consistent with broader research arguing that responsible AI use cannot be achieved through abstract principles alone, but requires concrete practices, accountability mechanisms and critical human evaluation (Mittelstadt, 2019; Dwivedi et al., 2023). It is also consistent with the broader orientation of the AI Act, which emphasizes transparency and human oversight as important safeguards in the governance of AI systems.

Finally, as the development and training of large-scale deep learning models can involve substantial computational resources, energy consumption and financial costs, environmental and resource-related concerns also form part of the responsible AI debate, raising questions about sustainability and unequal access to advanced AI capabilities (Bender et al., 2021; Strubell et al., 2019). Although these concerns relate more directly to the development of large models than to the everyday use of GenAI tools by SMEs, they remain relevant

when discussing the broader societal implications of GenAI adoption.

Succinctly, these problems suggest that the assessment of GenAI's strategic use should include dimensions such as reliability, transparency, human oversight, ethical risk, regulatory awareness and sustainability.

2.6 Opportunities and Risks of GenAI Adoption in SMEs

The adoption of AI and GenAI in organizational contexts is commonly associated with both strategic opportunities and implementation challenges. From a technology adoption perspective, the perceived usefulness and performance benefits of a technology are central to its acceptance and use (Davis, 1989; Venkatesh et al., 2003). Concretely, in the case of GenAI, these benefits may include automation of routine tasks, productivity gains, support for information processing, content generation and decision-making support (Duan et al., 2019; Dwivedi et al., 2023).

Prior technology adoption research highlights the importance of perceived compatibility, ease of use and organizational readiness in shaping adoption and implementation outcomes (Moore & Benbasat, 1991; Oliveira & Martins, 2011). Within SMEs, implementation challenges may include limited technical expertise, lack of financial and skilled human resources, data availability and quality issues, integration difficulties and uncertainty regarding the business value of AI applications (Oldemeyer et al., 2025).

Beyond implementation barriers, SMEs also face the reliability, privacy, ethical and governance concerns reviewed in Section 2.5. Thus, GenAI's efficiency or innovation benefits should be seen in light of its managerial and organizational challenges. Particularly, the literature on human-AI collaboration indicates that the value of AI depends on how automation and human augmentation are balanced (Jarrahi, 2018; Raisch & Krakowski, 2021), while responsible use requires governance, critical oversight and practices capable of translating ethical principles into concrete action (Mittelstadt, 2019; Dwivedi et al., 2023; Feuerriegel et al., 2024).

2.7 Research Gap and conceptual model

The preceding sections show that GenAI has attracted growing attention in organizational and innovation research, particularly due to its potential to support knowledge-intensive work, decision-making, content generation, experimentation and innovation-related activities. However, much of the existing literature remains focused on the technical

characteristics of GenAI systems, task-level productivity effects or broad discussions of AI and innovation. As a result, there is still limited empirical understanding of how GenAI is incorporated into firm-level strategic practices and whether its use is associated with perceived strategic value, particularly in SMEs.

A key distinction therefore concerns the extent to which GenAI goes beyond isolated use and becomes imbedded into organizational routines and managerial processes. Prior information-systems and digital-transformation research stresses organizational embedding and process transformation as major dimensions of technology assimilation and value creation (Liang et al., 2007; Vial, 2019; Verhoef et al., 2021).

Building on the RBV stepping stones presented in Section 2.3, GenAI's strategic relevance is expected to depend less on access to the technology itself and more on how it is combined with firm-specific resources, routines, knowledge and managerial capabilities.

Additionally, if GenAI helps firms identify market trends, interpret information, generate alternatives, mobilize resources or adapt internal processes, its value may be reflected in stronger sensing, seizing and reconfiguring capabilities. For this reason, Dynamic Capabilities are included as a theoretically relevant and complementary construct for examining how GenAI-related practices may relate to perceived strategic impact. Innovation Capability is also considered as a complementary construct, given the technology's potential connection to the generation and implementation of new ideas, products, services or processes.

In line with this rationale, the conceptual model links GenAI-related organizational practices to perceived strategic outcomes, distinguishing between GenAI use intensity, operational use, strategic use and GenAI integration. To synthesize, the conceptual model reflects the central argument of this dissertation: GenAI does not constitute a strategic resource in itself but may contribute to perceived strategic impact when it is used strategically, integrated into organizational routines and supported by managerial action. This perspective allows the study to move beyond the question of whether SMEs use GenAI and to focus instead on how different forms of use and integration are associated with perceived strategic value.

3. Methodology

This chapter presents the methodological approach adopted to examine the strategic impact of GenAI in Portuguese SMEs. The chapter begins by explaining the research design and the rationale behind the quantitative approach. It then addresses the target population, sampling strategy and data collection procedure, before presenting the operationalization of the main variables and constructs. Finally, it outlines the data preparation and screening process, the statistical techniques applied in the empirical analysis, the complementary qualitative coding procedure and the procedures adopted to ensure reliability, validity, research quality and ethical compliance.

3.1 Research Design

This study employs a predominantly quantitative, cross-sectional research design built around a structured questionnaire, an approach well suited to the objective of examining patterns in the use, integration and perceived strategic impact of Generative Artificial Intelligence (GenAI) among Portuguese small and medium-sized enterprises (SMEs). By collecting standardized responses, the questionnaire allowed the analysis of statistical associations between the main constructs included in the conceptual model.

Although the research design is primarily quantitative, it includes a complementary exploratory qualitative component, based on the open-ended responses included in the questionnaire, which were analysed to provide additional insight into respondents' perceptions of the main opportunities and risks associated with GenAI use. Therefore, the qualitative analysis was not designed as an independent research phase, but as a complementary source of interpretation supporting the quantitative findings.

The study is, in the first instance, exploratory, since the strategic implications of GenAI within SMEs remain insufficiently studied, particularly in the Portuguese context. The research therefore sets out to provide initial empirical evidence on how SMEs are actually using GenAI. At the same time, it has an explanatory dimension, as it examines whether particular variables are associated with perceived strategic impact, namely strategic use of GenAI, GenAI integration, top management support, dynamic capabilities and relevant control variables.

Given the cross-sectional and non-probability nature of the data, however, the study offers exploratory and explanatory evidence on the patterns and associations between GenAI use and perceived strategic outcomes in Portuguese SMEs, rather than trying to establish

causal relationships.

3.2 Population and Sampling

The target population of this study consists of Portuguese small and medium-sized enterprises (SMEs) that use Generative Artificial Intelligence. For the purposes of this study, SMEs were operationally identified using the employee-count criterion, considering firms employing fewer than 250 people for the main analysis. Although the European SME definition also includes turnover and balance-sheet thresholds, these financial criteria were not included in the questionnaire in order to avoid overburdening respondents and to keep the survey accessible to participants with different organizational roles (European Commission, 2019). By doing so, the screening procedure remained simple, clear and aligned with the employee-based threshold commonly associated with SME classification.

Since the purpose of the study is to examine how GenAI is used, integrated and perceived as strategically relevant within firms, organizations that did not report using GenAI were excluded in the main empirical analysis. The unit of analysis is the firm, but data was collected from individual respondents, meaning that each respondent acted as an informant about the organization's use of GenAI. For this reason, the questionnaire targeted individuals with knowledge of the firm's strategic activities, technological practices and use of GenAI. Preferred respondents included owners, founders, directors, senior managers and other professionals with involvement in strategic, managerial, innovation or digital transformation-related activities. This approach was considered appropriate because the constructs under analysis require respondents to have sufficient knowledge of firm-level practices.

A non-probability sampling strategy was adopted, combining purposive sampling with database-based outreach and institutional dissemination. Purposive sampling was appropriate because the study required firms and respondents meeting specific eligibility criteria, namely Portuguese SMEs using GenAI and individuals with sufficient knowledge of the organization's practices. First, the SABI database was used to identify companies operating in Portugal with fewer than 250 employees. Based on this filtering procedure, company contact details were collected and firms were contacted directly by email with an invitation to participate in the questionnaire.

In addition to this direct firm-level outreach, the questionnaire was also disseminated through intermediary organizations, notably major regional development organisms and business support groups, who were contacted and asked to share the questionnaire with firms

within their networks. Business incubators were also contacted for the same purpose, given their proximity to entrepreneurial, innovative and technology-oriented firms. This procedure aimed to broaden the reach of the study beyond the companies directly identified through SABI and to increase access to SMEs potentially engaged with emerging digital technologies.

Given the non-probability sampling strategy, the results should not be interpreted as statistically representative of all Portuguese SMEs. Rather, they provide exploratory and explanatory evidence about the relationships between GenAI use, integration, organizational capabilities and perceived strategic impact among the SMEs represented in the sample.

3.3 Data Collection Methods

3.3.1 Questionnaire

The quantitative data was collected through a structured online questionnaire administered using Google Forms, a method considered appropriate as it allowed standardized data to be collected from respondents across different firms, sectors and geographical areas, while facilitating the organization and export of responses for subsequent statistical analysis.

The questionnaire was designed to collect information on the organizational use of Generative Artificial Intelligence in Portuguese SMEs. It included the aforementioned initial set of screening questions to ensure that the final analysis focused only on eligible respondents, namely participants representing Portuguese SMEs that reported using GenAI. The main body covered firm and respondent characteristics, the core GenAI-related constructs included in the conceptual model and additional complementary responsible and future-oriented dimensions, such as ethics, explainability, sustainability and future orientation. This structure made it possible to distinguish between general, operational, and strategic use and organizational integration, which is central to the study's objective of examining whether GenAI is associated with perceived strategic impact beyond routine efficiency.

Most constructs were measured through multi-item seven-point Likert scales, allowing respondents to indicate their level of agreement with statements related to the firm's use, integration and perceived outcomes of GenAI. Whenever possible, items were adapted from existing literature. However, given the recent nature of GenAI and the limited availability of established scales specifically addressing its strategic use in SMEs, some items were developed specifically for this study in line with the conceptual framework.

The questionnaire was distributed online to the firms and intermediary organizations described in the population and sampling section. Participation was voluntary, and

respondents were informed about the academic purpose of the study before completing the questionnaire. The questionnaire did not request the names of respondents or companies, and the data was analysed and reported in aggregated form.

3.4 Variables and Constructs

The study focuses on a set of constructs designed to capture both the organizational use of GenAI and its potential strategic implications. The main outcome variable is perceived strategic impact, referring to the extent to which GenAI is perceived to improve decision-making, innovation, responsiveness and competitive positioning.

The main explanatory variables are strategic use of GenAI, GenAI integration, top management support and dynamic capabilities. Strategic use of GenAI refers to the use of GenAI in activities such as decision support, strategic planning, market analysis, scenario exploration and innovation-related tasks. GenAI integration captures the extent to which GenAI is embedded in recurring workflows, organizational routines and managerial processes. Top management support refers to the extent to which leadership encourages, supports and provides direction for the organizational use of GenAI. Finally, Dynamic capabilities are understood in terms of the firm's ability to sense opportunities and threats, seize opportunities and reconfigure resources and processes in response to the changing environment.

For concision in tables and figures, the main constructs are abbreviated as follows: DM = Digital Maturity; INT = GenAI Use Intensity; OU = Operational Use; SU = Strategic Use; SI = Strategic Integration; TMS = Top Management Support; DC = Dynamic Capabilities; IC = Innovation Capability and PSI = Perceived Strategic Impact.

In addition to these core constructs, the study also considers operational use of GenAI and innovation capability. The first refers to more routine and efficiency-oriented applications of GenAI, such as supporting everyday tasks or improving productivity, in contrast with more strategic forms of use. The second refers to the firm's ability to generate and implement new ideas, products, services or processes and is included as a complementary construct related to the broader strategic implications of GenAI.

The study additionally includes contextual and control variables, namely firm size, age and sector, digital maturity, GenAI use intensity and respondent's involvement in strategic decision-making. These variables were included to account for differences across firms and respondents that may influence how GenAI is used, integrated and perceived within the

organization.

The detailed operationalization of the main constructs is presented in Annex A, Table A1, including their role in the study, whether the items were adapted or developed for this research, and their theoretical basis. The questionnaire combined items adapted from established literature with GenAI-specific items developed for this study. This distinction is important because some constructs, such as top management support and dynamic capabilities, are grounded in established theoretical and empirical work, whereas other constructs, such as strategic use of GenAI, GenAI integration and perceived strategic impact, were developed specifically for the context of this dissertation due to the limited availability of validated scales addressing the strategic use of GenAI in SMEs.

3.5 Data Preparation and Screening

Before conducting the quantitative analysis, the questionnaire data was exported from Google Forms and prepared for analysis, a process that involved checking the dataset for incomplete responses, eligibility criteria, missing values and inconsistent entries.

First, the eligibility criteria presented in chapter 3.2 were applied. Only respondents who provided informed consent and confirmed that their firms used GenAI were included in the main quantitative analysis. Given that the study focuses on Portuguese small and medium-sized enterprises, only firms that met the employee-based SME criterion were retained. After applying this eligibility criterion, the quantitative sample comprised 87 valid responses.

Composite variables were then created for each of the constructs described in Section 3.4, by calculating the mean of the corresponding items, assessed by the responses given through the seven-point Likert scale format. Control variables were selected in accordance with the theoretical framework and included firm-level and respondent-level characteristics relevant to the interpretation of GenAI use and perceived strategic impact.

The dataset was then screened for potential response-quality issues, based on the literature on careless responding in survey research, which recommends using multiple indicators for screening to reduce reliance on a single imperfect criterion, since careless responding can appear in different forms (Curran, 2016; Goldammer et al., 2020; Meade & Craig, 2012; Ward & Meade, 2023). In line with this approach, the process considered within-response variability, the number of distinct response values used by each respondent, the long-string index, the proportion of items answered with the same response option, univariate outliers, and multivariate outliers. The response-quality screening criteria used in the analysis

are condensed in Annex E, Table E1.

These indicators were used as warning signs and not as automatic exclusion rules. Therefore, flagged cases were manually inspected to distinguish between substantively plausible response patterns and responses suggesting low effort or straight-lining. After this final process, 3 responses were excluded from the analysis. Therefore, the final quantitative sample consisted of 84 valid responses.

3.6 Quantitative Data Analysis

After the data preparation and screening procedures, the quantitative analysis followed several stages: descriptive analysis, reliability assessment, correlation analysis, OLS regression modelling, mediation analysis, diagnostic checks and complementary exploratory analyses.

First, descriptive statistics were used to characterize the sample and provide an overview of the main variables. Frequency tables were produced for categorical variables such as firm size, firm age, sector and respondent role, while for Likert-scale items and composite constructs, means, standard deviations, minimum and maximum values were calculated. This allowed the identification of general patterns in the use of GenAI, including differences between operational use, strategic use, organizational integration and perceived strategic impact. Second, reliability was assessed before using the multi-item constructs in the subsequent analyses.

Third, correlation analysis was conducted to examine preliminary associations between the main constructs. To this end, Pearson correlation coefficients were used in the main analysis to assess the direction and strength of linear relationships between variables (Pearson, 1895). Spearman rank-order correlations were also inspected as a robustness check, as this measure is less sensitive to deviations from linearity and to the ordinal nature of the original responses (Spearman, 1904). The Spearman correlation matrix is reported in Annex F, Table F1.

Subsequent steps estimated multiple linear regression models using ordinary least squares (OLS). This method was considered appropriate as the dependent variable, perceived strategic impact, was measured as a continuous composite score derived from multiple Likert-scale items (Norman, 2010). The OLS method is commonly used for survey-based research when multi-item scales are aggregated into composite scores. The main explanatory variables were strategic use of GenAI, GenAI integration, top management support and

dynamic capabilities. This modelling approach allowed for the estimation of the partial associations between these variables and perceived strategic impact, while controlling for relevant firm-level and respondent-level characteristics.

The modelling strategy followed a progressive logic. Model 5 included the main theoretical predictors only: strategic use of GenAI, GenAI integration, top management support and dynamic capabilities. Subsequently, the final controlled Model 6 was estimated, to account for relevant firm-level and respondent-level characteristics. This main controlled specification included firm size, digital maturity, GenAI use intensity and the respondent's involvement in strategic decision-making and can be represented as follows:

$$PSI_i = \beta_0 + \beta_1 SU_i + \beta_2 SI_i + \beta_3 TMS_i + \beta_4 DC_i + \gamma X_i + \varepsilon_i \quad \textbf{(3.1)}$$

In equation (3.1), PSI_i denotes the perceived strategic impact score for firm i; β_0 is the intercept; SU, SI, TMS and DC refer to Strategic Use, Strategic Integration, Top Management Support and Dynamic Capabilities, respectively; X_i denotes the vector of control variables included in Model 6 and γ represents the corresponding control-variable coefficients. Lastly, ε_i is the error term. Given the cross-sectional nature of the data, the regression models should be read as evidence of statistical association rather than of causal effect.

Firm age and sector were also considered in an extended model 7 specification. However, the inclusion of additional categorical controls was treated with caution due to the modest sample size and the number of categories involved. The specifications of the main and complementary empirical models are summarized in Annex C, Table C1.

In addition to the main regression models, a complementary exploratory analysis was conducted to examine whether dynamic capabilities helped explain the relationship between GenAI-related practices and perceived strategic impact. Specifically, Strategic Use, GenAI Integration and Top Management Support were examined as independent variables, Dynamic Capabilities as the mediator, and perceived Strategic Impact as the dependent variable. The mediation tests therefore assessed whether GenAI-related practices were associated with Strategic Impact indirectly through Dynamic Capabilities.

Indirect effects were tested using a non-parametric case bootstrap procedure with 5000 resamples, given that this method is widely recommended for mediation analysis and allows confidence intervals for indirect effects to be estimated without relying only on normal-theory assumptions (MacKinnon et al., 2004; Shrout & Bolger, 2002; Preacher & Hayes,

2008). However, because mediation presupposes a temporal process in which the independent variable precedes the mediator and the mediator in turn precedes the dependent variable, cross-sectional data cannot establish the temporal ordering that causality would require. Therefore, the results were interpreted as exploratory evidence of indirect association rather than as confirmation of a causal process (Maxwell & Cole, 2007).

Complementary exploratory analyses were also conducted, where innovation capability was examined as an alternative outcome. The controlled model included the same control variables used in the final Strategic Impact model (Model 6), namely Digital Maturity, GenAI Use Intensity, Respondent Strategic Involvement, and Firm Size. Furthermore, a regression tree was estimated to identify potential non-linear patterns and combinations of variables associated with perceived strategic impact. Unlike OLS regressions, which estimate linear associations, regression trees split the sample into subgroups based on predictor values that differentiate the dependent variables, making it possible to explore whether specific combinations of Strategic Use, GenAI Integration, Top Management Support, Dynamic Capabilities and control variables were associated with higher or lower levels of perceived Strategic Impact. Considering the modest sample size and its exploratory purpose, the tree was constrained in depth and like other complementary analysis, was used to complement, rather than replace, the main regression models.

Finally, several diagnostic procedures were performed to assess the robustness of the regression results. Multicollinearity was assessed using variance inflation factors (Kim, 2019), residual normality was assessed using the Shapiro-Wilk and Jarque-Bera tests, complemented by graphical inspection of the Q-Q plot (Shapiro & Wilk, 1965; Jarque & Bera, 1980). Homoscedasticity was evaluated using the Breusch-Pagan test together with visual inspection of the residuals-versus-fitted-values plot (Breusch & Pagan, 1979; Cook & Weisberg, 1982). Potentially influential observations were examined through Cook's Distance, leverage values, externally studentized residuals, and DFFITS, with conventional diagnostic thresholds used as screening rules rather than automatic exclusion criteria (Cook, 1977; Hoaglin & Welsch, 1978; Belsley et al., 1980). As a further sensitivity check, the final controlled model was re-estimated excluding observations with Cook's Distance greater than 4/n. It was also recalculated using HC3 robust standard errors, following recommendations for small to moderate samples (White, 1980; MacKinnon & White, 1985; Long & Ervin, 2000). These procedures were used to understand whether the main conclusions of the regression analysis remained stable under alternative diagnostic and robustness checks. Comprehensive multicollinearity

diagnostics are reported in Annex G, Tables G1-G3, while regression diagnostics and robustness checks for Model 6 are reported in Annex I, Tables I1 through I5 and Figures I1 through I2.

3.7 Qualitative Data Analysis

3.7.1 Introduction and purpose of the codebook

To complement the quantitative analysis, the questionnaire included a final open-ended question to identify respondents' perceptions on the future of GenAI utilization in SMEs, namely its main opportunities and risks. In order to systematically and transparently interpret these responses, a qualitative codebook was developed specifically for this study with the purpose of classifying recurring themes emerging from the short textual responses. Its development was grounded in the literature reviewed in chapter 2 and refined through an iterative reading of the responses, ensuring that the categories accurately reflected both the theoretical background of the study and the content of the data.

The codebook was organized around three dimensions: opportunities, risks or challenges and limitations or non-substantive responses. Opportunity codes captured identified positive contributions of GenAI, namely efficiency gains, decision support, innovation, process improvement, among others. In contrast, risks and challenges captured respondents' concerns around reliability, data governance, changes in the human role, to name a few. A separate code was reserved for responses that offered no substantive view on the topic.

3.7.2 Coding procedure

The qualitative analysis drew on the open-ended responses provided by respondents within the final analytical sample of 84. Of these, 59 were non-empty and formed the basis for the complementary qualitative content analysis.

The coding process followed a qualitative content analysis approach, supported at its initial stage by the use of GenAI, used specifically to help review the open-ended responses, identify recurring themes and propose an initial set of possible codes relating to the opportunities and risks of GenAI adoption. This stage was exploratory in nature and did not in itself, determine the final coding framework. The initial set of codes was thoroughly and critically reviewed, refined and consolidated, so that each code was clearly defined and conceptually distinct from the others. The final codebook therefore combined theory-informed and data-informed elements. Then, the categories were calibrated through repeated reading

of the empirical responses so as to reflect the language and concerns participants actually expressed and each response was ultimately read and classified according to this recalibrated codebook. Since each answer could identify several opportunities and concerns, the coding procedure allowed multiple codes to be assigned to the same response. As such, the resulting frequencies should be read as descriptive indicators of theme prevalence and not as mutually exclusive categories. Ultimately, the final codebook, the theoretical justification for the categories and all coding decisions remained the responsibility of the researcher.

Table 3.1 provides a summarized overview of the final codebook, listing for each category its code, a brief description of the theme it captures and the criteria used in its application. To keep the methodology section concise, Annex B, Tables B1 and B2 include coding examples and the theoretical grounding for each code.

Table 3.1: Summary of the qualitative codebook

Code	Theme	When applied
O1	Efficiency, automation and productivity / process optimisation	Mentions time saving, automation, productivity, cost reduction, process optimisation, resource profitability, or operational efficiency.
O2	Decision support and information processing	Refers to AI supporting analysis, summarisation, information processing, supplier/market/price comparisons, decision-making, documentation, or problem solving.
O3	Innovation, creativity, experimentation and new solutions	Alludes to innovation, experimentation, new products or services, new solutions, creativity, or technical solution development.
O4	Strategic integration and process/system improvement	Mentions integration into routines, workflows, systems, ERP/software, organisational processes, documentation chains, or process and system improvement.
O5	Competitive advantage, agility and strategic positioning	Touches on competitive advantage, agility, speed versus competitors, revenue growth or scaling, strategic positioning, or SMEs competing with larger firms.
O6	Marketing, communication and content generation	References marketing, design, communication, content creation, emails, presentations, multilingual communication, commercial documentation, or customer/supplier communication.
R1	Reliability, accuracy, validation and need for critical thinking	Mentions errors, misinformation, factual inaccuracy, hallucinations, need for human validation, auditing, verification, or critical evaluation of outputs.
R2	Data security, privacy, confidentiality and governance/control	Mentions security, privacy, confidentiality, leakage of internal/company/personal data, third-party data sharing, espionage, governance, control, or uncontrolled use.

R3	Legal, ethical, regulatory and intellectual property concerns	References legal, ethical, regulatory, compliance, intellectual property, or commercial/legal exposure.
R4	Workforce displacement and changing human role	Alludes to job losses, substitution of people/human creativity, reduced human contact, or changing the human role.
R5	Dependence, deskilling and erosion of human judgment or creativity	Comments on excessive dependence on AI, blind trust, loss of skills, autonomy, technical knowledge, critical thinking, human judgment, originality or creativity due to reliance on GenAI.
R6	Loss of differentiation, imitation and competitive homogenisation	References imitation by competitors, being copied, loss of differentiation, homogenisation of offers, or weakened competitive advantage.
R7	Implementation/adoption barriers and integration complexity	Mentions failure to adopt, slow adaptation, integration complexity, training needs, implementation difficulty, or technical/organisational readiness barriers.
R8	External dependence, costs and sustainability concerns	Acknowledges dependence on external AI providers, rising supplier costs, or sustainability impacts.
N1	Limited/no substantive answer or future-only comment	Non-substantive answer, no opinion, punctuation only, no current consideration, or future-only comment without a concrete opportunity/risk.

Note. O = Opportunity; R = Risk or challenge; N1 = non-substantive response. The table presents the final coding framework used in the qualitative analysis. Multiple codes could be assigned to the same response. Detailed coding examples and the literature-based rationale for each code are provided in Annex B, Tables B1 and B2.

3.8 Reliability, Validity and Research Quality

In order to ensure the quantitative analysis met acceptable standards of reliability, validity and overall rigour, a number of procedures were integrated in the research process. Because the study relied entirely on questionnaire data, care was taken over how the measurement scales were constructed, how internal consistency was checked, how responses were screened, and how the regression models were validated.

Reliability was assessed primarily through internal consistency, using Cronbach's alpha for each of the multi-item constructs measured on Likert scales (Cronbach, 1951; Cortina, 1993; Tavakol & Dennick, 2011), considering the .70 threshold as a reference point for acceptable internal consistency (Nunnally & Bernstein, 1994; Tavakol & Dennick, 2011). Additionally, for each alpha coefficient, 95% bootstrap confidence intervals were calculated to assess the precision of the reliability estimates. This approach uses repeated resampling with replacement from the observed data to approximate the sampling distribution of the

statistic (Efron, 1979; Efron & Tibshirani, 1993). Item-level diagnostics were also inspected, including corrected item-total correlations and Cronbach's alpha-if-item-deleted, particularly for the constructs with lower reliability values, in accordance with recommendations to inspect item-level behaviour rather than relying solely on the overall alpha coefficient (Cortina, 1993; Boateng et al., 2018; Tavakol & Dennick, 2011). The exhaustive item-level reliability diagnostics are reported in Annex E, Table E2.

Construct validity rested on the way the questionnaire was developed from the thesis' theoretical framework and on existing literature covering GenAI, strategic management, top management support, dynamic capabilities, innovation capability and perceived strategic impact. Some items were adapted from established scales, while others had to be developed specifically for this study, given the recent nature of the GenAI phenomenon. The operationalization of the constructs followed the distinctions drawn in the literature review and conceptual model. In particular, operational use, strategic use, use intensity and GenAI integration were treated as distinct constructs, since frequency of use, routine and productivity-oriented use, strategic application and organizational embedding represent conceptually different dimensions of GenAI adoption.

Research quality was further supported by the data-screening, diagnostic and robustness procedures described in Sections 3.5 and 3.6, used to assess the suitability of the dataset and the stability of the main regression conclusions.

Finally, these procedures should nevertheless be interpreted in light of the study's methodological limitations, discussed further in Section 6.2.

3.9 Ethical Considerations

Ethical considerations were addressed throughout the research process, with emphasis on informed consent, voluntary participation, confidentiality and the protection of participants' data. Prior to its distribution, the questionnaire was submitted for review to the Data Protection Unit of the University of Porto, which confirmed the adequacy of the process regarding informed consent, confidentiality and the handling of participants' data.

Prior to completing the questionnaire, participants were informed of the academic purpose of the study, the subject of the thesis, and the intended use of the data collected. Participation was entirely voluntary and only respondents who explicitly provided informed consent were included in the analysis. Furthermore, the questionnaire was designed so as to avoid the collection of direct personal identifiers, such as the names of respondents or

organizations. The data gathered focused on organizational characteristics, patterns of GenAI use and respondents' perceptions regarding integration, capabilities and strategic impact with all the corresponding results being analysed and reported in an aggregated form.

Confidentiality was likewise preserved throughout the analysis and reporting stages. No individual response was disclosed, and neither respondents nor organizations were identified at any point in the thesis.

4. Results

This chapter presents the empirical results of the study, beginning with the description of the sample selection process and the final analytical sample, followed by the descriptive statistics of the main constructs. It follows by reporting the reliability and correlation analysis, multicollinearity assessment, regression results, diagnostic and robustness checks, mediation and complementary exploratory analyses and concluding with the analysis of open-ended responses.

4.1 Data Screening Results and Final Analytical Sample

Before conducting the statistical analysis, the dataset was screened according to the eligibility and response-quality criteria described in Chapter 3. From the 140 raw responses collected, 95 both provided informed consent and confirmed that their firms used GenAI. After excluding firms with 250 or more employees, 87 eligible SME responses remained.

Response-quality screening then identified three cases displaying clear repetitive response patterns across long sequences of Likert-scale items, suggesting low response quality. These cases were excluded from the final analytical sample and other responses with high but substantively plausible scores were carefully inspected but retained. Therefore, the final analytical sample consisted of 84 valid SME responses. Table 4.1 summarizes the sample selection process.

Table 4.1: Sample selection process

Step	Responses
Raw responses collected	140
Responses with consent and GenAI use	95
Eligible SME responses	87
Responses excluded after response-quality screening	3
Final analytical sample	84

Note. The final analytical sample included only respondents who provided informed consent, confirmed their firms used GenAI and represented firms with fewer than 250 employees

4.2 Sample Description

4.2.1 Sector distribution

Regarding sector distribution, the sample includes firms from a diverse range of

economic activities, although some sectors are more strongly represented than others. For instance, manufacturing and industrial production was the most represented sector, with 24 firms, followed by wholesale and retail trade, with 21 firms. Together, these two categories account for more than half of the final sample, indicating a relatively strong presence of traditional production and commercial activities among the responding SMEs.

Other relevant sectors included construction and real estate, professional, scientific and technical services, information and communication, and accommodation and food service activities related to tourism. Smaller sectoral groups, such as human health and social work activities, agriculture and primary sector activities, education and training, financial and insurance activities, and other activities, were represented by fewer firms.

In a nutshell, although the sample presents sectoral variety, the distribution is uneven, with several categories being represented by relatively fewer firms.

4.2.2 Firm Size

In respect to firm size, the sample is composed mainly of small firms, particularly those with between 10 and 49 employees, representing the largest group in the sample, corresponding to approximately 67.9% of the final analytical sample. Micro firms, with 0 to 9 employees, account for 11 observations, while medium-sized firms, with 50 to 249 employees, account for 16 observations. This distribution indicates that the sample is strongly concentrated in the small-firm segment of the SME population.

4.2.3 Firm Age

The sample is mainly composed of established firms, as the largest group corresponds to firms with more than 21 years of activity, representing approximately 53.6% of the final total sample. Firms with 11 to 20 years of activity form the second-largest group, with 23 observations. Together, these two categories account for most of the sample, suggesting that the responding firms are predominantly mature organizations rather than recently created businesses. This is relevant for the interpretation of the results, since older firms may differ from younger firms in terms of accumulated experience, organizational routines, managerial formalization and capacity to integrate new technologies into existing processes. As such, the limited number of very young firms means that conclusions about recently created SMEs should be interpreted with caution.

4.2.4 Respondent Strategic Involvement

Concerning respondents' involvement in strategic decision-making, the sample is composed predominantly of individuals with a high level of strategic involvement in their firms. In fact, most respondents selected the two highest points of the scale, accounting for approximately 84.5% of the final analytical sample. This distribution suggests that the questionnaire was mainly answered by individuals who were closely involved in the definition of their firm's strategy. Detailed sample profile distributions are reported in Annex D, Table D1 and Figures D1 through D3.

4.3 Descriptive Statistics of Main Constructs

The descriptive statistics provide an initial overview of how GenAI is used and perceived among the responding SMEs. Overall, the results suggest relatively high levels of GenAI use intensity, operational use, top management support, dynamic capabilities, ethics, explainability and future orientation. Operational use presented a mean of 5.250, indicating that GenAI is already used to a considerable extent for routine and efficiency-oriented activities. By contrast, strategic use presented a lower mean of 4.426, while strategic integration showed an even lower mean of 3.674. This difference suggests that, although GenAI is being used by the responding firms, its incorporation into strategic routines, workflows and managerial processes remains less developed than its operational use. Table 4.2 condenses the descriptive statistics for the main constructs.

Table 4.2: Descriptive statistics of main constructs

	Mean	Std	Min	Max
DM	4.786	1.010	1.333	7.0
INT	5.026	1.126	2.000	7.0
OU	5.250	.995	2.000	7.0
SU	4.426	1.426	1.000	6.8
SI	3.674	1.253	1.000	7.0
TMS	5.472	1.372	1.667	7.0
DC	5.395	1.076	1.000	7.0
IC	5.131	1.328	1.000	7.0
PSI	4.681	1.461	1.000	7.0
ETH	5.464	1.382	1.000	7.0

EXP	5.464	1.265	2.000	7.0
SUS	4.054	1.863	1.000	7.0
FO	5.524	1.556	1.000	7.0

Note. N=84. Construct scores were calculated as the mean of their corresponding items, measured on seven-point Likert scales, with higher values representing higher levels of the construct.

Perceived strategic impact presented a moderately high mean of 4.681, suggesting that respondents generally perceive GenAI as contributing to decision-making, innovation, responsiveness or competitive positioning, although this perception is not as strong as the reported levels of operational use or top management support. In fact, top management support showed a high mean of 5.472, indicating that leadership support for GenAI is relatively strong among the firms in the sample. Dynamic capabilities also presented a high mean of 5.395, suggesting that respondents perceive their firms as relatively capable of sensing opportunities, seizing them and adapting organizational resources and processes.

4.4 Responsible and Future-Oriented GenAI Items

The descriptive results for the responsible and future-oriented GenAI items provide additional insight into how responding SMEs perceive the broader implications of GenAI use. Detailed item-level descriptive statistics for these items are reported in Annex D, Table D2. Overall, the strongest result regards human oversight, as the item stating that human supervision is necessary before GenAI outputs are used in important decisions recorded the highest mean among these items (mean of 6.369 and a median of 7). This suggests a strong consensus among respondents on the need for human supervision of GenAI outputs.

The results also indicate relatively strong concern with bias, misinformation and explainability. In fact, respondents reported high levels of apprehension regarding risks such as bias or misinformation in GenAI outputs (mean of 5.369), while the item concerning the search for explanations before using GenAI outputs in decision-making also presented a high mean of 5.845. However, the broader item concerning whether the firm considers ethical implications in the use of GenAI showed a comparatively lower mean of 4.655.

By contrast, sustainability-related items presented lower mean values and higher dispersion, suggesting that environmental considerations and sustainability criteria are less consistently incorporated into firms' decisions regarding GenAI use or tool selection. In fact,

the item capturing the broader environmental impact of technology recorded a mean of 4.095 and the item specifically addressing the environmental impact of GenAI use recorded a mean of 4.012.

Finally, both the item assessing expected future investment and the item recording GenAI's future strategic importance returned a mean of 5.524 and a median of 6, indicating that respondents generally expect GenAI to become more important in their companies, and anticipate increasing investment in the coming years.

4.5 Reliability Analysis

The results of the Cronbach's alpha showed acceptable to very high reliability for the five main constructs, namely: Strategic Use (α = .895), Strategic Integration (α = .755), Top Management Support (α = .822), Dynamic Capabilities (α = .880), and Strategic Impact (α = .922), supporting the aggregation of their respective items into composite mean scores.

On the other hand, some complementary constructs showed lower reliability. In fact, Digital Maturity (α = .580), Operational Use (α = .600), and Explainability (α = .527) were below the conventional .70 threshold commonly used as a reference point for acceptable internal consistency and were therefore interpreted with caution. The reliability results for the multi-item constructs are summarized in Table 4.3.

Table 4.3: Cronbach's alpha results

Construct	n	Cronbach alpha	CI_lower	CI_upper
digital_maturity	3	.580	.396	.714
gai_use_intensity	5	.829	.763	.880
operational_use	4	.600	.440	.724
strategic_use	5	.895	.855	.927
strategic_integration	5	.755	.661	.829
top_management_support	3	.822	.744	.879
dynamic_capabilities	6	.880	.836	.916
innovation	3	.818	.739	.877
strategic_impact	5	.922	.892	.945
ethics	3	.785	.690	.854
explainability	2	.527	.271	.694
sustainability	2	.927	.887	.952

future_orientation	2	.905	.854	.939

Note. N=84. Cronbach's alpha coefficients are reported for each multi-item construct. Confidence intervals correspond to 95% bootstrap confidence intervals.

The results from the item-level diagnostics were generally adequate and the removal of individual items did not substantially improve Cronbach's alpha. Therefore, all theoretically defined items were retained. Constructs with lower reliability, namely Digital Maturity, Operational Use and Explainability, were interpreted with caution. Since these constructs were not central dependent variables in the main theoretical model, they were retained for descriptive or control purposes and their lower reliability was acknowledged as a limitation. Comprehensive item-level diagnostics, including corrected item-total correlations and alpha-if-item deleted values are reported in Annex E, Table E2.

4.6 Correlation analysis

Pearson correlations indicated that all correlations were positive and statistically significant, with the strongest associations being found between Strategic Use and Strategic Impact ($r = .775$, $p < .001$) and between Strategic Integration and Strategic Impact ($r = .754$, $p < .001$) while Top Management Support was also moderately to strongly correlated with Strategic Impact ($r = .656$, $p < .001$). Table 4.4 synthesizes these results.

Table 4.4: Pearson correlation matrix

Construct	1	2	3	4	5
SU	1.000				
SI	.679***	1.000			
TMS	.463***	.543***	1.000		
DC	.251*	.379***	.432***	1.000	
PSI	.775***	.754***	.656***	.306**	1.000

Note. N = 84. Pearson correlation coefficients are reported. *p < .05; **p < .01; ***p < .001.

Dynamic Capabilities showed a positive but weaker correlation with the other constructs. Its correlation with Strategic Impact was statistically significant however moderate ($r = .306$, $p < .01$), suggesting that although Dynamic Capabilities are related to perceived

Strategic Impact, their relationship is weaker than the ones observed for constructs such as Strategic Use, Strategic Integration, and Top Management Support.

The results from the Spearman rank-order correlations proved substantively consistent with the Pearson correlations, supporting the robustness of the observed associations (Spearman, 1904). These results are disclosed in Annex F, Table F1.

4.7 Multicollinearity Assessment

For the main theoretical predictors, all values of the Variance Inflation Factor (VIF) were below 2.20, indicating no evidence of problematic multicollinearity. The final controlled model also showed acceptable VIF values, with all predictors below the commonly used threshold of 5 (Kim, 2019). In fact, for Model 6, the highest VIF was 2.582, associated with GenAI Use Intensity.

Additionally, an alternative VIF check including firm age was also appraised. However, some firm age dummy variables presented elevated VIF values, namely the categories "21+ years" and "11–20 years". Since the inclusion of firm age introduced multicollinearity concerns, this variable was not retained in the main controlled model. Similarly, the extended model including sector controls produced high VIF values for several sector dummy variables, reflecting the large number of sector categories relative to the sample size. Therefore, the sector-controlled specification was treated only as a robustness check and not as the main model. Exhaustive VIF results for Models 5, 6 and 7 are reported in Annex G, tables G1 through G3.

4.8 Regression models

OLS regression models were estimated to understand the predictors of Strategic Impact. Model 5 included the main theoretical predictors, while Model 6 added the final set of control variables. In the more concise model, Strategic Use, Strategic Integration, and Top Management Support were positive and statistically significant predictors of Strategic Impact and dynamic Capabilities did not show a statistically significant effect. The model explained 75.8% of the variance in Strategic Impact, with an adjusted R^2 of .745.

In the controlled model, these results remained consistent, as Strategic Use, Strategic Integration, and Top Management Support remained positive and statistically significant predictors of Strategic Impact, while Dynamic Capabilities remained non-significant. Model 6 explained 80.1% of the variance in Strategic Impact, with an adjusted R^2 of .777. These

findings are presented in Table 4.5 and indicate that perceived Strategic Impact is primarily associated with the strategic use of GenAI, its integration into strategic routines, and support from top management.

Table 4.5: OLS regression results predicting perceived strategic impact of GenAI

Variable	Model 5	Model 6
SU	.443***	.471***
	(.078)	(.079)
SI	.366***	.386***
	(.096)	(.094)
TMS	.330***	.343***
	(.074)	(.075)
DC	-.076	-.101
	(.085)	(.081)
DM		-.148
		(.096)
INT		.037
		(.108)
RSI		-.043
		(.089)
Firm size: 10–49		-.458
		(.232)
Firm size: 50–249		-1.011***
		(.284)
Constant	-.021	1.143
	(.457)	(.773)
Firm size controls	No	Yes
Digital maturity	No	Yes
GenAI use intensity	No	Yes
Respondent strategic involvement	No	Yes
Firm age controls	No	No
Sector controls	No	No
R^2	.758	.801

Adjusted R^2	.745	.777
N	84	84

Note. Dependent variable: perceived Strategic Impact. Unstandardized coefficients are reported, with standard errors in parentheses. The reference category for firm size is 0-9 employees. *p < .05; **p < .01; ***p < .001.

Standardized coefficients were computed as a complementary analysis, seeing that they express regression effects on a common standard-deviation scale, which allows for a comparison of the relative strength of predictors within the same model (Nathans et al., 2012). Among the continuous predictors, these coefficients indicated that Strategic Use presented the strongest relative effect, followed by Strategic Integration and Top Management Support. On the other hand, the control variables Digital Maturity, GenAI Use Intensity and Respondent Strategic Involvement were not statistically significant. Firm size was included as a control, with firms employing 50–249 employees reporting significantly lower Strategic Impact than the reference category. This result should however be interpreted cautiously, as firm size was not the main theoretical focus of the study.

As a robustness check, an extended model (model 7) including firm age and sector controls was also estimated and the results proved consistent: Strategic Use, Strategic Integration, and Top Management Support remained statistically significant predictors of Strategic Impact, while Dynamic Capabilities remained non-significant. The extended model is reported in Annex H, Table H1, while standardized coefficients pertaining to Model 6 are presented in Annex H, Table H2.

4.9 Diagnostics and Robustness Checks

The diagnostic and robustness checks did not indicate major violations of the OLS assumptions or issues that would compromise the interpretation of the results. Namely, residual normality tests were non-significant, the Q-Q plot did not suggest substantial deviations from normality and the Breusch-Pagan test did not provide evidence of heteroscedasticity. Additionally, although influence diagnostics identified seven observations above the conservative Cook's Distance threshold of 4/n, no case showed extreme influence. Nevertheless, sensitivity analysis excluding these observations and the consideration of HC3 robust standard errors confirmed that the main conclusions remained unchanged. Full diagnostic and robustness results are reported in Annex I, Tables I1 - I5 and Figures I1- I2.

4.10 Mediation analysis

The non-significant coefficient of Dynamic Capabilities in the main regression models suggested that mediation through Dynamic Capabilities was unlikely, as the indirect effect depends partly on the association between Dynamic Capabilities and Strategic Impact. Nevertheless, the indirect effects were tested directly, although the results did not provide evidence of significant mediation. In fact, the indirect effect of Strategic Use, Strategic Integration and Top Management support through Dynamic Capabilities were nonsignificant, as the 95% bootstrap confidence intervals included zero in all three cases: Strategic Use, b = .008, 95% CI [-.019, .045]; Strategic Integration, b = -.023, 95% CI [-.073, .021]; and Top Management Support, b = -.023, 95% CI [-.087, .016]. Therefore, Dynamic Capabilities did not significantly mediate any of the tested relationships.

Although Top Management Support was positively associated with Dynamic Capabilities, b = .230, p = .029, Dynamic Capabilities did not significantly predict Strategic Impact in the outcome model, b = -.101, p = .220. Moreover, the direct effects of Strategic Use, Strategic Integration, and Top Management Support on Strategic Impact remained positive and statistically significant. These findings suggest that the strategic impact of GenAI in SMEs is more directly associated with its strategic use, integration into strategic routines, and support from top management than with an indirect effect through Dynamic Capabilities. Table 4.6 summarizes the results of this mediation analysis.

Table 4.6: Complementary analysis of Dynamic Capabilities as a mediator

Relationship	A path	B path	Indirect Effect	95% CI	Direct Effect c'	Total effect c
SU -> DC -> PSI	-.082	-.101	.008	[-.019,.045]	.471***	.479***
SI -> DC -> PSI	.225	-.101	-.023	[-.073, .021]	.386***	.364***
TMS -> DC -> PSI	.230*	-.101	-.023	[-.087, .016]	.343***	.320***

Note. N = 84. Bootstrap confidence intervals are based on 5,000 bootstrap samples. DC = Dynamic Capabilities. *p < .05; **p < .01; ***p < .001. Indirect effects are considered significant when the 95% bootstrap confidence interval does not include zero.

4.11 Complementary Exploratory Analysis

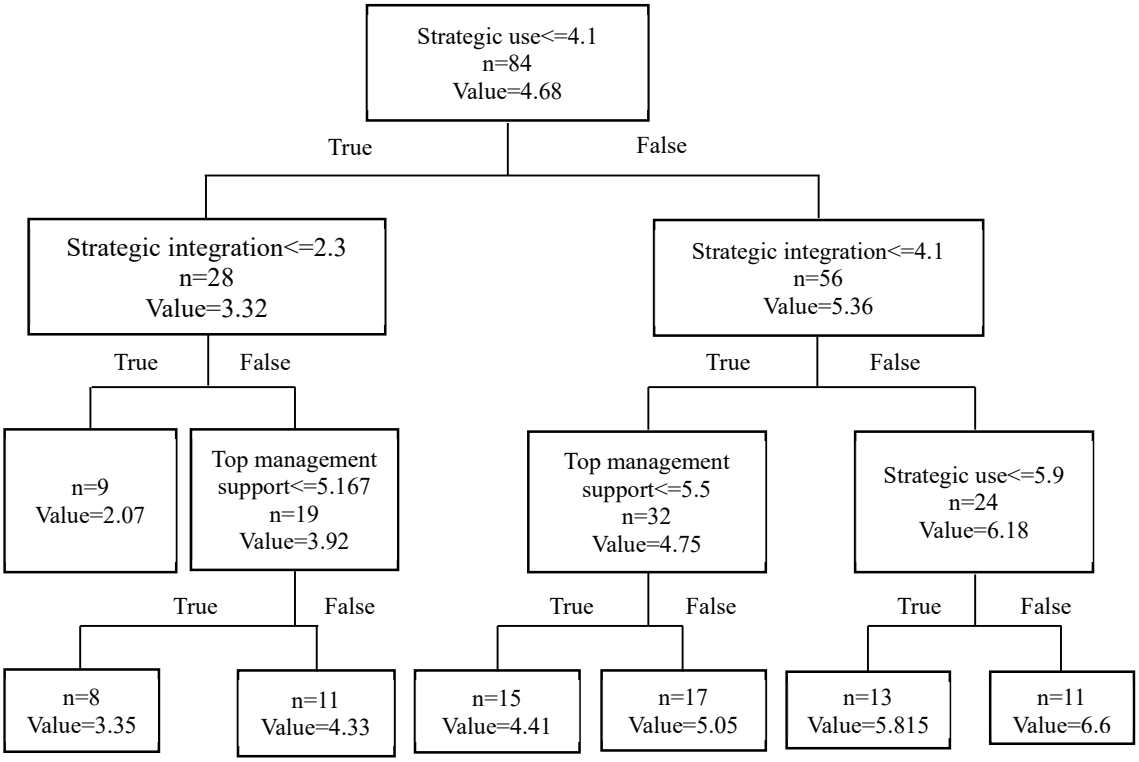
In addition to the main hypothesis-testing analyses, complementary exploratory analyses were conducted to provide further insight into the patterns observed in the data, including an exploratory decision tree analysis, an exploratory regression model considering Innovation Capability as an alternative outcome, and a complementary analysis of the open-ended responses.

4.11.1 Exploratory Decision Tree Analysis

As an exploratory analysis, a regression tree was estimated in order to identify non-linear patterns associated with Strategic Impact. The results of this analysis are presented in Figure 4.1. The process identified Strategic Use as the first splitting variable, separating firms with lower levels of perceived Strategic Impact from those with higher levels.

At the second level, among firms who reported lower Strategic Use values, Strategic Integration further differentiated firms with very low perceived Strategic Impact from those with more moderate impact. On the other hand, among firms with higher Strategic Use, Strategic Integration and Top Management Support further distinguished firms reporting moderate versus high levels of Strategic Impact.

Figure 4.1: Complementary regression tree analysis



Note. The figure presents an exploratory regression tree predicting perceived Strategic Impact. Values in the nodes represent mean perceived Strategic Impact while n denotes the number of observations in each subgroup.

Finally, the highest Strategic Impact was observed among firms combining high Strategic Use and high Strategic Integration, while the lowest Strategic Impact was observed among firms with low Strategic Use and low Strategic Integration. Overall, the decision tree supports the main OLS results by suggesting that the perceived strategic impact of GenAI is primarily associated with its strategic use, its integration into organizational routines, and support from top management. Dynamic Capabilities did not appear as a splitting variable in the tree, which is consistent with the non-significant direct and mediating effects found in the regression and mediation analyses.

4.11.2 Complementary exploratory analysis: Innovation as an alternative outcome

The results of the exploratory analysis of innovation capability as an alternative outcome are exhibited in Annex J, Table J1, while standardized coefficients and HC3 robust standard errors for this model are reported in Annex J, Tables J2 and J3. The controlled model explained 39.1% of the variance in Innovation Capability, although the adjusted R^2 was lower, at .317. The results showed that Dynamic Capabilities were the only robust predictor of Innovation Capability in the controlled model, $b = .658$, $p < .001$, a finding that remained stable when HC3 robust standard errors were used.

These outcomes suggest that firms with stronger firm-level Dynamic Capabilities also tend to report higher Innovation Capability. However, because both constructs were measured at the firm level rather than specifically in relation to GenAI, these results should be interpreted as exploratory and complementary and not as an implication that GenAI strategic use directly generates innovation capability.

4.12 Complementary analysis of open-ended responses

Overall, the qualitative findings show that respondents associated GenAI with both opportunities and risks. In fact, among the aforementioned 59 responses, 59.3% referenced at least one opportunity, while 71.2% referenced at least one risk or challenge. A further 37.3% referred to both opportunities and risks, which suggests that many respondents view GenAI adoption as simultaneously valuable and potentially problematic. These results are

exhibited in Annex B, Table B3.

In what pertains to the perceived opportunities, the most frequent theme was efficiency, automation and productivity, in 26 (44,1%) responses. Respondents commonly described GenAI as a tool for automating routine tasks, cutting down time spent on administrative or operational tasks, improving productivity and optimising internal processes. The second most frequent opportunity identified was decision support and information processing, in 13 responses, which pointed to the role of GenAI in accessing, organising, summarising and analysing information as well as in supporting problem solving and decision making. Other opportunities appeared less often but remained relevant nonetheless, namely innovation and experimentation, strategic integration into processes and systems, marketing, communication and content generation, and competitive positioning. A comprehensive breakdown of the identified opportunities through the open-ended responses is presented in Annex B, Table B4.

Turning to perceived risks and challenges, the prevalent theme was reliability, accuracy, validation and critical thinking, mentioned in 17 responses (28.8%), as respondents frequently voiced concern that GenAI-generated outputs might be inaccurate, misleading or insufficiently reliable, particularly when used without human verification. A second cluster of concerns centred on data security, privacy, confidentiality and governance, mentioned in 9 responses (15.3%), alongside workforce displacement and changes to the human role, mentioned in the same number of responses. Further risks identified included dependence on the technology and the erosion of human judgement or creativity, a loss of differentiation and competitive homogenisation, implementation barriers, legal or regulatory concerns and finally dependence on external providers or sustainability-related issues. The risks and challenges identified are concretely reported in Annex B, Table B5.

Essentially, the open-ended responses reflected both perceived opportunities and risks associated with GenAI use, with operational and informational benefits coexisting with concerns related to reliability, governance and human judgement.

5. Discussion

5.1 Summary of Main Findings

This study sought to understand how GenAI is used in the Portuguese SME context and how different forms of use contribute to perceived Strategic Impact. Overall, operational use proved more developed than Strategic Use and GenAI Integration, indicating that GenAI remains more strongly embedded in routine and productivity-oriented tasks as opposed to in strategic practices. The regression results indicated that Strategic Use, GenAI Integration and Top Management Support were positively and significantly associated with perceived Strategic Impact, whereas Dynamic Capabilities did not arise as a significant predictor or mediator, in spite of their association with broader Innovation Capabilities in the exploratory analysis. Lastly, the open-ended responses highlighted both opportunities, particularly efficiency, automation and information processing and concerns connected to reliability, validation, data governance and human oversight.

5.2 GenAI Use in SMEs: From Operational Use to Strategic Integration

The quantitative findings suggest that GenAI is already present within the organizational practices of the Portuguese SMEs included in the sample, although its use appears more developed at the operational level than in terms of its strategic use or integration. This distinction matters, since the use of GenAI does not necessarily mean the technology has become embedded in strategic routines or managerial decision-making processes. This indicates that responding firms tend to rely on GenAI more for routine, productivity and efficiency-related activities than for purposes that run deeper into strategic territory.

This pattern fits the current stage of GenAI diffusion seen across many organizations. Specifically, since GenAI tools are relatively new, accessible and easy to experiment with, firms may initially turn to them for tasks with more immediate and visible payoffs, such as drafting content, summarizing information or simply saving time on administrative work. Such uses, commonly known as quick wins, can generate real operational value without requiring substantial changes to organizational routines, decision processes and strategic planning. The results, in this sense, indicate that SMEs may be treating GenAI as a practical productivity tool first, before taking the leap into adopting it as a more integrated strategic resource.

The open-ended responses lend further support to this interpretation, as efficiency, automation and productivity emerged as the most frequently mentioned opportunity,

followed by decision support and information processing. Relevant as these opportunities are, they sit closer to operational improvements than to deeper strategic transformation. Nevertheless, the presence of themes such as decision support, innovation and process integration indicates that some firms already do see GenAI as holding broader strategic potential.

Integration concerns whether the tools have found their way into recurring workflows, managerial practices, organizational routines and decision-making processes, beyond their more surface level use. This distinction is important because frequent use does not imply organizational embeddedness. The lower mean recorded for GenAI integration therefore suggests that many firms may still be at an early stage of turning GenAI from an isolated productivity tool into a more stable organizational practice.

This finding is also relevant in light of the SME context, given that these firms tend to operate with more limited financial, technological and managerial resources than larger firms and their strategic processes are often less formalized. These characteristics may make it easier to experiment with accessible GenAI tools yet harder to integrate them systematically into organizational processes. At the same time, the flexibility and centralized decision-making typical of SMEs could support faster integration once managers recognize the technology's strategic relevance.

Taken as a whole, this section helps answer the first research question by showing that GenAI use among responding Portuguese SMEs is currently more developed at the operational than at the strategic or organizational levels. Overall, the findings point to a transitional pattern in which GenAI is already being used by Portuguese SMEs, but its movement from operational experimentation toward deeper strategic and organizational integration remains incomplete.

5.3 Organizational Drivers of GenAI Strategic Impact

The regression results point to strategic use of GenAI, GenAI integration and top management support as the variables most closely associated with perceived strategic impact within the sample. This finding is crucial to the study, suggesting that the tool's strategic value hinges not simply on whether firms use the technology but on how they use it, how deeply it is woven into organizational practices, and whether that use is backed by managerial action.

Concretely, Strategic use emerged as one of the strongest predictors of perceived Strategic Impact, suggesting that GenAI is more likely to be seen as strategically valuable

when applied to activities such as decision support, strategic planning, market analysis, scenario exploration and innovation related tasks. Put differently, the technology seems to carry more strategic weight once it moves from simple routine productivity support towards feeding into activities that shape the firm's direction, adaptation and competitive positioning.

GenAI integration was likewise positively and significantly associated with perceived strategic impact, reinforcing the distinction between using GenAI occasionally and embedding it within organizational routines, workflows and managerial processes. This distinction carries particular weight from a strategic management standpoint: A firm may use the tool frequently without ever turning it into an organizational capability, whereas GenAI that becomes incorporated into recurring processes is more likely to shape how information is analysed, how decisions are prepared, how alternatives are generated and how activities are coordinated across the organisation in a consistent manner. The significance of GenAI integration thus lends support to the Resource-Based View argument that technological tools become strategically valuable only once combined with firm-specific routines, knowledge and organizational practices.

Top management support stood out as the third main predictor of the dependent variable, underscoring how much managerial commitment shapes GenAI's strategic impact. In particular, in SMEs, where decision-making tends to be more centralized and strategic processes less formalized, top management support can play an outsized role in determining whether GenAI stays as a fragmented operational tool or becomes integrated into broader organizational priorities. For instance, management may direct attention, resources and reinforce legitimacy toward GenAI-related initiatives, helping employees understand when, where and how the technology ought to be used.

Overall, these findings point to perceived strategic impact as a function of use, integration and managerial support acting in combination. The first captures the purpose behind GenAI's application, the second reflects how far the technology has become embedded in organizational routines and the third refers to the managerial conditions that allow its use to become strategically meaningful. As such, these results answer the second, third and fourth research questions: Strategic Use, GenAI Integration and Top Management Support are positively associated with perceived Strategic Impact, suggesting that GenAI becomes strategically relevant when it is purposefully applied, embedded in organizational routines and supported by management.

5.4 Dynamic Capabilities and Innovation Capability

The role of Dynamic Capabilities in this study requires a more nuanced interpretation. Theoretically, Dynamic Capabilities were expected to matter in the sense that GenAI may help firms sense opportunities and threats, seize emerging possibilities and reconfigure resources or processes. On this basis, firms with stronger Dynamic Capabilities would be expected to translate the use of GenAI into stronger perceived strategic outcomes. However, empirical results did not bear this expectation out directly. In fact, in the main regression models, Dynamic Capabilities failed to emerge as a statistically significant predictor of perceived strategic impact, which suggests that, within the considered sample, broader firm-level adaptive capabilities were not enough to explain GenAI's perceived strategic impact, once strategic use, GenAI integration and top management support had been taken into account. In other words, the dependent variable appears to be more closely tied with GenAI-specific practices and managerial support than to general organizational adaptability alone.

The mediation analysis reinforced this conclusion, as Dynamic Capabilities did not significantly mediate the relationship between Strategic Use, GenAI Integration and Top Management Support and Perceived Strategic Impact. Top management support was indeed positively associated with Dynamic Capabilities, but the mediator itself failed to predict perceived strategic impact significantly. Therefore, the results offer no support to the idea that GenAI-related practices generate strategic impact mainly by strengthening firm's Dynamic Capabilities. Nevertheless, this does not mean Dynamic Capabilities are irrelevant, but rather that their role may differ from what the main conceptual model initially anticipated. The exploratory analysis using Innovation Capability as an alternative dependent variable helps clarify this matter. In it, Dynamic Capabilities stood as the only robust predictor of Innovation Capability, while strategic use, GenAI integration and top management support lost statistical significance once controls were introduced. This suggests Dynamic Capabilities may bear a closer relationship to broader firm-level innovation capacity than to the perceived strategic impact of GenAI specifically, which is a plausible reading, given how closely innovation capability relates to identifying opportunities, turning ideas into implemented solutions, and adapting organizational processes.

In short, these findings provide a cautious answer to the fifth research question, insomuch as in this sample, Dynamic Capabilities did not mediate the relationship between GenAI-related practices and perceived Strategic Impact. Nonetheless, their association with Innovation Capability suggests that they may still matter for broader organizational

innovation and adaptation. Given the cross-sectional design, this result should be interpreted as exploratory rather than causal, and it does not rule out the possibility that such a mechanism might surface in a longitudinal setting.

5.5 Responsible AI, Opportunities and Risks

The discoveries point to the importance of responsible and critical GenAI use within SMEs, as respondents viewed GenAI as a source of opportunity, yet also as a technology demanding validation, governance and human judgement.

Concretely, the responsible and future-oriented items suggest respondents do not regard GenAI as an autonomous substitute for managerial judgement. In fact, the strongest result concerned the need for human supervision before GenAI outputs are used in important decisions, indicating that respondents tend to see GenAI as a tool whose outputs must be interpreted, checked and contextualized by human users before use, a view consistent with the broader literature on responsible AI, which emphasizes accountability, human evaluation and the need to translate ethical principles into concrete organizational practices (Jobin et al., 2019; Mittelstadt, 2019). Furthermore, it also aligns well with the broader regulatory orientation of the EU AI Act, which places particular emphasis on risk management, transparency and human oversight in the governance of AI systems (European Parliament and Council of the European Union, 2024).

Going hand in hand with this finding, relatively strong concern also emerged around bias, misinformation and explainability. This matters because GenAI-generated outputs can appear coherent and convincing while still being inaccurate, biased or incomplete, a limitation that becomes especially problematic in strategic contexts, where managers may lean on GenAI outputs to support analysis, planning, market interpretation or decision-making (Duan et al., 2019; Jarrahi, 2018; Ji et al., 2023; Shrestha et al., 2019). As such, GenAI's strategic value hinges not only on whether it improves efficiency or supports decision-making, but on whether firms are equipped to evaluate its outputs critically. At the same time, responsible GenAI use appears to be understood, for now, more through concrete operational concerns than through formalized ethical lenses. Respondents showed strong agreement on the need for human validation and voiced concern over bias, misinformation and explainability, whereas the broader item on whether the firm considers ethical implications in GenAI use scored comparatively lower, suggesting SMEs may be more immediately attuned to practical risks than to broader or more formal governance structures.

The sustainability dimension seems even less developed, since sustainability-related items returned lower mean values and greater dispersion, suggesting environmental considerations have yet to be consistently built into how responding SMEs approach GenAI. One possible explanation is that much of the environmental burden emphasized in the literature relates to the computationally intensive development and training of large-scale models (Strubell et al., 2019), conceivably making these costs less visible at the point of organizational use. However, the present data does not directly test this explanation.

The open-ended responses reinforce this balanced picture, where respondents mainly associated GenAI with efficiency, automation, productivity and information processing, yet emphasizing risks related to reliability, validation, data governance, human oversight and dependence on the technology. This suggests a form of responsible optimism which ties well with the thesis' broader strategic value argument: GenAI is seen as useful and strategically promising, but not as a tool to be used without critical judgement, governance awareness and responsible managerial practice.

Overall, the findings answer the sixth research question by showing that Portuguese SMEs see GenAI as both opportunity and risk, appearing optimistic about its future relevance and its potential contribution to competitiveness, while remaining alert to its risks.

5.6 Theoretical Implications

The findings of this study offer three main theoretical implications. First, they support a post-adoption perspective on GenAI in SMEs, since, because the study focused on firms that already reported using GenAI, the relevant question was how it was used, integrated and supported within the organization, beyond its adoption. This perspective is particularly relevant in the SME context, where accessible technologies may be adopted relatively easily while their integration into strategic routines and managerial processes may remain less developed.

Second, the results extend Resource-Based View logic to the GenAI context. Since GenAI tools are increasingly accessible, their strategic relevance appears to rest less on possession or access and more on organizational embeddedness and strategic use. In other words, GenAI becomes theoretically relevant as a potential strategic resource when it is connected to firm-specific routines, knowledge, managerial processes and strategic activities. The significance of GenAI Integration and Top Management Support supports this interpretation, suggesting that strategic value depends not only on the technology itself, but also on

the organizational and managerial conditions through which it is deployed.

Third, the study refines the role of Dynamic Capabilities in this context, as although Dynamic Capabilities did not directly predict perceived Strategic Impact or operate as a mediator, their association with Innovation Capability suggests that they may be more relevant to broader organizational innovation and adaptation than to GenAI-specific strategic impact in the present model. This does not, however, undermine the relevance of Dynamic Capabilities theory, but instead suggests that broad firm-level adaptive capabilities may not fully explain the perceived strategic impact of a specific technology unless they are translated into more technology-specific forms of use and integration.

5.7 Practical Implications for SMEs

The findings of this dissertation carry practical implications for SME managers looking to extract real strategic value from GenAI. Overall, they indicate that this technology should not be managed as a purely individual productivity tool but as a tool whose value depends on strategic alignment, organizational integration, managerial support and responsible use. First, SMEs should move beyond occasional or purely operational GenAI use. The descriptive results show operational use running ahead of both strategic use and GenAI integration, suggesting that many firms are still leaning on GenAI mainly for quick productivity wins. While these applications are valid and comprehensible as a first stage of adoption, they may not go far enough to generate broader strategic impact on their own. Therefore, managers should also identify areas where GenAI can support market analysis, strategic planning, scenario exploration, customer understanding, innovation processes and decision support.

Second, SMEs should pay particular attention to organizational integration, since GenAI is far more likely to become strategically relevant once embedded in recurring workflows and managerial processes than when used in an isolated or informal way. In practice, this might involve defining specific use cases, clarifying when GenAI should be used, setting up validation procedures and incorporating the technology into regular activities such as reporting, planning, communication, product development or process improvement. This does not necessarily require large technological investment, but it does call for managerial intentionality and organizational coordination.

Third, top management support appears especially important. In SMEs, where decision-making tends to be concentrated and strategic processes less formalized, managers play

a central role in defining the purpose and scope of GenAI use. As such, top management can back GenAI use by legitimizing experimentation, allocating time and resources, encouraging employee learning and making sure GenAI initiatives tie back to business objectives. Without such support, GenAI use may stay fragmented and depend on isolated individual initiatives.

Fourth, SMEs should develop responsible and critical habits around GenAI use. Respondents in this study recognized the importance of human supervision and explainability, as well as risks related to misinformation, bias, data security and over-dependence on AI. Managers, in turn, should ensure that GenAI outputs are not accepted at face value, particularly when they inform important decisions. Concrete measures may include requiring human review, avoiding the use of confidential data in inappropriate tools, documenting assumptions, cross-checking GenAI outputs against other sources and clarifying responsibility for the final decision.

Fifth, managers should understand GenAI integration as part of an ongoing learning process, given the fast evolution of the technology and the relatively early stage of integration observed in the sample. Managers may therefore benefit from starting with a limited amount of focused, strategically relevant use cases, formalizing successful practices through guidelines, training and governance mechanisms. In this process, GenAI may additionally support experimentation and innovation, when combined with human expertise, organizational knowledge and managerial judgement.

6. Conclusion

This thesis set out to examine the perceived strategic impact of GenAI in Portuguese SMEs. Drawing on the Resource-Based View and Dynamic Capabilities perspectives, it analysed whether Strategic Use, GenAI Integration, Top Management Support and Dynamic Capabilities were associated with perceived Strategic Impact.

The findings showed that Strategic Use, GenAI Integration and Top Management Support were the main predictors of perceived Strategic Impact. Dynamic Capabilities did not operate as a significant direct predictor or mediator, although they were associated with Innovation Capability in the exploratory analysis. The results therefore suggest that GenAI's strategic relevance in SMEs is linked primarily to purposeful use, organizational integration and managerial support, rather than operational use alone. Additionally, responsible use is central to this process, particularly around human supervision, explainability, validation, data governance and critically assessing GenAI outputs.

6.1 Main Contributions

This study contributes to the literature on GenAI and strategic management in SMEs in three main ways. First, it adopts a post-adoption perspective in the context of Portuguese SMEs. Rather than focusing only on whether firms use GenAI, it shows that Strategic Use, GenAI Integration and Top Management Support are the variables most strongly associated with perceived Strategic Impact.

Second, it provides a more nuanced picture of Dynamic Capabilities, considering that although they did not mediate the relationship between GenAI-related practices and perceived strategic impact, their strong tie to Innovation Capability suggests they may still matter a great deal for broader innovation and adaptation, even where they fall short of explaining GenAI-specific strategic impact in this particular study.

Third, the thesis adds a complementary qualitative perspective by showing that SMEs perceive GenAI as both an opportunity and a risk, associating it with efficiency and information processing while emphasizing the need for reliability, validation, data governance and human oversight.

6.2 Limitations

A few limitations are worth noting. First, the sample was relatively small and drawn through non-probability sampling, limiting how far the findings can be generalized. In addition, the sample presented uneven sector representability and concentrated on firms with 10-49 employees and established organizations, with more than half of firms reporting 21 years of activity. Consequently, the findings may reflect more closely the experiences of established small firms than very young firms, whose perceptions should be cautiously generalized. This is particularly important for the interpretation of the results, inasmuch as older firms may differ from their younger counterparts in terms of accumulated experience, organizational routines, managerial formalization and capacity to integrate new technologies into existing processes.

What is more, the research relied on self-reported perceptions, meaning the results reflect perceived strategic impact rather than objective firm performance. The cross-sectional design also rules out establishing causal relationships or temporal sequences.

Additionally, even though the questionnaire was theoretically grounded and most constructs showed solid reliability, some scales presented weaker reliability and should therefore be interpreted with caution.

Moreover, Dynamic Capabilities were measured as broad firm-level capabilities rather than as capabilities specific to GenAI, a choice with solid theoretical grounding, seeing that Dynamic Capabilities are traditionally understood as firm-level capabilities rather than technology-specific. It also helped in preserving conceptual separation between Dynamic Capabilities and the GenAI-specific constructs in the model, namely Strategic Use and GenAI Integration. However, this choice does constrain how the mediation results can be read. What the study captured was firms' general ability to sense opportunities, seize them and reconfigure resources or processes, not whether GenAI itself was contributing to those capabilities. The non-significant mediation findings, then, show only that broad Dynamic Capabilities failed to mediate the relationship between GenAI-related practices and perceived strategic impact in this sample. Nonetheless, they do not rule out the possibility that more GenAI-specific capabilities could play a different role altogether.

Finally, the qualitative component was built on open-ended survey responses, offering useful complementary insight but without reaching the depth interviews or case studies would have allowed.

6.3 Future Research

Future work could address these gaps by drawing on larger, more representative SME samples, ideally spanning different sectors and regions. Longitudinal studies, in particular, would help clarify how GenAI use, integration and strategic impact shift over time, and whether Dynamic Capabilities develop before, during or after GenAI integration takes hold.

Future studies could also combine survey data with interviews, case studies or objective performance indicators, given that this would help clarify how SMEs actually integrate this technology into strategic routines and how managers evaluate its contribution to decision-making, innovation and competitiveness. Further research could examine GenAI-enabled capabilities more specifically, while avoiding conceptual overlap with strategic use and integration.

For Portuguese SMEs, the key challenge is to turn GenAI use into a coherent organizational and strategic practice, supported by managerial commitment and responsible human judgement.

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Annexes

Annex A: Operationalization of the main constructs

Table A1: Operationalization of the main constructs

Construct	Adapted or developed	Theoretical basis
SU	Developed for this study	Literature-informed items based on GenAI applications in decision support, strategic analysis, market analysis, scenario exploration and innovation-related activities. Supported by Duan et al. (2019), Jarrahi (2018), Shrestha et al. (2019), Doshi et al (2025), Mariani et al. (2023), Cockburn et al. (2019), Bharadwaj (2000) and Teece (2007).
SI	Developed for this study	Literature-informed items based on organizational integration, routinization, managerial use, technology assimilation, compatibility with existing processes and embedding into organizational capabilities. Supported by Bharadwaj (2000), Liang et al. (2007), Pavlou and El Sawy (2011), Moore and Benbasat (1991), Oliveira and Martins (2011), Vial (2019), Verhoef et al. (2021) and Oldemeyer et al. (2025).
TMS	Adapted from existing literature	Adapted from literature on top management support and organizational technology adoption and assimilation, particularly Liang et al. (2007) and Jeyaraj et al. (2006). Also conceptually supported by Thong (1999), Gibb and Scott (1985), Martin et al. (2016) and Andersén (2021) in the SME context, highlighting the owner-manager's role, centralized decision-making and managerial capabilities as dimensions shaping technology-related decisions and resource deployment.

DC	Adapted from existing conceptualizations	Based on the Dynamic Capabilities literature, particularly on sensing, seizing and reconfiguring capabilities. Supported by Teece et al. (1997), Teece (2007), Eisenhardt and Martin (2000), and Pavlou and El Sawy (2011).
PSI	Developed for this study	Literature-informed items based on strategic value, decision-making, innovation, responsiveness and competitive positioning. Supported by Barney (1991), Mata et al. (1995), Bharadwaj (2000), Newbert (2008), Teece (2007), Pavlou and El Sawy (2011), Mariani et al. (2023), Haefner et al. (2021) and Doshi et al. (2025).

Note. Table A1 summarizes the role of the main constructs, indicating if they were adapted from existing literature or developed specifically for this dissertation. The theoretical basis column identifies the main literature informing the operationalization of each construct.

Annex B: Qualitative Codebook and open-ended response coding

Table B1: Qualitative codebook – coding examples

Code	Theme	English translated response	Coding rationale
O1	Efficiency, automation and productivity / process optimisation	"Time-saving capacity on the most routine tasks"	This response was assigned to O1 because it explicitly refers to time savings in routine tasks, which directly reflects efficiency and productivity gains.
O2	Decision support and information processing	"With AI, I intend to create ways to compare supplier prices simply and automatically, and do the same to understand new market trends…"	This response was assigned to O2 because it refers to using GenAI to compare supplier prices and analyse market trends, indicating information processing and decision-support functions.

O3	Innovation, creativity, experimentation and new solutions	"New products and services can be created at a lower cost compared to the past"	This response was assigned to O3 because it explicitly links GenAI to the creation of new products and services, reflecting innovation and new solution development.
O4	Strategic integration and process/system improvement	"Generative AI is a crucial opportunity for the hyper automation and integration of organizational processes. Currently, we use the technology on an ad hoc basis for data analysis and reporting, but the real strategic leap will be its integration with our structural tools."	This response was assigned to O4 because it explicitly refers to the integration of GenAI into organizational processes and structural tools, moving beyond punctual use toward deeper process and system integration.
O5	Competitive advantage, agility and strategic positioning	"Generative AI opens paths for less developed companies to compete on a perceived equal footing with more developed companies…"	This response was assigned to O5 because it frames GenAI as a way for smaller or less developed firms to compete more effectively with more developed firms, reflecting competitive positioning.
O6	Marketing, communication and content generation	"Turn scientific studies into posts, create presentations, write video scripts, generate images, adapt emails in multiple languages…"	This response was assigned to O6 because it refers to content creation, presentations, video scripts, image generation and multilingual email adaptation, all of which relate to communication and content generation.

R1	Reliability, accuracy, validation and need for critical thinking	"The biggest risk is using AI without human verification. Its content often contains errors."	This response was assigned to R1 because it directly mentions the risk of using AI outputs without human verification and highlights the possibility of errors.
R2	Data security, privacy, confidentiality and governance/control	"That all the company's and personal information generated in AI is shared with third parties or used for marketing purposes or even commercial and industrial espionage"	This response was assigned to R2 because it raises concerns about company and personal information being shared with third parties, used for marketing or exploited for commercial and industrial espionage.
R3	Legal, ethical, regulatory and intellectual property concerns	"Legal and ethical issues, along with exposure of intellectual property, can be considered strategic risks."	This response was assigned to R3 because it explicitly refers to legal, ethical and intellectual property risks.
R4	Workforce displacement and changing human role	"Risk of job loss."	This response was assigned to R4 because it directly refers to the elimination of jobs, which reflects workforce displacement.
R5	Dependence, deskilling and erosion of human judgment or creativity	"The team may become overly dependent on these opinions, making the company's operations poorly functional."	This response was assigned to R5 because it refers to excessive dependence on AI-generated opinions, which may weaken human autonomy, judgement or functional decision-making.
R6	Loss of differentiation, imitation and competitive homogenisation	"Standardization of product and service offerings across all competitors."	This response was assigned to R6 because it describes the risk that firms' products and services become homogenised across

			competitors, reducing differentiation.
R7	Implementation/adoption barriers and integration complexity	"Most Significant Risk: the complexity of technical integration"	This response was assigned to R7 because it explicitly identifies technical integration complexity as the main risk associated with GenAI adoption, reflecting implementation and integration-related challenges.
R8	External dependence, costs and sustainability concerns	"Over-dependence on products whose cost could be substantially and unilaterally increased by suppliers... Impact on the overall sustainability of the company's activities..."	This response was assigned to R8 because it refers to dependence on external AI products or providers, possible unilateral cost increases and sustainability-related concerns.
N1	Limited/no substantive answer or future-only comment	"No opinion."	This response was assigned to N1 because it does not provide a substantive view on GenAI opportunities or risks.

Note. The samples presented are translated excerpts from the open-ended responses. They are illustrative and selected to clarify the application of each code to concrete responses.

Table B2: Qualitative codebook – theoretical grounding

Code	Theme / code	Theoretical Basis
O1	Efficiency, automation and productivity / process optimisation	Captures perceived improvements in efficiency, automation, productivity and process optimization. Literature on technology-adoption pinpoints perceived usefulness and performance gains as important drivers of technology use, while empirical GenAI research documents productivity

		enhancements in knowledge-intensive work (Brynjolfsson et al., 2025; Davis, 1989; Dwivedi et al., 2023; Noy & Zhang, 2023; Venkatesh et al., 2003).
O2	Decision support and information processing	Reflects the AI's and GenAI's role in supporting information processing, analysis, documentation, problem-structuring, evaluation of alternatives and organizational decision-making (Doshi et al., 2025; Duan et al., 2019; Jarrahi, 2018; Shrestha et al., 2019).
O3	Innovation, creativity, experimentation and new solutions	Relates to GenAI's potential to accelerate ideation, knowledge recombination, experimentation and contribute to innovation-related activities, thus easing the exploration and development of new solutions (Dwivedi et al., 2023; Haefner et al., 2021; Mariani et al., 2023).
O4	Strategic integration and process/system improvement	Reflects the organizational assimilation and integration of digital technologies into recurring routines, processes and capabilities. Supported by prior research that stresses compatibility, organizational embedding and changes to processes and capabilities as important dimensions of technology assimilation and digital transformation (Liang et al., 2007; Moore & Benbasat, 1991; Verhoef et al., 2021; Vial, 2019).
O5	Competitive advantage, agility and strategic positioning	Draws on RBV and related IT-capability literature, according to which technologies produce strategic value when combined with complementary firm-specific resources, capabilities and organizational processes, combinations that may support differentiation, adaptive capacity and stronger competitive positioning (Barney, 1991; Bharadwaj, 2000; Mata et al., 1995; Teece, 2007).
O6	Marketing, communication and content generation	Pertains to GenAI's capacity to support content creation, communication, documentation and other knowledge-intensive organizational activities, including applications

		relevant to marketing and customer-facing communication (Dwivedi et al., 2023; Feuerriegel et al., 2024).
R1	Reliability, accuracy, validation and critical thinking	Captures concerns regarding hallucinations, factual inaccuracies, misleading outputs and the need for human verification, contextual interpretation and critical oversight over outputs, especially when AI-generated information is used in organizational settings (Dwivedi et al., 2023; Feuerriegel et al., 2024; Jarrahi, 2018; Ji et al., 2023).
R2	Data security, privacy, confidentiality and governance/control	Reflects concerns arund data privacy, confidentiality, information leakage, security along with the need for appropriate governance and organizational controls when GenAI systems are used with organizational information (Dwivedi et al., 2023; Feuerriegel et al., 2024; Oldemeyer et al., 2025).
R3	Legal, ethical, regulatory and intellectual property concerns	Covers the broader ethical, legal and regulatory concerns associated with GenAI use, namely accountability, transparency, responsible governance and emerging compliance requirements, alongside intellectual-property-related concerns (Dwivedi et al., 2023; European Parliament & Council of the European Union, 2024; Jobin et al., 2019; Mittelstadt, 2019).
R4	Workforce displacement and changing human role	Pertains to concerns that AI-enabled automation may substitute or transform particular forms of human work and change the balance between automation and human contribution, judgement and interaction (Jarrahi, 2018; Li et al., 2026; Raisch & Krakowski, 2021).
R5	Dependence, deskilling and loss of critical thinking	Refers to concerns about excessive reliance on GenAI, notably reduced human autonomy and an erosion of independent judgement, expertise or creative contribution when AI systems are used uncritically. This is consistent with the need to preserve human agency and

		complementarity in human–AI interaction highlighted by the literature (Jarrahi, 2018; Li et al., 2026; Raisch & Krakowski, 2021).
R6	Loss of differentiation, imitation and competitive homogenisation	Is grounded primarily in the RBV: Widely accessible and imitable technologies are unlikely to constitute sustained sources of differentiation by themselves. Competitive value alternatively depends on how technologies are combined with firm-specific resources, capabilities and organizational processes that are harder to replicate (Barney, 1991; Bharadwaj, 2000; Mata et al., 1995).
R7	Implementation/adoption barriers and integration complexity	Reflects difficulties associated with organizational readiness, compatibility, technical expertise, financial and human resources, training requirements, integration with existing systems and uncertainty about business value, which are noticeably relevant to SMEs adopting emerging technologies (Moore & Benbasat, 1991; Oldemeyer et al., 2025; Oliveira & Martins, 2011).
R8	External dependence, costs and sustainability concerns	Captures concerns about dependence on external AI providers which may raise supplier costs and lead to possible sustainability impacts. This theme is less central in the literature section but can be linked to broader organizational and implementation challenges of AI adoption in SMEs (Oldemeyer et al., 2025; Feuerriegel et al., 2024).
N1	Limited/no substantive answer or future-only comment	Used to classify answers with no substantive opportunity or risk, such as "no opinion", punctuation only, or comments indicating no current consideration. This is an analytical category, not a theory-derived code.

Note. This table presents the theoretical foundations supporting each qualitative code, informed by the literature review in chapter 2 and refined through the analysis of the open-ended responses. N1 captures non-substantive responses.

Table B3: General classification of open-ended responses

Type of response	n	Frequency of non-empty

		responses
Mentions at least one opportunity	35	59.3%
Mentions at least one risk/challenge	42	71.2%
Mentions both opportunities and risks/challenges	22	37.3%
Mentions only opportunities	13	22.0%
Mentions only risks/challenges	20	33.9%
Limited/no substantive answer or future-only comment	4	6.8%

Note. Percentages are calculated based on the 59 non-empty open-ended responses. Since multiple codes could be assigned to the same response, categories are not mutually exclusive and percentages do not sum to 100%.

Table B4: Frequency of identified opportunities

Code	Theme	n	Frequency
O1	Efficiency, automation and productivity / process optimisation	26	44.1%
O2	Decision support and information processing	13	22.0%
O3	Innovation, creativity, experimentation and new solutions	9	15.3%
O4	Strategic integration and process/system improvement	7	11.9%
O6	Marketing, communication and content generation	6	10.2%
O5	Competitive advantage, agility and strategic positioning	5	8.5%

Note. Percentages are calculated based on the 59 non-empty open-ended responses. Multiple opportunity codes could be assigned to the same response and therefore, categories are not mutually exclusive nor do the percentages sum to 100%.

Table B5: Frequency of identified risks and challenges

Code	Theme	n	Frequency

R1	Reliability, accuracy, validation and need for critical thinking	17	28.8%
R2	Data security, privacy, confidentiality and governance/control	9	15.3%
R4	Workforce displacement and changing human role	9	15.3%
R5	Dependence, deskilling and erosion of human judgment or creativity	8	13.6%
R6	Loss of differentiation, imitation and competitive homogenisation	7	11.9%
R7	Implementation/adoption barriers and integration complexity	5	8.5%
R3	Legal, ethical, regulatory and intellectual property concerns	3	5.1%
R8	External dependence, costs and sustainability concerns	1	1.7%

Note. Percentages are calculated based on the 59 non-empty open-ended responses. Multiple risks or challenge codes could be assigned to the same response and as such, categories are neither mutually exclusive nor do the percentages add up to 100%.

Annex C: Specification of regression models and complementary analysis

Table C1: Specification of regression models and complementary analysis

Model	Purpose	Dependent variable	Main variables	Controls or notes
Model 5	Main theoretical model	PSI	SU, SI, TMS, DC	No controls

Model 6	Final controlled model	PSI	SU, SI, TMS, DC	Firm size, DM, INT, RSI
Model 7	Extended robustness specification	PSI	SU, SI, TMS, DC	Adds firm age and sector controls; interpreted as robustness check
Model INN1	Exploratory innovation model	IC	SU, SI, TMS, DC	No controls
Model INN2	Exploratory controlled innovation model	IC	SU, SI, TMS, DC	Same controls as Model 6
Mediation 1	Main mediation analysis	PSI	SU, SI, TMS as predictors; DC as mediator	Bootstrapped indirect effects; 5,000 samples

Note. The table encapsulates the empirical models estimated in the study. Model 5 represents the main theoretical model, Model 6 corresponds to the final controlled model and model 7 is treated as an extended robustness specification. Model INN1 and INN2 are exploratory and use Innovation Capability as an alternative outcome. The mediation analysis examines Dynamic Capabilities as a mediator between the main GenAI-related predictors and perceived Strategic Impact.

Annex D: Sample profile and descriptive distributions

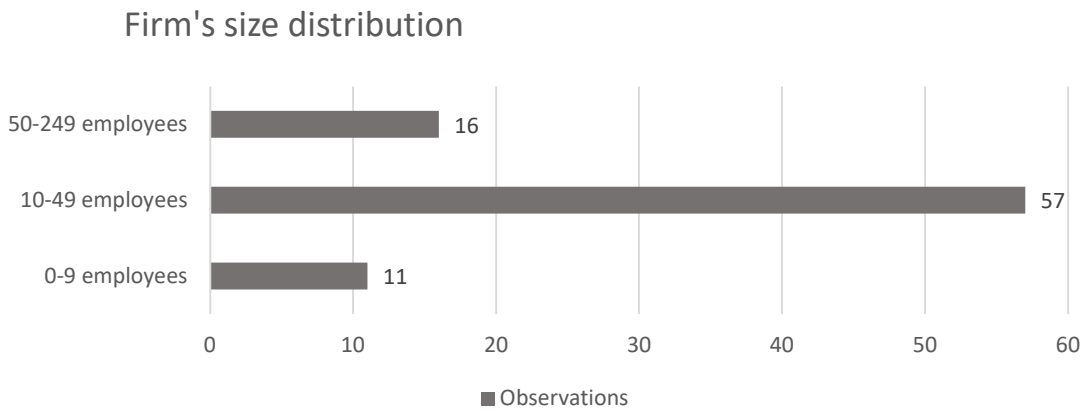
Table D1: Firm sector distribution

Category	n	Frequency
Manufacturing / Industrial production	24	28.6
Wholesale and retail trade	21	25.0
Construction / Real estate	9	10.7

Professional, scientific and technical services	8	9.5
Information and Communication (ICT, software, digital services)	7	8.3
Accommodation and Food Service (Tourism)	6	7.1
Human health and social work activities	4	4.8
Agriculture / primary sector	2	2.4
Financial and insurance activities	1	1.2
Other	1	1.2
Education and training	1	1.2

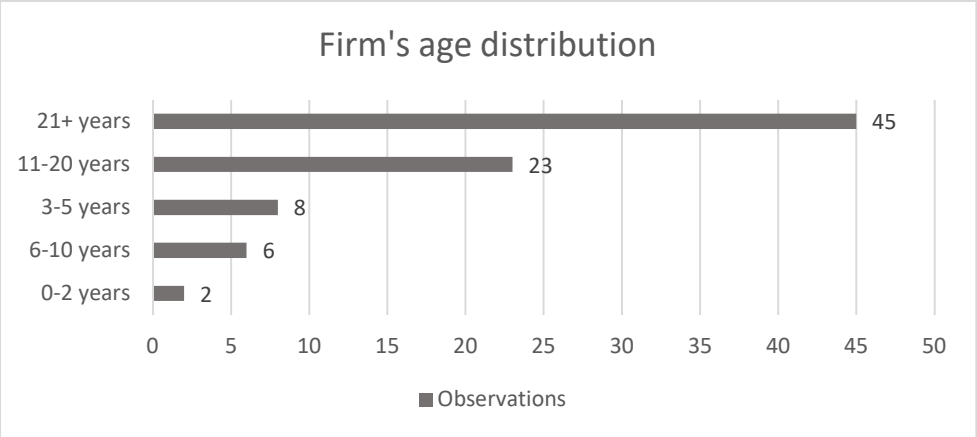
Note. Percentages are calculated based on the final analytical sample of 84 valid responses and sector categories were harmonized before analysis to group substantively similar responses.

Figure D1: Firm size distribution



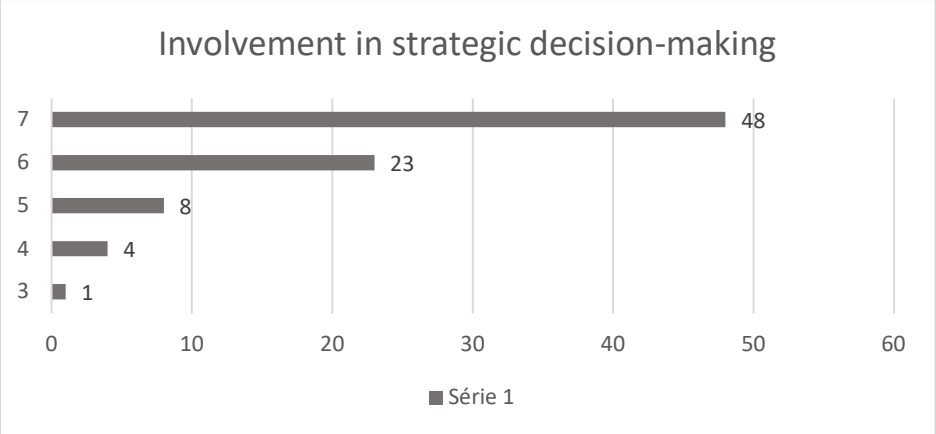
Note. Figure D1 reports the number of firms in each employee-size category within the final analytical sample.

Figure D2: Firm age distribution



Note. The figure reports the number of firms in each age category within the final analytical sample.

Figure D3: Respondent's involvement in strategic decision-making



Note. The figure reports respondent's self-reported involvement in strategic decision-making on a seven-point Likert scale, where higher values represent higher involvement.

Table D2: Item-level descriptive statistics for ethical, explainability, sustainability and future-oriented items

Dimension	Substantive focus	N	Mean	Median	SD
Ethics	The firm is concerned with broad ethical concerns	84	4.655	5.0	1.892
Ethics	The firm is concerned with bias or misinformation	84	5.369	6.0	1.782
Ethics	Supervision on AI outputs is needed	84	6.369	7.0	1.200
Explainability	Employees need to seek explain-ability in AI outputs	84	5.845	6.0	1.375
Explainability	Lack of explainability limits use	84	5.083	5.0	1.681

Sustainability	The firm considers broad environmental impact of technology in the firm's decisions	84	4.095	4.0	1.973
Sustainability	The firm considers the environmental impact of AI use	84	4.012	4.0	1.885
Future orientation	Firm is likely to invest more in AI in the next 2/3 years	84	5.524	6.0	1.624
Future orientation	The firm considers GenAI as strategically important to the future of the firm	84	5.524	6.0	1.632

Note. N=84. Items were measured on seven-point Likert scales, with higher values representing stronger agreement with the statement. This table reports item-level descriptive statistics for ethics, explainability, sustainability and future-oriented GenAI dimensions.

Annex E: Data Screening and Reliability Diagnostics

Table E1: Response quality screening criteria used in the analysis

Screening criterion	Purpose	Use in analysis
Within response variability	Detect low variation across items	Screening flag
Number of distinct response values	Detect excessive use of few scale points	Screening flag
Longstring index	Detect long sequences of identical responses	Screening flag
Same-value proportion	Detect excessive repetition of one response option	Screening flag
Univariate outliers	Identify extreme construct-level values	Screening flag
Mahalanobis distance	Identify unusual multivariate response profiles	Screening flag
Manual inspection	Distinguish plausible profiles from low-quality responses	Final exclusion decision

Note. The criteria listed in this table were used as screening indicators, rather than automatic exclusion rules, as final exclusion decisions were based on the combined assessment of response-pattern indicators and manual inspection.

Table E2: Corrected item-total correlation and alpha-if-deleted results

Construct	Item	Item mean	Item SD	Corrected item-total correlation	Cronbach alpha if item deleted
DM	DM1	5.024	1.388	.344	.547
DM	DM2	4.631	1.387	.486	.323
DM	DM3	4.702	1.333	.343	.544
INT	INT1	5.131	1.446	.649	.788
INT	INT2	5.012	1.427	.740	.762
INT	INT3	3.667	1.717	.477	.847
INT	INT4	5.095	1.534	.698	.772
INT	INT5	6.226	1.123	.629	.800
OU	OP1	5.060	1.570	.288	.604
OU	OP2	4.762	1.595	.307	.590
OU	OP3	5.607	1.397	.475	.459
OU	OP4	5.571	1.320	.485	.459
SU	SU1	4.810	1.594	.698	.882
SU	SU2	4.512	1.587	.787	.863
SU	SU3	4.131	1.815	.729	.876
SU	SU4	4.012	1.746	.859	.845
SU	SU5	4.667	1.738	.650	.893
SI	SI1	3.643	1.625	.536	.708
SI	SI2	4.286	1.625	.505	.718
SI	SI3	4.167	1.656	.691	.652
SI	SI4	2.595	1.876	.571	.693
SI	SI5	3.679	1.995	.353	.780
TMS	TMS1	5.762	1.304	.645	.801
TMS	TMS2	5.286	1.753	.787	.634
TMS	TMS3	5.369	1.699	.638	.798
DC	DC1	5.560	1.409	.563	.881
DC	DC2	5.571	1.273	.627	.870

DC	DC3	5.524	1.366	.788	.843
DC	DC4	5.369	1.333	.756	.849
DC	DC5	5.179	1.372	.734	.852
DC	DC6	5.167	1.404	.675	.862
IC	INN1	4.845	1.753	.660	.778
IC	INN2	5.179	1.364	.677	.755
IC	INN3	5.369	1.511	.701	.721
PSI	IMP1	4.905	1.526	.808	.903
PSI	IMP2	4.798	1.597	.861	.892
PSI	IMP3	4.405	1.673	.818	.900
PSI	IMP4	4.619	1.849	.694	.928
PSI	IMP5	4.679	1.709	.828	.898
ETH	ETH1	4.655	1.892	.679	.656
ETH	ETH2	5.369	1.782	.780	.517
ETH	ETH3	6.369	1.200	.487	.849
EXP	EXP1	5.845	1.375	.365	NaN
EXP	EXP2	5.083	1.681	.365	NaN
SUS	SUS1	4.095	1.973	.864	NaN
SUS	SUS2	4.012	1.885	.864	NaN
FO	FUT1	5.524	1.624	.827	NaN
FO	FUT2	5.524	1.632	.827	NaN

Note. Corrected item-total correlations indicate the association between each item and the remaining items in the same construct, while Alpha-if-deleted values specify Cronbach's alpha if the corresponding item was removed. Items were maintained when their removal did not substantially improve internal consistency and when theoretical considerations supported their inclusion.

Annex F: Spearman Correlations Between the Main Constructs

Table F1: Spearman correlation matrix for the main constructs

Construct	1	2	3	4	5
SU	1.000				
SI	.672***	1.000			

TMS	.468***	.526***	1.000		
DC	.221*	.306**	.338**	1.000	
SI	.775***	.751***	.647***	.258*	1.000

Note. N=84. Spearman rank-order correlation coefficients are reported. *p<.05; **p<.01; ***p<.001

Annex G – Multicollinearity Diagnostics

Table G1: VIF values for model 5 and 6

Variable	Model 5 VIF	Model 6 VIF
SU	1.905	2.198
SI	2.192	2.407
TMS	1.591	1.845
DC	1.280	1.328
DM	-	1.648
INT	-	2.582
RSI	-	1.184
Firm size: 10–49	-	2.075
Firm size: 50–249	-	2.182
Highest VIF	2.192	2.582

Note. VIF=Variance Inflation Factor. Model 5 includes only the main theoretical predictors and Model 6 corresponds to the final controlled model. Values below the threshold of 5 were considered acceptable.

Table G2: VIF values for model 7

Variable	VIF
C(firm_age)[T.21 + anos]	14.477
C(firm_age)[T.11 - 20 anos]	11.667
C(sector)[T.Manufatura / Produção industrial]	10.420
C(sector)[T.Comércio por grosso e a retalho]	10.072
C(firm_age)[T.3 - 5 anos]	6.362
C(sector)[T.Serviços profissionais, científicos e técnicos]	5.933
C(sector)[T.Construção / Imobiliário]	5.674

C(sector)[T.Informação e Comunicação]	5.448
C(sector)[T.Hotelaria e Turismo]	4.836
C(firm_age)[T.6 - 10 anos]	4.159
C(firm_size)[T.50-249 colaboradores]	3.661
C(sector)[T.Saúde e serviços sociais]	3.591
C(firm_size)[T.10-49 colaboradores]	3.080
INT	2.988
SI	2.655
SU	2.527
TMS	2.179
C(sector)[T.Atividades Financeiras e de seguros]	1.914
DM	1.844
C(sector)[T.Other]	1.707
DC	1.656
C(sector)[T.Educação e formação]	1.596
RSI	1.466

Note. VIF = Variance Inflation Factor. Model 7 includes firm age and sector controls in addition to the variables of the main controlled model. Elevated VIF values mainly reflect the inclusion of several categorical dummy variables when compared to the sample size. As such, Model 7 was interpreted as an extended specification rather than as the main controlled model.

Table G3: Summary of alternative model specifications

Model / Specification	Highest VIF	Main concern	Decision
Main theoretical predictors	2.192	None	Acceptable
Final controlled model	2.582	None	Retained as main model
Intermediate specification with firm age controls	12.015	Firm age dummy variables	Not retained as main model
Extended model with firm age and sector	14.477	Sector and firm age dummy variables	Robustness check only

Note. VIF = Variance Inflation Factor. Values below 5 were considered acceptable. The final

controlled model presented no evidence of problematic multicollinearity and was retained as the main model. Alternative specifications including firm age and sector controls produced elevated VIF values, particularly among categorical dummy variables, and were therefore interpreted as robustness checks.

Annex H: Additional regression results for Strategic Impact

Table H1: Extended robustness specification: Model 7 with Firm Age and sector controls

Variable	Model 7
SU	.451***
	(.082)
SI	.402**
	(.096)
TMS	.342***
	(.079)
DC	-.060
	(.088)
DM	Included
INT	Included
RSI	Included
Firm size controls	Yes
Firm age controls	Yes
Sector controls	Yes
R^2	.848
Adjusted R^2	.790
N	84

Note. N=84. Unstandardized coefficients are reported, with standard errors in parentheses. *p<.05; **p<.01; ***p<.001

Table H2: Standardized coefficients – Model 6

Predictor	Unstandardized b	Standard error	Standardized beta	t_value	p_value
SU	.471	.079	.459	5.972	.000

SI	.386	.094	.331	4.114	.000
TMS	.343	.075	.322	4.568	.000
DC	-.101	.081	-.074	-1.238	.220
DM	-.148	.096	-.102	-1.530	.130
INT	.037	.108	.028	.341	.734
RSI	-.043	.089	-.027	-.486	.628

Note. Standardized beta coefficients are reported for continuous predictors in order to support comparison of relative effect sizes within Model 6. Unstandardized coefficients remain the main basis for interpretation of the regression results.

Annex I: Regression Diagnostics and Robustness Checks for Model 6

Table I1: Residual normality tests for Model 6

Test	Statistic	P_value
Shapiro-Wilk	.991	.810
Jarque-Bera	1.128	.569

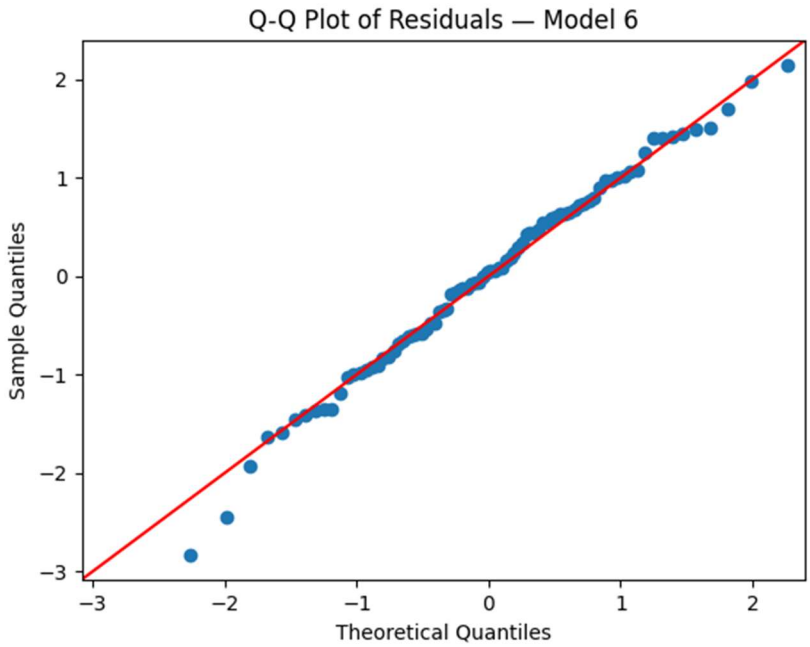
Note. The null hypothesis of the Shapiro-Wilk and Jarque-Bera tests is that the residuals do not significantly deviate from normality. Non-significant p-values therefore indicate no evidence of substantial departure from residual normality.

Table I2: Breusch-Pagan tests for heteroscedasticity in Model 6

Test	Statistic	P_value	Interpretation
Breusch-Pagan LM	12.241	.200	No evidence of heteroscedasticity
Breusch-Pagan F	1.403	.203	No evidence of heteroscedasticity

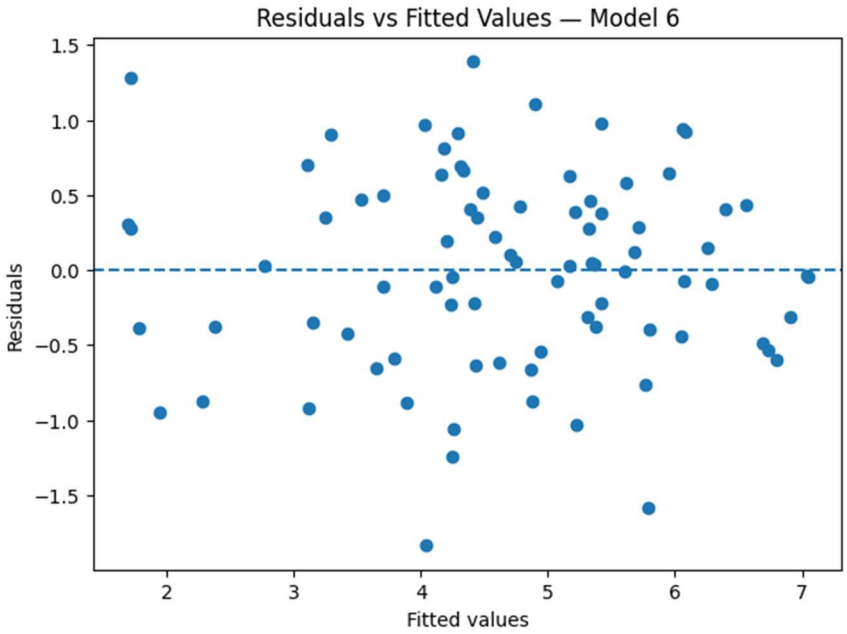
Note. The null hypothesis of the Breusch-Pagan test is homoscedasticity. As such, non-significant p-values indicate no evidence of heteroscedasticity in Model 6.

Figure I1: Q-Q plot of residuals for Model 6



Note. The Q-Q plot compares the distribution of standardized residuals within the theoretical normal distribution. Points close to the diagonal line suggest non-deviation from normality.

Figure I2: Residual vs fitted values plot for Model 6



Note. The residual versus fitted values were inspected with the intention of assessing if the

residuals were randomly distributed around zero. The absence of a clear funnel shape or systematic patterns suggest no strong visual evidence of heteroscedasticity or misspecification in Model 6.

Table I3 - Robustness check for the final controlled model using HC3 standard errors

Variable	Coef	SE	t-value	p-value	Coef (HC3 SE)
Constant	1.143	.823	1.389	.1691	1.143 (.823)
Firm size: 10–49	-.458	.233	-1.964	.0533	-.458+ (.233)
Firm size: 50–249	-1.011	.292	-3.464	.0009	-1.011*** (.292)
SU	.471	.110	4.266	.0001	.471*** (.110)
SI	.386	.101	3.844	.0003	.386*** (.101)
TMS	.343	.077	4.441	.0000	.343*** (.077)
DC	-.101	.099	-1.017	.3124	-.101 (.099)
DM	-.148	.112	-1.321	.1907	-.148 (.112)
INT	.037	.104	.355	.7235	.037 (.104)
RSI	-.043	.096	-.453	.6521	-.043 (.096)

Note. Dependent variable: perceived Strategic Impact. Unstandardized coefficients are reported. HC3 heteroscedasticity-consistent standard errors were used as a robustness check for Model 6 and are reported in parenthesis. +p<.10; *p<.05; **p<.01; ***p<.001.

Table I4: Model 6 influential observations

n	UV	LSVR	MSVP	Cook's D	Lev	ESR	DFFITS
55	7	8	.562	.176675	.247086	2.393228	1.370994
71	5	9	.479	.162540	.258076	2.218177	1.308247
35	7	8	.521	.107321	.147776	-2.581245	-1.074866
60	7	4	.312	.067718	.209575	1.615419	.831810
39	6	9	.500	.055795	.129565	-1.973589	-.761435
25	7	8	.375	.054804	.191278	-1.536128	-.747068
32	6	8	.292	.051798	.064198	-2.880094	-.754352
19	7	9	.292	.018334	.295880	-.657993	-.426536
80	7	7	.229	.014044	.255580	-.637004	-.373248

Note. Observations were flagged based on Cook's distance values above the conservative

threshold of 4/n. Additional diagnostics, including leverage, externally studentized residuals and DFFITS were inspected to understand whether flagged cases exerted excessive influence on the model.

Table I5: Model 6 sensitivity analysis excluding influential observations flagged by Cook's distance

Model	Term	Coef	SE	T value	P value	R^2	Adj R^2
M6 main	Intercept	1.143	.773	1.478	.144	.801	.777
M6 main	C(firm_size)[T.10-49 colaboradores]	-.458	.232	-1.971	.052	.801	.777
M6 main	C(firm_size)[T.50-249 colaboradores]	-1.011	.284	-3.567	.001	.801	.777
M6 main	SU	.471	.079	5.972	.000	.801	.777
M6 main	SI	.386	.094	4.114	.000	.801	.777
M6 main	TMS	.343	.075	4.568	.000	.801	.777
M6 main	DC	-.101	.081	-1.238	.220	.801	.777
M6 main	DM	-.148	.096	-1.530	.130	.801	.777
M6 main	INT	.037	.108	.341	.734	.801	.777
M6 main	RSI	-.043	.089	-.486	.628	.801	.777
M6 excluding Cook-flagged	Intercept	.519	.696	.746	.458	.857	.838
M6 excluding Cook-flagged	C(firm_size)[T.10-49 colaboradores]	-.276	.195	-1.414	.162	.857	.838
M6 excluding Cook-flagged	C(firm_size)[T.50-249 colaboradores]	-.702	.239	-2.933	.005	.857	.838
M6 excluding Cook-flagged	SU	.445	.072	6.196	.000	.857	.838
M6 excluding Cook-flagged	SI	.405	.083	4.902	.000	.857	.838
M6 excluding Cook-flagged	TMS	.393	.062	6.291	.000	.857	.838

M6 excluding Cook-flagged	DC	-.012	.076	-.157	.876	.857	.838
M6 excluding Cook-flagged	DM	-.235	.087	-2.688	.009	.857	.838
M6 excluding Cook-flagged	INT	.041	.092	.444	.658	.857	.838
M6 excluding Cook-flagged	RSI	-.020	.080	-.249	.804	.857	.838

Note. This table compares the original Model 6 estimates with estimates obtained after excluding observations flagged through Cook's distance, using the 4/n threshold. The sensitivity analysis was used so as to assess whether the main regression conclusions remained stable after removing potential influential observations.

Annex J: Exploratory Innovation Capability model

Table J1: Exploratory OLS regression with Innovation Capability as alternative outcome

Variable	Model INN1	Model INN2
Constant	.872	.080
	(.671)	(1.229)
SU	.061	.054
	(.115)	(.125)
SI	-.201	-.238
	(.140)	(.149)
TMS	.218*	.200
	(.109)	(.119)
DC	.635***	.658***
	(.125)	(.129)
DM		.215
		(.153)
INT		-.034
		(.172)
RSI		-.005
		(.142)

Firm size: 10–49		.255
		(.370)
Firm size: 50–249		.251
		(.451)
R^2	.368	.391
Adjusted R^2	.336	.317
N	84	84

Note. Dependent variable: Innovation Capability. Unstandardized coefficients are reported, with standard errors in parentheses. Model INN1 includes the main theoretical predictors only. Model INN2 includes the same controls used in the final controlled Strategic Impact model. The reference category for firm size is 0–9 employees. *p < .05; **p < .01; ***p < .001.

Table J2: Standardized coefficients for exploratory Innovation Capability model

Variable	Unstandardized coefficient	Standardized beta	t-value	p-value
SU	.054	.058	.428	.670
SI	-.238	-.224	-1.592	.116
TMS	.200	.206	1.673	.099
DC	.658	.533	5.099	< .001
DM	.215	.163	1.400	.166
INT	-.034	-.029	-.196	.845
RSI	-.005	-.004	-.037	.971

Note. Dependent variable: Innovation Capability. Standardized beta coefficients are reported so as to support comparison of the relative strength of the continuous predictors within the exploratory controlled innovation model.

Table J3: Robustness check for the exploratory Innovation Capability model using HC3 standard errors

Variable	**Coefficient**	**SE non-robust**	**p non-robust**	**SE HC3**	**p HC3**
Constant	.080	1.229	.948	1.056	.940
Firm size: 10–49	.255	.370	.492	.422	.546
Firm size: 50–249	.251	.451	.580	.488	.608

SU	.054	.125	.670	.141	.704
SI	-.238	.149	.116	.145	.102
TMS	.200	.119	.099	.134	.135
DC	.658	.129	< .001	.123	< .001
DM	.215	.153	.166	.168	.202
INT	-.034	.172	.845	.166	.839
RSI	-.005	.142	.971	.128	.967

Note. Dependent variable: Innovation Capability. This table compares non-robust standard errors with HC3 heteroskedasticity-consistent standard errors for the exploratory controlled innovation model, serving as a robustness check. *p<.05; **p<.01; ***p<.001