ISRG Journal of Economics, Business & Management (ISRGJEBM)

ISRG PUBLISHERS

Abbreviated Key Title: Isrg J Econ Bus Manag

ISSN: 2584-0916 (Online)

Journal homepage: https://isrgpublishers.com/isrgjebm/

Volume – I Issue-II (November – December) 2023

Frequency: Bimonthly



Beyond Adoption: How SMEs Convert Generative AI Use into Organizational Capability and Firm Performance

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| **Received:** 18.12.2023 | **Accepted:** 21.12.2023 | **Published:** 25.12.2023

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Abstract

Purpose: *Small and medium-sized enterprises (SMEs) can now buy access to generative artificial intelligence (GenAI) for the price of a software subscription, yet many of those that adopt it report little change in firm performance. This paper asks why GenAI adoption creates value for some SMEs and not for others.*

Design/methodology/approach: *The paper is conceptual and reports no empirical data. It positions itself against recent work on GenAI adoption in SMEs and against established research on post-adoption use, organizational learning, digital transformation and IT-enabled value creation. It builds a two-stage model in which the technology-organization-environment (TOE) framework explains adoption, realized absorptive capacity explains how adoption becomes a firm-level GenAI capability, and the resource-based view and dynamic capabilities theory explain why that capability, rather than tool use, is the main source of performance differences. Data readiness, task orientation and governance capability are treated as boundary conditions. Nine propositions are derived, and a three-wave panel design with sample measures and validation procedures is proposed to test them.*

Theoretical propositions: *The paper argues, rather than demonstrates, that adoption, capability and value are three separate states. It proposes that adoption may have a modest direct effect on operational performance through task-level efficiency gains, but that its effects on innovation, market and risk-adjusted performance run mainly through GenAI capability. The conversion from adoption to capability is proposed to depend on realized absorptive capacity, understood as the firm's routines for evaluating, transforming and exploiting model outputs, and to be stronger where firm data are ready for use. The conversion from capability to performance is proposed to depend jointly on whether GenAI augments or automates judgment-intensive work and on governance capability, with governance most consequential for risk-adjusted performance and where tasks are automated. These are theoretical expectations that require empirical validation.*

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DOI: 10.5281/zenodo.24028510

Conclusion: *Recent studies explain which factors drive GenAI adoption in SMEs and how adoption unfolds over time. This paper addresses the step those studies leave open: the mechanism and conditions under which adoption turns into a capability and the capability turns into measurable performance. It contributes a distinction between absorptive capacity as a learning routine and GenAI capability as the operational capability that routine builds, a multidimensional definition of GenAI capability, a disaggregated view of performance, and a testable research design that separates the stages in time. The propositions are provisional and are offered for empirical testing.*

Keywords: *generative artificial intelligence, SMEs, absorptive capacity, dynamic capabilities, AI capability, post-adoption use, organizational learning, firm performance, AI governance.*

1. Introduction

For most of the history of enterprise computing, small firms adopted new technology late because they could not afford it. Enterprise resource planning, electronic data interchange and business analytics all required capital outlay, specialist staff and data infrastructure that SMEs rarely had (Iacovou et al., 1995; Thong, 1999). Generative AI breaks this pattern. Large language models are sold as monthly subscriptions, need no in-house training and are operated in ordinary language. A ten-person accounting practice can use the same model as a multinational bank.

The productivity evidence is encouraging but uneven. In a controlled experiment, professionals given access to a chat-based model completed writing tasks faster and with higher assessed quality (Noy & Zhang, 2023). In a large customer-support setting, access to a GenAI assistant raised the number of issues resolved per hour, with the largest gains among less experienced agents (Brynjolfsson et al., 2025). A field experiment with consultants found that the same tool improved performance on tasks within its competence and lowered it on a task outside that competence (Dell'Acqua et al., 2023). These studies measure individuals and tasks. They do not tell us whether a firm that adopts GenAI becomes a better firm.

For SMEs this question has become pressing. Adoption is spreading through informal routes: an owner tries a chatbot, an employee uses one to draft proposals, a marketing contractor brings one in. Use of this kind can make individual people faster without changing what the firm produces, how well it serves customers or how much it earns. The fall in the cost of access has not removed the costs of converting access into advantage. Those costs are managerial, cognitive and organizational, and they fall hardest on firms without spare staff, formal processes or structured data.

Research on GenAI in SMEs has grown quickly since 2024. Practitioner-oriented work has set out the promises and risks of GenAI for small firms and proposed deployment roadmaps (Rajaram & Tinguely, 2024). Survey studies have applied the TOE framework to GenAI and identified the technological, organizational and environmental factors associated with adoption (Hughes et al., 2026). Work in developing economies has added knowledge assimilation as a mechanism linking TOE pressures to adoption ("Barriers to Generative AI Adoption," 2026). Qualitative research has described adoption as a process that moves from individual experimentation through organizational legitimization to embedding and value realization (Siljeur et al., 2026). Taken together, this work answers the question of what drives adoption reasonably well and has begun to describe how adoption unfolds. It does less to explain why firms at similar levels of adoption obtain different results.

The difficulty is not unique to GenAI. Information systems research has long separated the adoption decision from post-adoption use and from business value (Jasperson et al., 2005; Melville et al., 2004; Zhu & Kraemer, 2005), and research on the returns to IT has shown that they depend on complementary organizational investments (Brynjolfsson & Hitt, 2000). Three features of GenAI, however, change how these insights apply. First, because the cost of access is close to zero, complementary investments account for almost all of the difference between firms. Second, because outputs are fluent but of uncertain accuracy, the firm must judge each output itself, which places learning routines at the center of value creation. Third, because use in SMEs often begins with individuals rather than with an organizational investment decision, adoption can be widespread while organizational assimilation remains shallow. Existing frameworks were not developed with these features in mind.

This paper addresses that gap. Its central research question is: *why does GenAI adoption create value for some SMEs but not for others?* Two subsidiary questions follow. First, through what mechanism does the adoption of GenAI tools become a firm-level GenAI capability? Second, under what conditions does that capability improve performance, and which dimensions of performance does it affect?

We argue that adoption, capability and value are distinct states and that the transitions between them are where SMEs differ. Our model treats the TOE framework as an account of adoption antecedents only. It treats realized absorptive capacity as the learning mechanism that turns adoption into capability, draws on the resource-based view and dynamic capabilities theory to explain why capability rather than usage generates most performance differences, and specifies data readiness, task orientation and governance capability as conditions on the conversion steps.

The framework advances three bodies of research. For *technology adoption research*, it moves the explanation beyond the adoption decision. TOE and acceptance models treat adoption as the dependent variable, and post-adoption research examines continued and deeper use (Bhattacherjee, 2001; Jasperson et al., 2005) without specifying the organizational capacity that turns use into value. We identify that capacity, realized absorptive capacity with an explicit evaluation step, and specify when adoption may and may not affect performance directly. For *organizational capabilities research*, the framework distinguishes a learning routine (realized absorptive capacity) from the operational capability it builds (GenAI capability), following the distinction

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between dynamic and ordinary capabilities (Winter, 2003; Zollo & Winter, 2002). This separates two constructs that are easily conflated in AI research and corrects a common misreading of absorptive capacity by distinguishing a GenAI system from the knowledge it gives access to. It also defines GenAI capability as a multidimensional construct that cannot be reduced to intensity of use. For *research on firm performance and IT-enabled value creation*, the framework specifies the complements particular to GenAI, namely data readiness, augmentation and governance, and disaggregates SME performance into operational, innovation, market and risk-adjusted dimensions. This allows the model to predict trade-offs, such as faster output with more errors, rather than a single positive effect. A three-wave design with sample measures is proposed so that the temporal order implied by the theory can be observed rather than assumed.

The paper proceeds as follows. Section 2 positions the study against recent GenAI research and against broader research on post-adoption use, IT-enabled value creation, organizational learning and digital transformation. Section 3 sets out the theoretical foundations and the boundaries between constructs. Section 4 develops the framework and nine propositions. Section 5 defines the constructs and their measurement, with sample items in Appendix A, and Section 6 proposes a research design. Section 7 discusses contributions and implications, Section 8 addresses limitations and Section 9 concludes.

2. Positioning the Study in Prior Research

The claim that adoption and value creation should be studied separately is not new in information systems research, and it would be inaccurate to present it as an open field for GenAI. Four recent streams on GenAI and three established streams in information systems and management research already cover parts of the ground. This section sets out what each explains and identifies the question none of them answers directly.

2.1 Deployment roadmaps for SMEs

Rajaram and Tinguely (2024) discuss how SMEs can deal with the promises and challenges of GenAI and propose a deployment roadmap. They identify employee competency, leadership and work values, organizational culture, collaboration, and relationships with third parties as the strategic dimensions of deployment. The contribution is practical and descriptive. It does not specify causal mechanisms or offer testable relationships between deployment choices and outcomes.

2.2 TOE-based studies of GenAI adoption

Hughes et al. (2026) combine exploratory interviews with a survey of 304 decision-makers across several regions and use structural equation modeling to test a TOE model of organizational GenAI adoption. Their results link complexity, skills and capacity for change to the extent of adoption. The study confirms that the TOE framework transfers to GenAI. Its dependent variable is adoption, and it is not specific to SMEs.

A second line of work, focused on SMEs in developing economies, integrates knowledge assimilation into the TOE framework as a mechanism through which internal learning shapes the response to organizational and external pressures ("Barriers to Generative AI Adoption," 2026). This is the study closest to ours, because it places a learning mechanism inside an adoption model. The difference lies in where the mechanism sits. In that study, assimilation helps explain whether firms adopt. In our model, absorptive capacity explains what happens after adoption and whether adoption becomes a capability.

2.3 Process accounts of GenAI adoption in SMEs

Siljeur et al. (2026) interviewed 31 SME decision-makers, mainly in Germany and France with supplementary cases from South Africa and Vietnam. Using the Gioia method, they describe GenAI adoption as three overlapping phases: activation of individual trust and engagement, legitimizing and direction setting, and embedding and sustained value realization. They extend TOE from a static to a processual account and draw on bricolage to explain how resource-constrained firms make do with available tools. They also report that value realization is fragile, constrained by data quality, inaccurate outputs and weak integration. The authors note that their phases rest on retrospective accounts and that the transitions between phases are inferred rather than observed.

This study comes closest to our concern with value. It describes the sequence through which adoption becomes embedded. It does not specify the organizational capacity that determines whether a firm passes from legitimized use to sustained value, and it does not distinguish among the kinds of value that embedding produces.

2.4 AI capability and performance

Mikalef and Gupta (2021) conceptualize AI capability as a bundle of tangible, human and intangible resources and show that it is associated with organizational creativity and firm performance. Their construct was developed for predictive AI in larger organizations. It does not address the specific demands of generative systems, such as evaluating plausible but incorrect outputs, and it does not model the step from adoption to capability.

2.5 Post-adoption use and assimilation

Information systems research has long recognized that the adoption decision is only the beginning. Jasperson et al. (2005) conceptualize post-adoptive behavior as the feature adoption, use and extension decisions that follow implementation, and argue that organizations typically use only a fraction of the functionality available to them, so that much of the potential value of IT depends on what happens after adoption. Bhattacherjee (2001) explains why individuals continue to use a system once it has been adopted, and Burton-Jones and Straub (2006) show that system use must be defined in relation to the task and the outcome of interest, since time spent with a system says little about how well it is employed. At the firm level, Zhu and Kraemer (2005) use the TOE framework to explain both the extent of e-business use and its value, and find that use is a significant driver of value, while Zhu et al. (2006) describe assimilation as a staged progression from initiation through adoption to routinization.

Two lessons carry over to GenAI. The depth and quality of use, not the adoption decision, are the proximate drivers of value. And use itself is usually treated as the endpoint of the organizational process; the learning capacity that determines whether use becomes a routinized capability is left unspecified. For GenAI this omission matters more than for earlier enterprise systems, because use is often initiated by individuals without any organizational decision and because the quality of use depends on judging outputs that may be wrong.

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2.6 IT-enabled value creation and complementarities

A second established stream asks how information technology creates business value. Melville et al. (2004) integrate this work in a model in which IT resources affect performance through business processes, in combination with complementary organizational resources and conditional on the competitive environment. Bharadwaj (2000) shows, from a resource-based perspective, that firms with superior IT capability outperform their peers, and Wade and Hulland (2004) argue that IT resources contribute to sustained advantage mainly through their interaction with other firm resources. Aral and Weill (2007) find that similar IT investments are associated with different performance outcomes depending on organizational practices, and Brynjolfsson and Hitt (2000) attribute much of the return on IT to complementary changes in work practices and organizational design. Devaraj and Kohli (2003) add that actual usage, rather than investment, is the link between IT and performance. More recently, Brynjolfsson et al. (2021) argue that general-purpose technologies require intangible complementary investments whose costs are incurred before their benefits appear, producing a productivity J-curve.

This stream supplies two premises of our model: that a widely available technology creates firm-level value mainly through firm-specific complements, and that such value takes time to appear. It also cautions against assuming that usage has no direct effect on performance, a point taken up in Proposition 3. What it does not provide is an account of the complements specific to GenAI, such as the evaluation of probabilistic outputs, data readiness for generative use, task orientation and governance, or of how SMEs with few slack resources build them.

2.7 Organizational learning and digital transformation

Organizational learning research treats learning as a change in the organization's knowledge that occurs as it acquires experience (Argote & Miron-Spektor, 2011). Zollo and Winter (2002) distinguish three learning mechanisms, namely experience accumulation, knowledge articulation and knowledge codification, and argue that the deliberate mechanisms of articulation and codification are what turn experience into dynamic capabilities. Tippins and Sohi (2003) show that IT competency improves firm performance largely through organizational learning. Absorptive capacity research is a branch of this literature concerned specifically with external knowledge (Lane et al., 2006).

Research on digital transformation reaches a similar conclusion from a different direction. Vial (2019) describes digital transformation as a process in which digital technologies trigger strategic responses and structural changes that alter the paths by which firms create value, and Verhoef et al. (2021) distinguish digitization, digitalization and digital transformation as phases that require increasingly substantial organizational change. In SMEs, Li et al. (2018) show that owner-managers drive digital transformation by building managerial and organizational capabilities incrementally from limited resources. These literatures support placing a learning mechanism between technology use and capability, and they identify the owner-manager as central in small firms. They have not, however, specified what learning involves when the technology itself generates content of uncertain reliability.

2.8 The remaining gap

Table 1 summarizes these positions.

Table 1. Positioning of the study against prior research

Study or stream	Context and method	What it explains	What it leaves open
Rajaram & Tinguely (2024)	SMEs; conceptual and practitioner-oriented	Strategic dimensions and a roadmap for deploying GenAI	Causal mechanisms; testable links to outcomes
Hughes et al. (2026)	Organizations in several regions; interviews and survey of 304 decision-makers; SEM	TOE antecedents of the extent of GenAI adoption	What follows adoption; SME specificity
"Barriers to Generative AI Adoption" (2026)	SMEs in developing economies; survey	Knowledge assimilation as a mediator of TOE effects on adoption	Conversion of adoption into capability and performance
Siljeur et al. (2026)	SMEs, mainly Germany and France; 31 interviews; Gioia method	Phases of adoption from individual activation to embedding	The capacity that governs transitions; types of value; temporal evidence
Mikalef & Gupta (2021)	Firms using predictive AI; survey	AI capability as a resource bundle linked to performance	GenAI-specific demands; SMEs; the adoption-to-capability step
Post-adoption research (e.g., Jasperson et al., 2005; Zhu & Kraemer, 2005)	Enterprise systems and e-business; individual and firm level	Continued, deepened and routinized use; use as a driver of value	The learning capacity that converts use into capability; probabilistic outputs
IT business value research (e.g., Melville et al., 2004; Aral & Weill, 2007)	Firms across industries; mostly large firms	Complementary resources and practices as conditions of IT value	GenAI-specific complements; resource-constrained SMEs
Organizational learning and digital transformation (e.g., Tippins & Sohi, 2003; Li et al., 2018; Vial, 2019)	IT and digital technologies; large firms and SMEs	Learning as the link between technology and performance; owner-led capability building	What learning involves when the technology generates content of uncertain reliability

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The question the table leaves unanswered is why SMEs at similar levels of GenAI adoption obtain different performance outcomes. Answering it requires four things the existing work does not combine: a mechanism that operates after adoption, a clear distinction between that mechanism and the capability it builds, a definition of GenAI capability that is distinct from use, and a performance construct broad enough to register trade-offs. The rest of the paper supplies these. We treat the TOE antecedents of adoption as largely established and include them only to complete the model and to serve as controls in testing. The theoretical contribution lies in the second stage.

3. Theoretical Foundations

The model draws on several theories, and a fair criticism of integrative models is that they stack frameworks without showing why each is needed. We therefore assign each theory one role. The TOE framework explains adoption. Absorptive capacity, as a branch of organizational learning theory, explains the conversion of adoption into capability. The resource-based view and dynamic capabilities theory explain why capability, and not adoption, is the main source of performance differences. Task-technology fit and the automation-augmentation argument, together with governance, specify when capability translates into performance. Individual acceptance models are not given separate status.

3.1 Definitions

We follow the European Commission (2003) in defining SMEs as enterprises with fewer than 250 employees and either annual turnover of no more than EUR 50 million or a balance-sheet total of no more than EUR 43 million. Researchers working elsewhere should substitute the relevant national definition.

Generative AI refers to machine-learning systems that produce new text, code, images or audio in response to prompts. Two features distinguish it from the predictive AI on which most SME research has focused. It is general-purpose, so the same tool can be applied to marketing copy, contract review and spreadsheet formulas. And it is operated through natural language, so its use does not require data-science skills. Both features lower the barrier to adoption. Neither lowers the barrier to using it well, because its outputs are probabilistic and can be fluent and wrong at the same time.

3.2 Adoption antecedents: the TOE framework

The TOE framework holds that a firm's adoption of an innovation depends on its technological context, its organizational context and its environment (Tornatzky & Fleischer, 1990). It is the most widely used framework for firm-level technology adoption (Oliveira & Martins, 2011) and has been applied to small businesses (Thong, 1999) and now to GenAI (Hughes et al., 2026; Siljeur et al., 2026).

In small firms the owner-manager usually makes technology decisions personally, so individual perceptions of usefulness and ease of use carry more weight than in large organizations (Davis, 1989; Venkatesh et al., 2003). We do not model these perceptions separately. We include the owner-manager's GenAI literacy as an element of the organizational context, which captures the same influence without adding a further framework.

The TOE framework is well suited to explaining whether and how extensively a firm adopts. It is silent on what the firm does with the technology afterwards, and we use it for adoption only.

3.3 The conversion mechanism: absorptive capacity

Absorptive capacity is a firm's ability to recognize the value of new external knowledge, assimilate it and apply it to commercial ends (Cohen & Levinthal, 1990). Zahra and George (2002) separate potential absorptive capacity, which covers acquisition and assimilation, from realized absorptive capacity, which covers transformation and exploitation. Todorova and Durisin (2007) argue that recognizing the value of external knowledge should be retained as a distinct first step, which matters here for reasons explained below.

It would be easy, but mistaken, to say that adopting a GenAI tool is itself an act of acquiring external knowledge. A GenAI system is a technological artifact. It gives access to outputs generated from statistical representations of very large bodies of text and other material, but those outputs are not knowledge in the sense the absorptive capacity literature intends. They may be correct, partly correct or confidently wrong, and they carry no information about which. Alavi et al. (2024) make a related point in arguing that GenAI changes how organizations create, store and apply knowledge rather than simply supplying it.

The more defensible formulation is that GenAI exposes the firm to externally generated knowledge resources. Value depends on whether the firm can evaluate those outputs, assimilate what is useful, recombine it with its own knowledge of customers, products and processes, and exploit the result in its work. Evaluation is the step where GenAI differs most from earlier sources of external knowledge. With a consultant's report or a trade publication, the source carries some signal of reliability. With a model's output, the firm must supply the judgment itself, and that judgment depends on domain expertise the firm already holds (Cohen & Levinthal, 1990).

This reformulation has two consequences for the model. Absorptive capacity is placed after adoption, as the mechanism that converts exposure into capability. And the realized dimensions of transformation and exploitation, together with the evaluation step, become the focus, because acquisition is no longer the constraint once the tool is in use.

3.4 Why capability matters: the resource-based view and dynamic capabilities

The resource-based view holds that sustained advantage comes from resources that are valuable, rare, difficult to imitate and difficult to substitute (Barney, 1991). A GenAI subscription available to any firm meets the first criterion and fails the others. Two SMEs can buy the same tool on the same day. If one benefits and the other does not, the difference must lie in resources and routines that the firms do not share.

Dynamic capabilities theory explains how firms build, integrate and reconfigure competences as conditions change (Teece et al., 1997). Eisenhardt and Martin (2000) emphasize that such capabilities consist of identifiable routines, such as product development or alliance management, rather than abstract potential. Winter (2003) distinguishes these higher-order capabilities from ordinary capabilities, which allow a firm to carry out its current activities. Applied to AI, Mikalef and Gupta (2021) define AI capability as the firm's ability to select, orchestrate and leverage AI-specific resources, and they find it associated with creativity and performance.

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We adopt this logic and adapt it to GenAI in SMEs. A GenAI capability is the firm's ability to deploy GenAI in coordination with its people, data, technology and management routines. Because those complements are firm-specific and accumulate through practice, the capability is harder to imitate than the tool. The resource-based view therefore does not appear in our model as a separate explanatory framework. It is the reason the model distinguishes capability from adoption.

3.5 Boundary conditions: data readiness, task fit, augmentation and governance

A capability does not create value in every application. Task-technology fit theory holds that information technology improves performance when its functions match the requirements of the tasks it supports (Goodhue & Thompson, 1995). The field evidence on GenAI fits this view closely: performance rose on tasks within the model's competence and fell on a task beyond it (Dell'Acqua et al., 2023).

Raisch and Krakowski (2021) add a second consideration. AI can be used to automate tasks, removing human involvement, or to augment human work, combining the two. They argue that pursuing either alone has harmful effects over time and that the two must be balanced. For SMEs using GenAI, full automation of tasks that require judgment removes the human evaluation that catches errors. Augmentation keeps that evaluation in place.

Governance is the third condition. Usage policies, human review of outputs, data protection rules and assigned accountability limit the damage from inaccurate outputs, disclosure of confidential information and inappropriate use (Berente et al., 2021). Siljeur et al. (2026) found that SMEs that formalized governance in the legitimization phase were better able to embed GenAI. We treat governance as a capability in its own right and as a moderator of the capability-performance relationship, for reasons set out in Section 4.

A fourth condition, data readiness, operates earlier in the model, on the conversion of learning into capability. Its rationale is set out with Proposition 5.

3.6 Construct boundaries: resources, routines, capabilities and outcomes

Because the model links several constructs that are sometimes used interchangeably, we distinguish four categories and assign each construct to one of them. *Resources* are stocks of assets the firm owns or controls, such as tool licenses, data and staff skills (Amit & Schoemaker, 1993). *Routines* are repeated, recognizable patterns of interdependent action carried out by multiple actors (Feldman & Pentland, 2003). *Capabilities* are the firm's capacity to deploy resources, usually in combination and through routines, to perform a particular activity (Amit & Schoemaker, 1993; Helfat & Peteraf, 2003). *Performance outcomes* are the observable results of that activity for the firm. Within capabilities, Winter (2003) separates ordinary capabilities, which allow a firm to make a living in the present, from dynamic capabilities, which change ordinary capabilities.

Realized absorptive capacity and GenAI capability fall on different sides of these distinctions. Realized absorptive capacity is a set of learning routines: the activities through which the firm evaluates model outputs, articulates and codifies what it learns, and applies the result. It is change-oriented, and its object is knowledge. GenAI capability is the operational capability those routines produce: a configuration of human, data, technical and managerial resources that allows the firm to deploy GenAI reliably in its work. Its object is deployment. The two also differ in three further respects. *Temporally*, absorptive capacity is a flow and GenAI capability a stock: the former describes what the firm does with outputs over time, the latter what the firm is able to do at a point in time as a result. *In their sources*, GenAI capability can be partly acquired without learning, for example by hiring a skilled employee or buying an integrated tool, whereas realized absorptive capacity must be developed through practice. *In their indicators*, absorptive capacity is measured by the frequency and formality of learning activities, such as whether outputs are checked and lessons recorded, whereas GenAI capability is measured by the state of resources and their integration, such as whether staff can judge output quality and whether GenAI is connected to business systems. This distinction follows Zollo and Winter's (2002) argument that deliberate learning mechanisms shape operating routines, and it allows the two constructs to be separated empirically (Section 5.7).

Table 2 classifies every construct in the second stage of the model.

Table 2. Construct classification and boundaries

Construct	Category	Definition	Distinguished from	Role in the model
Extent of GenAI adoption	Resource deployment (use)	Breadth of business functions in which GenAI is used and depth of that use	GenAI capability: adoption records use, not how well GenAI is used	Stage 1 outcome; Stage 2 predictor (P3, P4)
Data readiness	Resource	Pre-existing state of the firm's business data (digitized, organized, accessible, cleared for use), independent of GenAI	Data dimension of GenAI capability, which concerns the integration of firm data into GenAI workflows	Moderator (P5)
Realized absorptive capacity for GenAI	Routine (learning, change-oriented)	Routines for evaluating, transforming and exploiting GenAI outputs	GenAI capability, the stock these routines build	Mediator (P4)
GenAI capability	Capability (operational)	Capacity to deploy GenAI in coordination with the firm's people, data, technology and management	Adoption (use); absorptive capacity (learning); governance (control)	Mediator and focal predictor (P3, P6)

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Construct	Category	Definition	Distinguished from	Role in the model
GenAI governance capability	Capability (control)	Capacity to oversee and control GenAI use through policies, review, data rules and accountability	GenAI capability, which concerns deployment rather than control	Moderator (P8, P9)
Augmentation orientation	Deployment practice	Degree to which GenAI supports rather than replaces human judgment on judgment-intensive tasks	Governance: augmentation is informal review at the point of use, governance is formal control	Moderator (P7, P8b)
Firm performance	Outcome	Operational, innovation, market and risk-adjusted results	The capabilities that produce them	Outcome (P3, P6 to P9)

3.7 How the theories connect

Read in sequence, the theories form a single argument. TOE conditions determine how extensively an SME adopts GenAI. Adoption exposes the firm to externally generated outputs, and realized absorptive capacity determines whether that exposure is turned into a GenAI capability, more readily where firm data are ready for use. Because the tool is a commodity and the capability is not, the capability explains most of the performance differences between firms. Whether the capability raises performance in practice depends on how it is applied and how well its use is governed.

4. Framework and Propositions

Figure 1 presents the model. It has two stages. The first, which we keep brief, links TOE conditions to the extent of GenAI adoption. The second, which carries the paper's argument, links adoption to performance through absorptive capacity and GenAI capability and specifies the conditions under which each link holds. The propositions are theoretical expectations derived from the reasoning below and from evidence on related technologies; none has yet been tested for GenAI in SMEs.

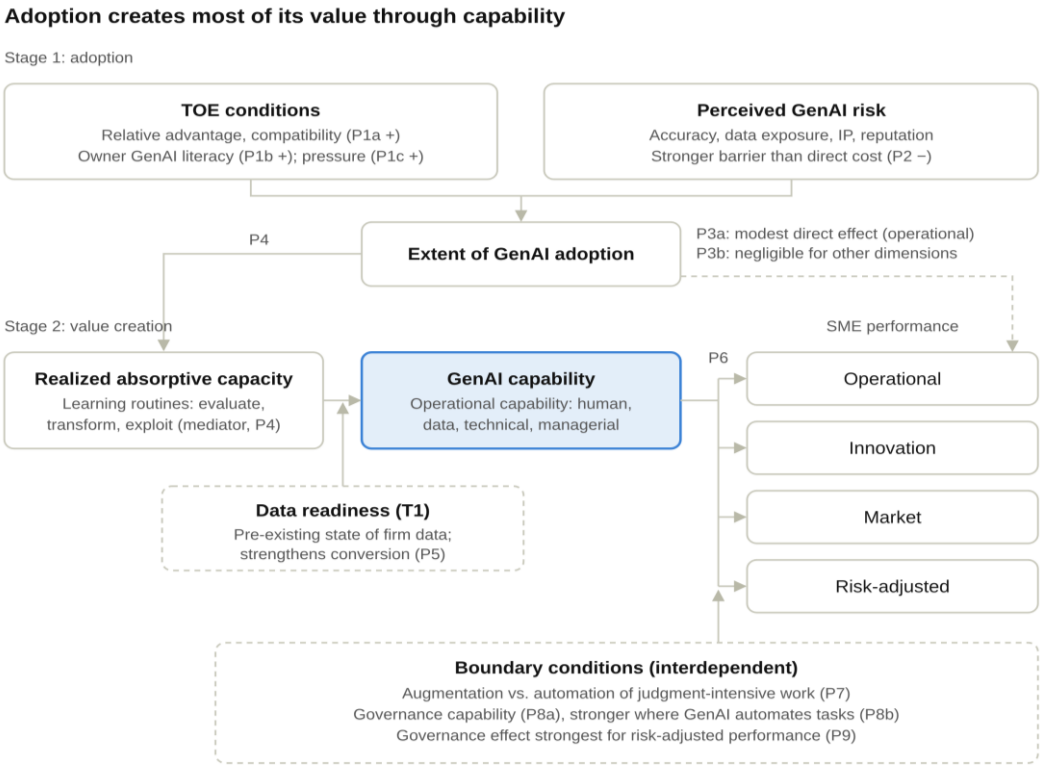


Figure 1. Conceptual framework. Stage 1 links TOE conditions and perceived risk to the extent of adoption (P1a to P1c, P2). Stage 2 links adoption to four dimensions of performance through realized absorptive capacity and GenAI capability (P4, P6), with data readiness conditioning the conversion of learning into capability (P5). The dashed path from adoption to performance represents a direct effect expected to be modest and confined to operational performance (P3a) and negligible for the other dimensions (P3b). Task orientation and governance capability jointly condition the capability-performance relationship (P7 to P9).

4.1 Stage 1: Adoption

The antecedents of GenAI adoption have been examined empirically (Hughes et al., 2026; "Barriers to Generative AI Adoption," 2026), and we do not claim novelty for them. They are stated here to complete the model and because any test of the second stage must control for them. We nevertheless specify each relationship separately, so that each can be tested on its own.

In the technological context, relative advantage and compatibility are long-standing predictors of innovation adoption (Moore & Benbasat, 1991; Rogers, 2003). For GenAI, relative advantage is

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the expected improvement over current ways of producing text, analysis and customer communication, and compatibility is the fit with existing work practices.

Proposition 1a (technological context). Perceived relative advantage and compatibility of GenAI are each positively associated with the extent of GenAI adoption in SMEs.

In the organizational context, the owner-manager usually makes or approves technology decisions (Thong, 1999). The owner's GenAI literacy, meaning familiarity with what the tools can and cannot do reliably, therefore shapes whether the relative advantage of GenAI is recognized at all, and also whether it is acted upon.

Proposition 1b (organizational context). The owner-manager's GenAI literacy is positively associated with the extent of GenAI adoption in SMEs and strengthens the association between perceived relative advantage and adoption.

In the environmental context, competitive and trading-partner pressure have predicted IT adoption in small firms (Iacovou et al., 1995; Zhu & Kraemer, 2005), and are likely to operate for GenAI as customers and competitors adopt it visibly.

Proposition 1c (environmental context). Competitive and trading-partner pressure are each positively associated with the extent of GenAI adoption in SMEs.

One antecedent deserves separate statement because it reverses an established pattern. Earlier research on SME technology adoption treated financial cost as a primary barrier (Iacovou et al., 1995; Thong, 1999). For GenAI, direct cost is low. The risks, by contrast, are new and hard for a small firm to assess: inaccurate outputs, disclosure of client data, uncertain ownership of generated content and reputational harm. SMEs rarely have legal or information-security staff to evaluate these risks, so uncertainty about them is likely to weigh more heavily than price.

Proposition 2. Perceived GenAI risk is negatively associated with the extent of GenAI adoption in SMEs, and the magnitude of this association is greater than that of the association between perceived direct cost and adoption.

4.2 Stage 2: From adoption to value

Direct and indirect effects of adoption. If GenAI tools are equally available to all SMEs, adoption alone cannot account for lasting performance differences (Barney, 1991). This does not imply that adoption has no direct effect. The experimental evidence shows that individual access to GenAI raises the speed and volume of task completion without any change in organizational routines (Noy & Zhang, 2023; Brynjolfsson et al., 2025), and IT value research shows that actual usage can itself be associated with performance (Devaraj & Kohli, 2003). In a small firm, where a few individuals account for much of the output, such task-level gains can aggregate directly into operational performance. The same mechanism is unlikely to carry over to innovation, market or risk-adjusted performance, which depend on changes in what the firm offers, how customers perceive it and how errors are controlled. Those changes require coordinated resources and routines, that is, capability. A direct operational effect of adoption is also likely to be smaller than the effect that runs through capability and to erode over time, because it rests on a resource that rivals can acquire equally (Barney, 1991). In mediation terms, the model predicts complementary partial mediation for operational performance and indirect-only mediation for the other three dimensions (Zhao et al., 2010).

Proposition 3a. The extent of GenAI adoption has a positive direct association with operational performance in SMEs, but this direct association is smaller than the indirect association through GenAI capability.

Proposition 3b. The association between the extent of GenAI adoption and innovation, market and risk-adjusted performance is predominantly indirect, operating through GenAI capability, and any direct association is expected to be negligible once GenAI capability is accounted for.

The conversion mechanism. Adoption gives the firm a stream of model outputs. Turning that stream into a capability requires evaluating outputs against what the firm knows, deciding which uses are worth keeping, recording effective prompts and workflows so that others can repeat them, and combining generated material with the firm's own knowledge of its customers and operations. These are the activities of realized absorptive capacity (Zahra & George, 2002), with evaluation added as a distinct first step (Todorova & Durisin, 2007). Siljeur et al. (2026) observed that individual experimentation in SMEs remains fragmented unless it is formalized and embedded. We identify realized absorptive capacity as the organizational ability that accomplishes this.

The indirect pathway has three links. First, adoption supplies the material for learning: each use generates outputs and experience that can be evaluated, which corresponds to experience accumulation in Zollo and Winter's (2002) terms. Routines for evaluation and codification develop only when there is enough use to make them worthwhile, so adoption is expected to be positively associated with realized absorptive capacity. Second, realized absorptive capacity converts that experience into shared knowledge by articulating what works and codifying it in prompts, templates and procedures. Third, the result is GenAI capability: staff who can judge outputs, firm data connected to workflows, tools embedded in systems and management that knows which uses to scale. Without the middle link, experience accumulates in individuals, remains invisible to others in the firm and leaves when they do. The mediation is expected to be partial rather than full, because some elements of GenAI capability, particularly technical integration and hired skills, can be acquired without internal learning.

Proposition 4. Realized absorptive capacity partially mediates the positive relationship between the extent of GenAI adoption and GenAI capability: adoption is positively associated with realized absorptive capacity, which in turn is positively associated with GenAI capability. Together with Propositions 3 and 6, this implies a serial indirect path from adoption through realized absorptive capacity and GenAI capability to performance.

The role of data. Generic uses of GenAI, such as drafting emails, require no firm data. Uses that could distinguish one firm from another, such as answering customer questions from the firm's own product information or summarizing its sales history, require data that is organized, accessible and permissible to use. We define data readiness as the pre-existing state of the firm's business data, independent of GenAI, and distinguish it from the data dimension of GenAI capability, which concerns whether firm data have actually been integrated into GenAI workflows.

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Data readiness is placed as a moderator of the link between realized absorptive capacity and GenAI capability, rather than as an antecedent of adoption or a direct cause of capability, for three reasons. First, generic GenAI use requires no firm data, so data readiness should have little bearing on whether a firm adopts. Second, data alone does not create capability: organized data that nobody has learned to use with GenAI remain unused. Third, and central to the argument, data readiness determines what learning can produce. When firm data are ready, the evaluation and transformation routines of realized absorptive capacity can recombine model outputs with proprietary information, producing firm-specific workflows that rivals cannot copy. When data are not ready, the same routines can produce only generic skills, such as better prompting, which are valuable but imitable. This is a complementarity argument of the kind established in IT value research (Aral & Weill, 2007; Melville et al., 2004): the return on one resource depends on the level of another.

Proposition 5. Data readiness positively moderates the relationship between realized absorptive capacity and GenAI capability, such that the relationship is stronger in SMEs with higher data readiness. Consequently, the indirect effect of adoption on GenAI capability through realized absorptive capacity is stronger when data readiness is high.

Capability and performance. We distinguish four dimensions of performance because GenAI is unlikely to affect them equally. Operational performance covers time, cost and output per employee. Innovation performance covers the generation and development of new products, services and processes. Market performance covers customer responsiveness, satisfaction and sales. Risk-adjusted performance covers the quality of outputs and the incidence of errors, complaints and compliance breaches. The experimental evidence shows the clearest and fastest effects on the time and volume of task completion (Noy & Zhang, 2023; Brynjolfsson et al., 2025). Effects on innovation and on customers depend on further changes in what the firm offers and how it is perceived, and should appear later and less consistently, a pattern consistent with the lag between complementary investment and measured returns described by Brynjolfsson et al. (2021). The relationship with risk-adjusted performance is not signed here, because the model predicts that it depends on governance (Proposition 9).

Proposition 6. GenAI capability is positively associated with operational, innovation and market performance, and the association with operational performance is stronger and appears sooner than the associations with innovation and market performance.

4.3 Boundary conditions

The moderators of the capability-performance relationship are conceptually different and are stated separately before their interdependence is considered.

Task orientation. Where GenAI is used to augment work that requires judgment, a person evaluates the output before it is used, and errors on tasks beyond the model's competence are more likely to be caught. Where the same work is fully automated, those errors pass through (Dell'Acqua et al., 2023; Raisch & Krakowski, 2021). Automation of routine, well-specified tasks carries less of this risk, which is consistent with task-technology fit (Goodhue & Thompson, 1995). The advantage of augmentation is therefore expected where tasks are judgment-intensive, where errors are costly or visible to customers, and where staff have the domain expertise to evaluate outputs.

Proposition 7. The positive relationship between GenAI capability and SME performance is stronger when GenAI is deployed mainly to augment human work on judgment-intensive tasks than when it is deployed to automate those tasks. For routine, well-specified tasks with a low cost of error, no such difference is expected.

Governance capability. Governance practices, including written usage rules, human review of client-facing outputs, rules on which data may be entered into which tools, and named responsibility for GenAI use, reduce the frequency and cost of errors, inappropriate use and data exposure. They therefore protect the gains a GenAI capability produces. Governance should matter most where errors are costly: in client-facing use, in regulated activities such as financial, legal and health services, and where confidential data are handled. Governance also has costs. Rules that are too restrictive in the early stage of use can suppress the experimentation through which absorptive capacity develops. The argument therefore concerns governance proportionate to the firm's use, rather than the number of rules in place.

Proposition 8a. GenAI governance capability positively moderates the relationship between GenAI capability and SME performance, and the moderation is stronger in client-facing and regulated activities.

Interdependence of task orientation and governance. Augmentation and governance both limit the damage from incorrect outputs, but in different ways. Augmentation places an informed person at the point of use; governance establishes rules and checks that apply regardless of who uses the tool. They are therefore partial substitutes. Where GenAI is used mainly to augment, human review already catches many errors and formal governance adds less. Where GenAI is used to automate, for example to answer customers or generate documents without review, governance is the main safeguard and its absence is most costly. Augmentation also has limits as a safeguard. It relies on reviewers having the expertise and time to check outputs, which may be scarce in very small firms, and on reviewers not over-trusting fluent outputs. Governance can supply the explicit requirement that review takes place. The two conditions are therefore expected to interact.

Proposition 8b. The positive moderating effect of governance capability on the relationship between GenAI capability and SME performance is stronger when GenAI is deployed to automate judgment-intensive tasks than when it is deployed to augment them.

Trade-offs. The disaggregation of performance allows a more specific prediction. A firm with strong GenAI capability and weak governance can produce more, faster, while also producing more errors. Its operational performance would rise while its risk-adjusted performance stagnated or fell. Governance should matter most for the dimension that captures this downside.

Proposition 9. The moderating effect of governance capability is strongest for risk-adjusted performance. Where governance capability is low, GenAI capability is positively associated with operational performance but not with risk-adjusted performance, and may be negatively associated with it.

Table 3 summarizes the expected interactions and the organizational conditions under which each is expected to hold.

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Table 3. Expected interactions and conditions for Propositions 7 to 9

Proposition	Expected interaction	Conditions under which it is expected to hold	Conditions under which it may weaken or not hold
P7	GenAI capability × augmentation orientation	Judgment-intensive tasks; costly or customer-visible errors; staff with domain expertise to evaluate outputs	Routine, well-specified tasks with low cost of error; reviewers lacking expertise or time
P8a	GenAI capability × governance capability	Client-facing use; regulated activities; handling of confidential data; firms beyond initial experimentation	Internal, low-stakes use; governance so restrictive that it suppresses experimentation in early use
P8b	GenAI capability × governance capability × automation of judgment-intensive tasks	Automated or unreviewed use on judgment-intensive tasks	Firms in which nearly all GenAI use is augmented and reviewed
P9	Governance effect strongest for risk-adjusted performance	Outputs reach customers; errors, complaints and compliance incidents are recorded	Outputs used only internally; observation windows too short for errors to surface

5. Construct Definitions and Measurement

A conceptual model of this kind is only as useful as the precision of its constructs. The risk we most want to avoid is that GenAI capability is measured, in practice, as more intensive GenAI use, or as the same learning activities that define absorptive capacity, either of which would make Propositions 3 and 4 untestable. This section defines each construct and indicates how it can be measured. Sample items, response scales and sources for every construct are given in Appendix A, and Section 5.7 sets out the validation procedures. Unless otherwise stated, perceptual items use seven-point scales (1 = strongly disagree, 7 = strongly agree).

5.1 Extent of GenAI adoption

Adoption is defined as the breadth and depth of GenAI use in the firm, following measures of the extent of technology use in post-adoption research (Burton-Jones & Straub, 2006; Zhu & Kraemer, 2005). Breadth is the number of business functions in which GenAI is used, from a standard list of marketing, sales, customer service, finance, operations, human resources and product development (range 0 to 7). Depth is the frequency of use in each function (1 = never, 7 = several times a day) and the degree to which tools are licensed by the firm rather than used informally by individuals (1 = individual free accounts only, 2 = some firm-paid licenses, 3 = firm-wide licensed tools). Adoption is specified as a formative index. The measure deliberately records use only. It says nothing about how well GenAI is used, which is the province of capability.

5.2 Realized absorptive capacity for GenAI

Realized absorptive capacity is the firm's set of routines for evaluating GenAI outputs, transforming useful outputs into shared practice and exploiting them in its work. It has three dimensions. Evaluation covers routines for checking outputs against domain knowledge and sources before use. Transformation covers the recording and sharing of effective prompts, workflows and lessons, and the combination of generated material with internal knowledge. Exploitation covers the application of transformed knowledge in decisions, offerings and procedures. It refers to the act of applying what has been learned, not to the resulting state of integration, which belongs to GenAI capability. All items describe activities and their frequency over a reference period (for example, "In the past six months, how often...") so that they remain distinct from the capability items, which describe the current state of resources. Transformation and exploitation items are adapted from validated absorptive capacity scales built on the Zahra and George (2002) dimensions (Flatten et al., 2011; Jansen et al., 2005). Evaluation items are written for this study. Each dimension is specified as reflective.

5.3 GenAI capability

GenAI capability is the firm's capacity to deploy GenAI in coordination with its people, data, technology and management. Following Mikalef and Gupta (2021), it is specified as a higher-order construct, but with dimensions suited to generative systems and to small firms. Each first-order dimension is measured reflectively, and the dimensions form the higher-order construct, which makes it a reflective-formative construct (Sarstedt et al., 2019). Table 4 sets out the dimensions.

Table 4. Dimensions of GenAI capability

Dimension	Definition	Example indicators
Human	The knowledge and skills of staff to use GenAI well	AI literacy; ability to frame tasks and prompts; ability to judge output quality; domain expertise applied to outputs
Data	The extent to which firm data are integrated into and usable within GenAI workflows	Use of proprietary product, customer or process information in GenAI workflows; clarity on which data may be used with which tools; ability to keep that information current for GenAI use
Technical	The integration of GenAI into the firm's systems and work	Connection to existing software; embedding in workflows rather than standalone use; interoperability between tools

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Dimension	Definition	Example indicators
Managerial	The ability of management to direct GenAI use	Selection of use cases against business priorities; allocation of time and budget; structured experimentation; decisions to scale or stop uses

The human dimension measures skills, which are a state, whereas the evaluation dimension of absorptive capacity measures whether outputs are actually checked, which is an activity. Similarly, the data dimension measures whether firm data are already integrated into GenAI workflows, whereas data readiness (Section 5.4) measures the condition of firm data independently of GenAI.

Governance appears in some definitions of AI capability. We model it separately, as GenAI governance capability, for two reasons. Governance is theorized here as a condition that changes the effect of capability on performance, and including it inside capability would confound the predictor with its moderator. And governance may be strong where capability is weak, for example in a cautious firm that writes policies before it uses the tools, or weak where capability is strong. Treating the two separately allows these combinations to be observed.

5.4 Boundary conditions

GenAI governance capability is the firm's capacity to oversee and control GenAI use. Its indicators include human oversight of outputs before external use, privacy and security rules on the data entered into tools, validation of outputs used in decisions, and accountability through a named person responsible for GenAI use. It is measured as a formative index of practices in place (0 = not in place, 1 = in place), supplemented by the owner-manager's assessment of how consistently they are followed (1 = never, 7 = always). Items are written for this study and informed by Berente et al. (2021) and the NIST AI Risk Management Framework (National Institute of Standards and Technology [NIST], 2023).

Augmentation orientation is the degree to which the firm uses GenAI to support human judgment rather than to replace it on judgment-intensive tasks. Respondents list their three main GenAI uses and classify each by task type (routine or judgment-intensive) and by whether a person reviews and modifies the output before it is used (1 = never, 7 = always). The score is the mean review rating across judgment-intensive uses, and the share of judgment-intensive uses that are automated without review provides the automation indicator used in Proposition 8b.

Data readiness, the moderator in Proposition 5, is the pre-existing state of the firm's business data. It is measured at T1 with items on whether customer, product and process information is held in digital form, organized, of adequate quality and cleared for use with external software. The items are written without reference to GenAI, so that data readiness is conceptually and temporally distinct from the data dimension of GenAI capability measured at T2.

5.5 Performance

Performance is measured in four dimensions, each with perceptual and, where possible, objective indicators. Table 5 lists them. Perceptual operational and market items are adapted from Venkatraman and Ramanujam (1986), innovation items from Jiménez-Jiménez and Sanz-Valle (2011), and risk-adjusted items are written for this study.

Table 5. Performance dimensions and indicators

Dimension	Perceptual indicators	Objective indicators where available
Operational	Time to complete core tasks; cost of producing outputs; output per employee	Revenue per employee; labor cost ratio
Innovation	Number and speed of new or improved products, services and processes	Count of launches in the period
Market	Customer responsiveness; satisfaction; sales growth relative to competitors	Sales growth from accounts
Risk-adjusted	Quality of outputs; frequency of errors reaching customers; complaints; compliance incidents	Logged complaints and incidents

Perceptual items ask for change over the period since the previous wave (1 = greatly worsened, 7 = greatly improved) and for comparison with main competitors (1 = much worse, 7 = much better). Objective indicators reduce the dependence on single-respondent judgment and are essential for Proposition 9, where the predicted effect on risk-adjusted performance runs against the effect on operational performance and a single optimistic respondent could mask it.

5.6 Stage 1 constructs and controls

The TOE antecedents in Propositions 1a to 1c and 2 can be measured with established scales: relative advantage and compatibility adapted from Moore and Benbasat (1991), trading-partner and competitive pressure adapted from Iacovou et al. (1995) and Zhu and Kraemer (2005), and owner-manager GenAI literacy adapted from self-efficacy items in the acceptance literature (Venkatesh et al., 2003), with additional items on the ability to recognize unreliable outputs. Perceived GenAI risk is measured across accuracy, data exposure, intellectual property and reputation, adapting the risk facets of Featherman and Pavlou (2003), and perceived direct cost with a short separate scale so that the comparison in Proposition 2 can be made. Controls include firm size, firm age, sector, ownership type and the level of digitalization before GenAI adoption.

5.7 Construct validation procedures

Because several measures are new or adapted, validation follows established procedures for construct development (MacKenzie et al., 2011) in five steps.

First, content validity is established. Items for the evaluation routines, the GenAI-specific capability dimensions, governance, augmentation orientation, data readiness and risk-adjusted

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performance are generated from the definitions in Section 3.6 and reviewed by a panel of academics and SME owner-managers, who assign each item to a construct. Items assigned to the wrong construct by a substantial share of judges are revised or dropped. This step is particularly important for separating absorptive capacity items from capability items.

Second, the instrument is pretested and piloted. Cognitive interviews with eight to ten owner-managers test the wording, followed by a pilot survey of about 100 SMEs for exploratory factor analysis and item reduction.

Third, the measurement model is assessed in the main study. Reflective constructs are assessed for indicator loadings (0.70 or above), internal consistency reliability (composite reliability between 0.70 and 0.95), convergent validity (average variance extracted of 0.50 or above) and discriminant validity using the heterotrait-monotrait ratio (HTMT below 0.85), supplemented by the Fornell-Larcker criterion (Fornell & Larcker, 1981; Hair et al., 2022; Henseler et al., 2015). Formative constructs, including the adoption and governance indices, are assessed for collinearity (variance inflation factor below 3), the significance and relevance of indicator weights, and convergent validity through redundancy analysis against a global single item. The reflective or formative specification of each construct follows the criteria of Jarvis et al. (2003), and the higher-order GenAI capability construct is validated with the disjoint two-stage approach (Sarstedt et al., 2019).

Fourth, discriminant validity between realized absorptive capacity and GenAI capability is tested specifically. The HTMT ratio between the two constructs, and between each absorptive capacity dimension and each capability dimension, should be clearly below 0.85, with a bootstrapped confidence interval that excludes 1. If this test fails, Propositions 4 and 5 cannot be evaluated, and the items should be revised before the structural model is estimated.

Fifth, common method variance and measurement invariance are addressed. Procedural remedies include temporal separation of predictors and outcomes, a second informant and varied scale formats (Podsakoff et al., 2003). Statistical checks include a theoretically unrelated marker variable (Lindell & Whitney, 2001) and a full collinearity assessment (Kock, 2015). Because adoption and capability are measured repeatedly, measurement invariance across waves, and between single- and dual-informant firms, is tested with the MICOM procedure before comparisons are made (Henseler et al., 2016). Agreement between owner-manager and employee responses at T2 is assessed with intraclass correlation coefficients.

6. Research Design for Testing the Model

The model claims a temporal sequence: adoption precedes the development of absorptive capacity routines, which precede capability, which precedes performance. A single cross-sectional survey cannot establish such a sequence, and cross-sectional estimates of longitudinal mediation can be substantially biased (Maxwell & Cole, 2007). If adoption, absorptive capacity and capability are all reported at one time by the same owner-manager, a significant indirect effect for Proposition 4 would show that the three perceptions are correlated, not that the organization converted one into the other. We therefore propose a three-wave panel survey followed by comparative case studies.

6.1 Panel survey

Table 6 sets out the waves.

Table 6. Panel survey waves

Wave	Timing	Respondents	Constructs measured
T1	Baseline	Owner-manager	TOE antecedents; perceived risk and cost; extent of adoption; data readiness; baseline performance; marker variable; controls
T2	About 6 months after T1	Owner-manager and a second informant who uses GenAI in daily work	Realized absorptive capacity (second informant); GenAI capability; governance capability; augmentation orientation; extent of adoption repeated
T3	About 12 months after T1	Owner-manager; objective records where available	Four performance dimensions; extent of adoption and GenAI capability repeated

The interval between waves reflects the expectation that absorptive capacity routines take months to form and that effects on innovation and market performance take longer than effects on operations (Proposition 6). Spacing measurement occasions according to the expected timing of change is a central principle of longitudinal design (Ployhart & Vandenberg, 2010). Shorter intervals would risk measuring capability before it has developed. Longer intervals would raise attrition, which is a particular concern in SME panels because some firms close or change ownership.

The second informant at T2 serves two purposes. Employees who use GenAI daily are better placed than owners to report on evaluation and transformation routines, and separating the source of the mediator from the source of the predictor and outcome reduces common method variance (Podsakoff et al., 2003). Where a firm has no suitable second informant, as in micro-enterprises, the owner-manager completes both sections and the analysis tests for differences between single- and dual-informant firms.

The population consists of SMEs meeting the definition in Section 3.1 that reported some GenAI use at T1. Non-adopters are excluded from the second-stage analysis because the model concerns conversion after adoption, but they are retained in a separate test of Propositions 1a to 1c and 2. The sample should be stratified by sector and size band and drawn from a business register or chamber of commerce database.

Minimum sample size is set by a priori power analysis for the most demanding test, the interaction terms in Propositions 7 to 9, estimated separately for each performance dimension. As an illustration, detecting an incremental effect size of $f^2 = 0.03$ for a single interaction term in a model with 14 predictors (focal constructs, interaction terms, baseline performance and controls), with $\alpha = 0.05$ and power of 0.80, requires about 264 firms with

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complete data at T3 (Faul et al., 2009). Assuming 30% attrition at each follow-up wave, the T1 target is about 540 adopting SMEs. These figures should be recalculated once the final set of controls and the effect sizes observed in the pilot are known. Non-response bias at T1 can be assessed by comparing early and late respondents (Armstrong & Overton, 1977), and attrition bias by comparing the T1 characteristics of firms that do and do not complete later waves.

Where resources allow only two waves, a reduced design is still preferable to a single survey. Antecedents, adoption and data readiness would be measured at T1, and absorptive capacity, capability, the boundary conditions and performance at T2, with the second informant reporting on the mediator.

6.2 Analysis

The structural model is estimated with partial least squares structural equation modeling, which suits prediction-oriented models with several mediators and moderators and with newly developed measures (Hair et al., 2022). Because constructs are measured in temporal order, each path from an earlier to a later wave can be estimated while controlling for the baseline value of the outcome. Missing data within waves are handled by multiple imputation where the proportion missing is small, and sensitivity analyses compare results with and without imputed cases.

Each proposition maps onto a specific test. Propositions 1a, 1c and 2 are tested through the paths from T1 antecedents to T1 adoption, with the comparison in Proposition 2 made by testing the difference between the standardized coefficients for perceived risk and perceived cost. Proposition 1b adds the interaction between owner-manager GenAI literacy and relative advantage. Propositions 3a and 3b are tested by estimating the direct path from T1 adoption to each T3 performance dimension alongside the indirect path through T2 capability, and by classifying the type of mediation for each dimension (Zhao et al., 2010): Proposition 3a predicts complementary partial mediation for operational performance, with a direct effect smaller than the indirect effect, and Proposition 3b predicts indirect-only mediation for the other three dimensions. Proposition 4 is tested through the bootstrapped indirect effect of adoption on capability through absorptive capacity, and Proposition 5 through the index of moderated mediation, in which data readiness conditions the second leg of that path (Hayes, 2015). Propositions 7 and 8a are tested through two-way interaction terms and Proposition 8b through a three-way interaction, probed with simple slopes at high and low levels of governance and automation. All interactions are estimated separately for each performance dimension so that the differential effects in Propositions 6 and 9 can be compared.

The repeated measures of adoption and capability at T2 and T3 allow a check on reverse causality. If high-performing firms adopt more GenAI because they can afford to experiment, adoption at T2 should be predicted by performance at T1. Because PLS-SEM is not designed for cross-lagged panel models, this check is estimated with covariance-based structural equation modeling as a robustness test.

Two complementary analyses address features the structural model handles poorly. Fuzzy-set qualitative comparative analysis can identify whether different combinations of capability, governance and task orientation lead to high performance, which is plausible in a heterogeneous SME population (Ragin, 2008). Necessary condition analysis can test whether a minimum level of governance capability is required for any positive effect on risk-adjusted performance, which is a stronger form of the claim in Proposition 9 (Dul, 2016).

6.3 Comparative case studies

After T3, six to eight SMEs are selected in pairs. Each pair is matched on sector, size and extent of adoption at T1 but differs in performance at T3. Data come from semi-structured interviews with the owner-manager and employees, internal documents such as usage policies and prompt libraries, and observation of GenAI-supported work. The cases are designed to show how absorptive capacity routines and governance practices develop in firms that started from similar positions, which the survey can detect but not explain. They also provide a check on the measures: if firms scoring high on capability turn out to be firms that simply use GenAI often, the construct has not been measured as intended.

6.4 Ethics

The study requires institutional ethics approval and informed consent from every respondent. Firm and participant identities should be anonymized. Because the topic concerns data practices, interviewers should take care not to collect confidential business information, and objective performance data should be obtained only with explicit permission.

7. Discussion

The argument of this paper can be stated briefly: for SMEs, GenAI has lowered the cost of access but not the cost of conversion. Access is now within reach of almost any firm. Converting access into capability, and capability into performance, still requires judgment, learning routines, usable data and oversight, and these are scarce in small firms. If the propositions hold, differences in performance among SMEs that have adopted GenAI should be traced mainly to these conversion steps rather than to adoption itself.

7.1 Theoretical contributions

The first contribution concerns where explanation is located. Recent studies explain the antecedents of GenAI adoption (Hughes et al., 2026), add learning mechanisms to adoption models ("Barriers to Generative AI Adoption," 2026) and describe how adoption unfolds through phases (Siljeur et al., 2026). Post-adoption research has examined continued and deeper use (Jasperson et al., 2005; Zhu & Kraemer, 2005). This paper places its explanation after adoption and specifies the learning capacity that governs the conversion of use into capability. Proposition 3 is the clearest statement of the difference. It predicts that adoption has, at most, a modest direct effect on operational performance and that its effects on other dimensions run through capability. If supported, it would imply that adoption measures, which are the dependent variable in most of this literature, are an incomplete proxy for the outcomes that matter to SMEs.

The second contribution is a more careful use of absorptive capacity and a clearer boundary between learning and capability. The AI literature sometimes treats a model as a source of external knowledge in the same sense as a supplier or a research partner. We argue that a GenAI system is better understood as an artifact that gives access to generated outputs, whose reliability the firm must judge for itself. This places evaluation at the front of the absorptive capacity process and explains why existing domain expertise matters more for GenAI than for many earlier technologies, a point consistent with Cohen and Levinthal's (1990)

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DOI: 10.5281/zenodo.24028510

original emphasis on prior related knowledge. By treating realized absorptive capacity as a set of learning routines and GenAI capability as the operational capability those routines build, the framework also connects research on absorptive capacity with research on IT and AI capability (Bharadwaj, 2000; Mikalef & Gupta, 2021), consistent with the view that deliberate learning shapes operating routines (Zollo & Winter, 2002).

The third contribution is a definition of GenAI capability that separates it from use, from learning and from governance. By specifying human, data, technical and managerial dimensions, and by modeling governance as a distinct moderating capability, the framework makes it possible to observe firms that use GenAI heavily without capability, and firms with capability but weak control. Both combinations are likely to be common in SMEs.

The fourth contribution is the specification of GenAI-specific complements and the disaggregation of performance. IT value research has established that technology creates value in combination with complementary resources (Aral & Weill, 2007; Melville et al., 2004). The framework identifies data readiness, augmentation and governance as the complements that matter for GenAI and specifies how augmentation and governance interact. Separating operational, innovation, market and risk-adjusted performance allows the model to predict that the same capability can raise productivity while lowering quality, and that governance determines which of these effects dominates. This links the SME literature to the automation-augmentation debate (Raisch & Krakowski, 2021) in a form that can be tested.

7.2 Managerial implications

The managerial implications follow from the propositions and should be read as provisional until they are tested. For owner-managers, the model suggests that buying tools is the least important decision. Before widening use, the owner and the staff who will use GenAI most need enough familiarity with it to judge its outputs in their own field. This is expected to reduce perceived risk, which the model identifies as a larger barrier than cost, and to build the evaluation ability on which conversion depends.

Governance should be put in place early and kept simple. A one-page usage policy, a rule that anything sent to a client is checked by a person, a short list of data that must not be entered into public tools, and a named person responsible for GenAI use cost little. The model predicts that these practices matter most for the quality of what the firm delivers, which is where unsupervised use does the most harm, and most of all where tasks are automated rather than reviewed.

Use should begin with augmentation of tasks the firm understands well, such as drafting, summarizing and first responses to routine customer questions, where staff can recognize a poor output. Full automation should be reserved for well-specified tasks with a low cost of error.

The gains that distinguish one firm from another are expected to come from combining GenAI with the firm's own data, so organizing product, customer and process information is an investment worth making early. And individual experimentation needs to be turned into shared practice. Recording prompts and workflows that work, reviewing them as a team and building them into standard procedures is what realized absorptive capacity looks like in a small firm.

Finally, owner-managers should judge GenAI by more than speed. Tracking errors, complaints and rework alongside time saved will show whether productivity gains are being bought at the expense of quality.

7.3 Policy implications

Public programs that subsidize software licenses address a barrier that has largely disappeared. The model points instead to support for managerial and staff training in the evaluation of GenAI outputs, templates for basic governance suited to small firms, and advisory help with data organization. Programs could also encourage peer learning among SMEs, which can substitute in part for the internal knowledge-sharing that small firms struggle to organize on their own.

8. Limitations and Future Research

The propositions are untested, and the paper's value depends on whether they survive empirical examination. They are derived from theory and from evidence gathered mainly on individuals, on earlier technologies and on larger firms, and they should be treated as provisional. Several further limitations should be stated.

The theoretical framework has limits of its own. The distinction between realized absorptive capacity and GenAI capability is analytically clear but may be difficult to sustain empirically in micro-enterprises, where the same person may perform the learning routines and embody most of the capability. The model is also recursive, whereas in practice capability and performance may feed back into further adoption and learning. And the model integrates several theories by assigning each a single role, which improves clarity but may understate the ways in which, for example, governance also shapes learning.

The model is specified for a technology that is changing quickly. Constructs such as compatibility, perceived risk and the boundary between tasks within and beyond a model's competence will shift as tools improve and as regulation such as the EU AI Act takes effect. The relationships proposed here may hold while the specific indicators need revision.

The model treats SMEs as one population. Micro-enterprises with a handful of staff may have no one other than the owner to develop absorptive capacity routines, family firms may weigh risk differently, and professional service firms may depend more heavily on GenAI than manufacturers. Multi-group analysis in the proposed design can address some of this heterogeneity, but sector- and size-specific models may prove necessary.

Even a three-wave design cannot rule out all alternative explanations. Firms with more capable owners may both adopt more and perform better for reasons the model does not capture. The baseline controls and cross-lagged checks reduce this concern without removing it, and stronger causal claims would require experimental or quasi-experimental evidence.

The theories underpinning the model were developed mainly in large firms in Western economies. Siljeur et al. (2026) included cases from South Africa and Vietnam, and work on developing economies suggests that institutional conditions shape GenAI adoption ("Barriers to Generative AI Adoption," 2026). The second stage of our model may operate differently where data infrastructure, regulation and access to skills differ.

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DOI: 10.5281/zenodo.24028510

These limitations point to a research agenda. Longitudinal studies over longer periods could examine whether GenAI capability, once built, is durable as tools change, or whether it must be rebuilt with each generation of models. Field experiments in partnership with SME support agencies could test whether training in output evaluation or the introduction of basic governance raises risk-adjusted performance, which would provide causal evidence for Propositions 4 and 8. Studies of employees in small firms could examine how GenAI changes job content, skill requirements and workload where there is little room to redeploy staff. Research linking capability to firm survival and growth using administrative data would move beyond self-reported outcomes. And research on the unintended consequences of GenAI use in SMEs, including errors that reach customers and the loss of skills when tasks are automated, would test the downside that Proposition 9 anticipates.

9. Conclusion

Generative AI may be among the first advanced technologies that nearly every SME can access affordably. This paper has argued that affordability settles less than it appears to. Adoption is driven by familiar factors, among which perceived risk is expected to outweigh cost. But adoption is only the first of three states. We propose that it becomes a capability when the firm can evaluate, assimilate and recombine model outputs with its own knowledge, and that the capability becomes value when it is applied to augment judgment rather than replace it and when its use is governed.

By locating the explanation of performance differences mainly after adoption, distinguishing the learning routines that build GenAI capability from the capability itself, defining that capability so that it is distinct from use and from governance, and separating the kinds of performance GenAI can affect, the framework offers nine propositions and a design for testing them in sequence.

These propositions are provisional. They are theoretical expectations, not findings, and four relationships are most in need of empirical validation because the argument depends on them: whether the direct effect of adoption on performance is in fact limited to operational performance and smaller than the indirect effect through capability (Proposition 3); whether realized absorptive capacity and GenAI capability can be measured as distinct constructs, and whether the former mediates the conversion of adoption into the latter (Proposition 4); whether data readiness conditions that conversion (Proposition 5); and whether governance protects risk-adjusted performance, particularly where GenAI is used to automate judgment-intensive work (Propositions 8 and 9). If these relationships are not supported, the model would need to be revised. If they are, whether GenAI narrows or widens the long-standing gap between small and large firms will depend less on who adopts it than on who learns to use it well.

Declarations

Funding

This research received no specific grant from any funding agency in the public, commercial or not-for-profit sectors.

Conflicts of interest

The author(s) declare no conflicts of interest with respect to the research, authorship or publication of this article.

Ethics approval and consent to participate

Not applicable. This is a conceptual paper and involves no human participants, personal data or animal subjects. The empirical study proposed in Section 6 will require approval from the relevant institutional ethics committee and informed consent from all participants before data collection begins.

Consent for publication

Not applicable.

Data availability

No data were generated or analyzed for this article. All sources used are cited in the reference list.

Use of generative AI in the preparation of this manuscript

During the preparation of this manuscript, the author(s) used generative AI tools for language editing and to assist in drafting revisions in response to peer review. The author(s) reviewed, edited and verified all content, including the propositions and references, and take full responsibility for the content of the publication.

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DOI: 10.5281/zenodo.24028510

Appendix A. Sample Measurement Items

Table A1 lists sample items for each construct. Final items will be confirmed through the content validity, pretest and pilot procedures described in Section 5.7. Unless otherwise stated, items use a seven-point scale (1 = strongly disagree, 7 = strongly agree).

Table A1. Sample measurement items, response scales and sources

Construct (wave; informant)	Sample items	Response scale	Source
Relative advantage and compatibility (T1; owner-manager)	"Using GenAI enables our firm to complete work more quickly." "Using GenAI improves the quality of our work." "Using GenAI fits well with the way our firm works."	7-point agreement	Adapted from Moore & Benbasat (1991)
Competitive and trading-partner pressure (T1; owner-manager)	"Our main competitors are using GenAI." "Our customers or suppliers expect us to use GenAI."	7-point agreement	Adapted from Iacovou et al. (1995); Zhu & Kraemer (2005)
Owner-manager GenAI literacy (T1; owner-manager)	"I understand what GenAI tools can and cannot do reliably." "I can usually tell when a GenAI output is likely to be wrong."	7-point agreement	Adapted from Venkatesh et al. (2003); new items
Perceived GenAI risk (T1; owner-manager)	"GenAI outputs could contain errors that harm our reputation." "Using GenAI could expose our clients' confidential information." "Ownership of content produced with GenAI is unclear to us."	7-point agreement	Adapted from Featherman & Pavlou (2003)
Perceived direct cost (T1; owner-manager)	"The subscription and setup costs of GenAI are a significant expense for our firm."	7-point agreement	New
Extent of GenAI adoption (T1, T2, T3; owner-manager)	Breadth: "In which of the following functions does your firm use GenAI?" Depth: "How often is GenAI used in [function]?" "How is GenAI access provided in your firm?"	Breadth: count 0–7; frequency: 1 = never, 7 = several times a day; access: 1–3	Adapted from Zhu & Kraemer (2005); Burton-Jones & Straub (2006)
Data readiness (T1; owner-manager)	"Our customer, product and process information is held in digital form." "Our business data are well organized and easy to retrieve." "It is clear which of our data may be used with external software."	7-point agreement	New
Realized absorptive capacity: evaluation (T2; second informant)	"In the past six months, how often have GenAI outputs been checked against our own knowledge or sources before use?"	1 = never, 7 = always	New
Realized absorptive capacity: transformation (T2; second informant)	"In the past six months, we have recorded prompts and workflows that work well so that colleagues can reuse them." "We discuss as a team what we have learned from using GenAI."	7-point agreement	Adapted from Flatten et al. (2011); Jansen et al. (2005)
Realized absorptive capacity: exploitation (T2; second informant)	"In the past six months, lessons from GenAI use have led us to change how we serve customers or make decisions."	7-point agreement	Adapted from Flatten et al. (2011)
GenAI capability (T2, T3; owner-manager)	Human: "Our staff have the skills to judge the quality of GenAI outputs in their area of work." Data: "Our own product, customer or process information is used within our GenAI workflows." Technical: "GenAI tools are connected to the software we use for our core work." Managerial: "We decide systematically whether to scale up or stop particular GenAI uses."	7-point agreement	Adapted from Mikalef & Gupta (2021)

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Construct (wave; informant)	Sample items	Response scale	Source
GenAI governance capability (T2; owner-manager)	"We have written rules on how GenAI may be used." "Outputs sent to clients are reviewed by a person before release." "We have rules on which data may be entered into which GenAI tools." "A named person is responsible for GenAI use."	Each practice 0 = not in place, 1 = in place; consistency 1 = never, 7 = always	New; informed by Berente et al. (2021); NIST (2023)
Augmentation orientation (T2; second informant)	"For each of your three main GenAI uses: Is the task routine or judgment-intensive? How often does a person review and modify the output before it is used?"	Task type: routine or judgment-intensive; review: 1 = never, 7 = always	New; based on Raisch & Krakowski (2021)
Operational performance (T1, T3; owner-manager)	"Compared with the previous survey, the time needed to complete our core tasks has..." "Compared with our main competitors, our output per employee is..."	1 = greatly worsened, 7 = greatly improved; 1 = much worse, 7 = much better	Adapted from Venkatraman & Ramanujam (1986)
Innovation performance (T1, T3; owner-manager)	"Compared with the previous survey, the number of new or improved products, services or processes we introduced has..."	1 = greatly decreased, 7 = greatly increased	Adapted from Jiménez-Jiménez & Sanz-Valle (2011)
Market performance (T1, T3; owner-manager)	"Compared with our main competitors, our customer satisfaction is..." "Compared with our main competitors, our sales growth is..."	1 = much worse, 7 = much better	Adapted from Venkatraman & Ramanujam (1986)
Risk-adjusted performance (T1, T3; owner-manager and records)	"Compared with the previous survey, the frequency of errors in work delivered to customers has..." Number of logged complaints and compliance incidents in the period.	1 = greatly worsened, 7 = greatly improved; counts	New

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