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Activate, legitimize, embed: enacting generative artificial intelligence adoption in small and medium-sized enterprises

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Abstract

Purpose – Generative artificial intelligence (GenAI) holds transformative potential for small and medium-sized enterprises (SMEs). Yet, despite increasing access to GenAI tool use, many SMEs face significant challenges in moving beyond experimentation toward sustained adoption. While extant literature covers the strategic benefits, ethical considerations and performance implications, limited insight exists into how adoption is enacted across individual and organizational levels. This study, therefore, adopts an enactment perspective to examine how SMEs adopt GenAI, and how enablers and barriers across technological, organizational and environmental (TOE) dimensions interact to shape this process.

Design/methodology/approach – This exploratory, qualitative study draws on 31 semi-structured interviews with SME decision-makers across European–Mediterranean contexts (Germany and France), supplemented by data from South Africa and Vietnam to enrich analytical depth across varying levels of digital maturity and institutional contexts. Data were analyzed inductively, using the Gioia methodology.

Findings – The study develops a three-phase process model of GenAI adoption enactment in SMEs: (1) activation of individual trust and engagement, (2) legitimizing and direction setting and (3) embedding and sustained value realization. GenAI unfolds through the interplay of bottom-up individual experimentation and top-down organizational legitimization, with distinct TOE dimensions dominating each phase. Sustained adoption emerges when these dynamics are deliberately coordinated.

Originality/value – The study offers two theoretical contributions. First, it extends the TOE framework from a static-factor model to a dynamic, processual account of GenAI adoption enactment in SMEs. Second, it complements TOE with bricolage to explain how structural conditions are operationalized through micro-level "making do" practices in resource-constrained contexts.

Keywords Generative artificial intelligence, AI adoption, Small and medium-sized enterprises (SMEs), Technology adoption, TOE framework, Bricolage

Paper type Research article

1. Introduction

The past 2 decades have been marked by an unprecedented technological transformation, culminating in the current rise of artificial intelligence (AI) (Agrawal *et al.*, 2022) and advances in both traditional and generative AI. Traditional AI encompasses a range of

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techniques, such as machine learning and deep learning, which enable systems to identify patterns in data and generalize these patterns to new contexts, often through artificial neural networks that approximate aspects of human cognition. In contrast, generative artificial intelligence (GenAI) represents a distinct evolution of these capabilities. Building on generative modeling and advances in deep learning, GenAI systems are designed to produce novel outputs rather than merely analyzing existing data (Gupta *et al.*, 2024). Specifically, GenAI refers to machine learning models capable of generating diverse forms of content, such as text, images, audio, or video, by learning from large datasets and recombining this knowledge to create new, contextually relevant artifacts (Bankins *et al.*, 2024; Gupta *et al.*, 2024).

While large enterprises have been quick to prioritize GenAI opportunities, with over 75% of executives ranking GenAI as a strategic priority (Apotheker *et al.*, 2025), small and medium-sized enterprises (SMEs) are less clear about their adoption approaches. SMEs face unique challenges in adopting generative tools, including limited resources and restricted access to technology. Yet, SMEs can benefit disproportionately from GenAI, which can alleviate constraints, enhance productivity, improve customer experience, and support data-driven decision-making (Raji *et al.*, 2024; Schwaeke *et al.*, 2025). This duality introduces a fundamental tension: while GenAI expands technological affordances, it simultaneously amplifies uncertainties related to trust, governance, and fears of workforce displacement (Cubric, 2020; Vanneste and Puranam, 2025).

SMEs represent over 90% of enterprises worldwide and employ approximately 60% of the workforce (Raji *et al.*, 2024; World Bank, 2019) and are therefore widely considered the backbone of many European and Mediterranean economies (e.g. Germany and France). Unlike large organizations, SMEs are characterized by leaner structures, closer proximity between employees and operational challenges, with shortened communication lines and informal employee experimentation (Prouska *et al.*, 2023). In such settings, innovation often emerges bottom-up, as individuals closest to the operational challenges are often first to identify opportunities to experiment informally (Bankins *et al.*, 2024; Neumann *et al.*, 2024). While this bottom-up experimentation plays an important role in uncovering use cases and potential value, fragmented and informal use rarely translates to transformative impact without embedding use into everyday practices (Neumann *et al.*, 2024; Yang *et al.*, 2024). However, much of the GenAI adoption literature continues to conceptualize adoption through static, factor-based models that assume linear progression from intention to use toward sustained adoption (e.g. Qabrati *et al.*, 2026; Yavetz and Nakash, 2026). As a result, these approaches offer limited insight into the tension between bottom-up experimentation and top-down legitimization and provide insufficient explanation of how GenAI adoption unfolds within SMEs.

Addressing this limitation, and acknowledging phased traditional AI adoption diffusion as a process of maturity (e.g. Gursoy *et al.*, 2019; Hansen *et al.*, 2024), the study adopts an enactment perspective to examine how SMEs adopt GenAI in practice. Instead of treating individual and organizational factors as static antecedents, we conceptualize it as a process that unfolds through individual engagement, organizational legitimization, and the embedding of GenAI into daily work routines. This perspective may allow for a more thorough capture of the nuances of individual and organizational adoption, which may mutually influence one another. Particularly in the context of SMEs, these dynamics may be of particular relevance, as individual actors may exercise a stronger influence on organizational GenAI adoption behavior. Nested within this enactment perspective, we adopt an enablers and barriers lens, grounded in the technology-organization-environment (TOE) framework (A. Al-Okaily, 2025a, b; Tornatzky and Fleischer, 1990; Gupta *et al.*, 2024), to examine the individual- and organizational-level conditions that enable or constrain GenAI adoption across each phase. This framing further allows for the consideration of micro-level experimentation and “making do” practices, consistent with bricolage (Baker and Nelson, 2005; Karanasios *et al.*, 2025), through which technological, organizational and environmental conditions are enacted throughout the adoption process.

The enactment process describes how GenAI adoption unfolds in SMEs, while the enablers and barriers lens explains why each phase succeeds or breaks down. While the study focuses on European-Mediterranean business environments (e.g. Germany and France), it acknowledges cross-regional institutional differences that may shape GenAI adoption trajectories. Accordingly, this paper addresses the following research questions:

RQ1. How do small and medium-sized businesses enact the adoption of generative artificial intelligence?

RQ2. How do enablers and barriers, across the technological, organizational, and environmental dimensions, interact to shape the phases of this enactment process?

Through positioning the process of enactment, this study advances understanding of how GenAI adoption transitions beyond fragmented experimentation toward sustained and embedded practice in SMEs. In doing so, it makes two theoretical contributions. First, it extends the TOE framework from a static-factor model to a dynamic, processual account of GenAI adoption enactment, advancing on prior sequential AI adoption research that predominantly focused on traditional AI instead of GenAI. The study thereby moves beyond existing phased models of AI adoption in SMEs, which have largely treated adoption as static, factor-based progression from intention to use. Instead, it demonstrates how TOE conditions are unevenly and dynamically enacted across distinct phases of activation, legitimization, and embedding. Second, the study complements TOE with the concept of bricolage to explain how structural conditions are operationalized through micro-level "making do" practices in resource-constrained SMEs. Whereas TOE identifies macro-structural conditions shaping GenAI adoption, bricolage highlights micro-level dynamics co-evolving with the proposed adoption enactment phases.

The remainder of this study is organized as follows: Section 2 reviews extant literature on GenAI adoption across the TOE dimensions in the SME context. Section 3 outlines the theoretically grounded approach supported by triangulated data artifacts. Section 4 presents the findings by explaining the three-phase enactment process model through which adoption unfolds. Section 5 discusses how TOE conditions are dynamically enacted across phases. Section 6 concludes with the theoretical contribution, practical implications, limitations and future research.

2. Literature review

2.1 GenAI adoption in SMEs

GenAI adoption represents a promising pathway for enhancing employee performance (Noy and Zhang, 2023) and has become a cornerstone of digital transformation across industries (e.g. Gupta *et al.*, 2024). While GenAI tools continue to redefine the dimensions of work, their diffusion within SMEs – companies that have fewer than 250 employees and an annual revenue below 50 million euros (European Commission, 2023) – remains uneven and often constrained. Existing research on AI adoption in SMEs has predominantly centered on predictive intelligence, big data, and automation (Schwaeke *et al.*, 2025), focusing on themes such as problem-solving, innovativeness, and organizational processes (El Abiad *et al.*, 2025; Hansen and Bøgh, 2021). These studies emphasize the importance of perceived usefulness, willingness to change, and strategic alignment (M. Al-Okaily, 2025a, b; Dörr *et al.*, 2023), while also noting persistent barriers such as technological complexity, change management challenges, and limited financial resources (Dörr *et al.*, 2023; Hansen and Bøgh, 2021).

Moreover, research suggests that AI adoption is shaped by multilevel factors influencing the incorporation of AI technologies into organizations. Scholars often emphasize the explanatory power of the TOE framework in SME technology adoption and outline facets along the three dimensions. For instance, technological considerations often group around compatibility, relative (functional) advantage, and observability; organizational factors focus on leadership commitment, organizational knowledge, resources, and culture; and environmental aspects emphasize operations within networks of competition, customers, and regulatory bodies (M. Al-Okaily, 2025a, b; Gupta *et al.*, 2024; Nguyen *et al.*, 2022; Schwaeke *et al.*, 2025). Particularly in the context of GenAI, the TOE framework offers a systematic lens of examination, which proves promising, as organizations need to assess technological efficiency and effectiveness while simultaneously examining organizational resources and environmental conditions influencing the diffusion of GenAI within organizations (Gupta *et al.*, 2024).

Yet, the generative capabilities of GenAI and increasing socio-technological interactions reveal limitations in applying more static models. While traditional AI adoption functions largely as an extension of existing adoption mechanisms and human-machine interactions – particularly due to its enhanced technological efficiency – GenAI requires more thorough and interpretative interactions. As generative algorithms increasingly act as social actors, and GenAI outputs require careful examination in terms of correctness, users' perceptions and experiences become central to adoption. The non-deterministic and co-creative nature of GenAI elevates the importance of human-AI interaction and highlights shifts in cognitive responses to generative models. In this context, a culture of experimentation and psychological safety may encourage responsible exploration (Shao *et al.*, 2025; Vinarski Peretz and Kidron, 2023), while affective commitment may foster individuals' innovativeness (Vinarski-Peretz *et al.*, 2011). In turn, the development of personal and social resources may become instrumental for improving organizational performance more broadly (Kidron and Vinarski-Peretz, 2024).

SME characteristics (e.g. constraint resources, experimentation) may simultaneously facilitate and hinder GenAI adoption and shape the enactment of generative tools within SMEs. On the one hand, smaller firms possess agility that allows rapid pivoting and integration into processes and business models without the bureaucratic inertia typical of large corporations (Morgan *et al.*, 2020). This aligns with a technology-in-practice lens, which theorizes ongoing rather than static reconfiguration when adopting generative models (Orlikowski, 2000). On the other hand, they often lack the digital maturity, data infrastructure, and technical expertise necessary to deploy GenAI responsibly and at scale (Choudrie *et al.*, 2023).

While the academic discourse has elaborated on the determinants of GenAI adoption within SMEs, we know less about how GenAI becomes routinized under resource constraints. Understanding GenAI diffusion within SMEs, from both the bright and dark side of AI, therefore may carry significant theoretical and practical significance.

2.2 Enacting technologies in SMEs

Technology in SMEs is rarely implemented as a one-off, linear project. Instead, it is typically enacted through ongoing use and shaped by resource constraints, managerial agency, and continuous alignment between tools and everyday work.

Applying a practice lens, SME employees enact what technology becomes through recurrent use, improvisation, and adaptation in daily routines. As individuals engage with technology in ongoing work practices, they actively enact structures that shape how the technology is used in situated and evolving ways (Orlikowski, 2000). Yet enactment is not purely emergent: SME leaders often structure use through rules, tool choices, and informal norms, creating a persistent tension between local improvisation and centralized boundary-setting (Orlikowski *et al.*, 1995). Accordingly, structures of technology use are produced in action, evolve over time, and are shaped by micro-level behaviors (Canhoto *et al.*, 2021).

Moreover, outcomes of technology use often depend heavily on what leaders and employees do with systems, emphasizing how human agency shapes interpretations, experimentation, and technology's role in work (Boudreau and Robey, 2005). However, agency is exercised in relation to material affordances and constraints that co-evolve with routines (Leonardi, 2011). Managers play a disproportionate role in sensing opportunities and building capabilities for technology adoption in SMEs (Li *et al.*, 2018), and orchestrate enactment through selective reconfiguration. Yet, because SMEs typically face constrained resources, they often assemble workable solutions – known as bricolage – by recombining available digital tools, leveraging low-cost platforms, and iterating incrementally. While bricolage is simultaneously a capability (enabling adaptation) and a liability (accumulating fragmentation), it may support short-term endeavors but impede long-term value creation due to limited functionality and poor system integration (Baker and Nelson, 2005; Karanasios *et al.*, 2025). To circumvent these dynamics, SMEs often enact technology through relationships with peer networks, communities, and partners, and rely on external and internal reconfiguration to make digital practices viable.

The SME enactment literature remains fragmented across improvisation, bricolage, and managerial agency streams, offering limited guidance on how generative systems are enacted responsibly over time. In GenAI contexts, tensions of automation versus augmentation (Raisch and Krakowski, 2021) or rapid experimentation versus opacity and accountability (Dörr *et al.*, 2023) require additional attention and call for process explanations of how SMEs build sustainable GenAI diffusion.

3. Methodology

3.1 Research design

To investigate the research questions, an exploratory, qualitative research approach was employed to examine how SMEs enact the adoption of GenAI. Given the emergent nature of GenAI and the limited understanding of how SMEs evaluate and integrate these technologies, a qualitative approach is particularly suitable (Choudrie *et al.*, 2023; Palmucci *et al.*, 2025). It allows for an in-depth exploration of decision-makers' interpretations and sensemaking processes that are not easily captured through predefined quantitative measures.

Accordingly, the study follows an interpretivist perspective. Rather than testing prior hypotheses, the study aims to qualitatively build theory on processual GenAI enactment in SMEs, applying the Gioia methodology (Gioia *et al.*, 2013). The methodology was chosen due to its ability to cluster qualitative data into themes and overarching dimensions, and its proven capacity to generate new theories (e.g. Dörr *et al.*, 2023).

3.2 Sample and data collection

We collected data from individuals occupying key decision-making roles in SMEs. A purposive sampling strategy was employed to identify experts with direct responsibility for strategic, digital, or innovation-related decisions. As a starting point, contacts from the authors' networks were recruited as interview partners and asked to suggest further qualified contacts and cases (Glaser and Strauss, 2017). A detailed list of interview partners can be viewed in Appendix 1.

The study draws on 31 semi-structured interviews with SME decision-makers across Germany and France, supplemented by data from South Africa and Vietnam to enrich analytical depth across varying levels of digital maturity and institutional contexts. A semi-structured approach was adopted to gather a wider breadth of responses, as it allows interviewees to function as participants in meaning-making rather than as conduits from which pre-specified information is extracted (Dicicco-Bloom and Crabtree, 2006). Germany serves as the empirical context for this study as it is the largest economy in the European Union (EU), with SMEs forming the backbone of its economic structure and operating under the EU AI Act and GDPR. Second, France, as a major EU member state and Mediterranean economy, provides a complementary European context shaped by a similar regulatory environment, enabling within-region analysis. Together, these two focal contexts anchor the study in the European-Mediterranean orientation of this journal. Data from South Africa and Vietnam supplement the primary dataset, enriching analytical depth across varying levels of digital maturity and institutional contexts.

Interviews were conducted both online and in person, lasted on average 51 min, and were held between April and June 2025. An interview guide was developed based on prior technology adoption literature (Hughes *et al.*, 2026; Mikalef and Gupta, 2021; wael AL-khatib, 2023), while allowing flexibility to probe emergent themes related to individual perceptions and organizational practices. To accommodate interviewees' language preferences, the interview guideline was developed in English and translated into German using ChatGPT. Subsequently, the translations were validated by German native speakers within the team of authors. The full interview guideline in English and German is provided in Appendix 2. All interviews were audio-recorded with participants' consent and transcribed verbatim using Otter.ai. Data collection proceeded until theoretical sufficiency was reached.

3.3 Qualitative data analysis and synthesis

The qualitative analysis followed a three-step approach of open, axial, and theoretical coding (Corbin and Strauss, 2015) within the Gioia methodology framework (see Figure 1) (Gioia *et al.*, 2013). In the first step, we derived information-centric first-order concepts from the interviews, coding perceived enablers and barriers which shape GenAI adoption at individual- and organizational-level. Microsoft Excel was used to organize concepts and enable iterative comparison.

In the second step, an iterative process involving two of the three authors was utilized to translate the first-order concepts into second-order recurring themes. Initially, the two authors independently coded 10 interview transcripts to establish preliminary second-order concepts. Upon reaching full consensus, the coding scheme was refined. This approach ensured investigator triangulation, thereby reducing individual bias and enhancing the reliability of the findings as supported by Abdalla *et al.* (2018). Throughout the analysis, constant comparison was applied across interviews, allowing the identification of common patterns.

In the third phase, second-order themes were mapped onto three distinct phases of GenAI adoption: (1) *Activation of Individual Trust and Engagement*, (2) *Legitimizing and Direction Setting*, and (3) *Embedding and Sustained Value Realization*. These phases reflect analytically derived patterns rather than strictly sequential stages. The mapping was achieved through iterative analysis of how themes clustered around recurring patterns of behavior, decision-making, and organizational responses.

To further enhance the empirical rigor, interview data were triangulated with organizational artifacts related to GenAI adoption. Artifacts included internal AI usage guidelines, strategic roadmaps, prompt libraries, training material, hackathon briefs, and process workflows, which provided insights into how GenAI adoption was operationalized within organizations. In addition, triangulation was used analytically to support the interpretation of process phases. For instance, interview data that described early-stage experimentation were corroborated through documented hackathon structures and training material. At the same time, examples of governance and organizational alignment were cross-validated against AI usage policies and process workflows. These artifacts supported the interpretation of how enablers and barriers manifest differently across phases of GenAI adoption, strengthening the validity of the phase-based process model.

To ensure transparency and traceability, quotes from interview participants were used throughout the results section to support each phase's enabling and constraining conditions. Quotes are attributed by interview numbers to reflect diversity in perspectives represented in the dataset.

4. Results

Acknowledging cross-regional regulatory and institutional disparities, and drawing on the TOE framework on how conditions shape adoption, our study reveals three dominant phases through which GenAI adoption in SMEs is enacted. Each phase is shaped by distinct

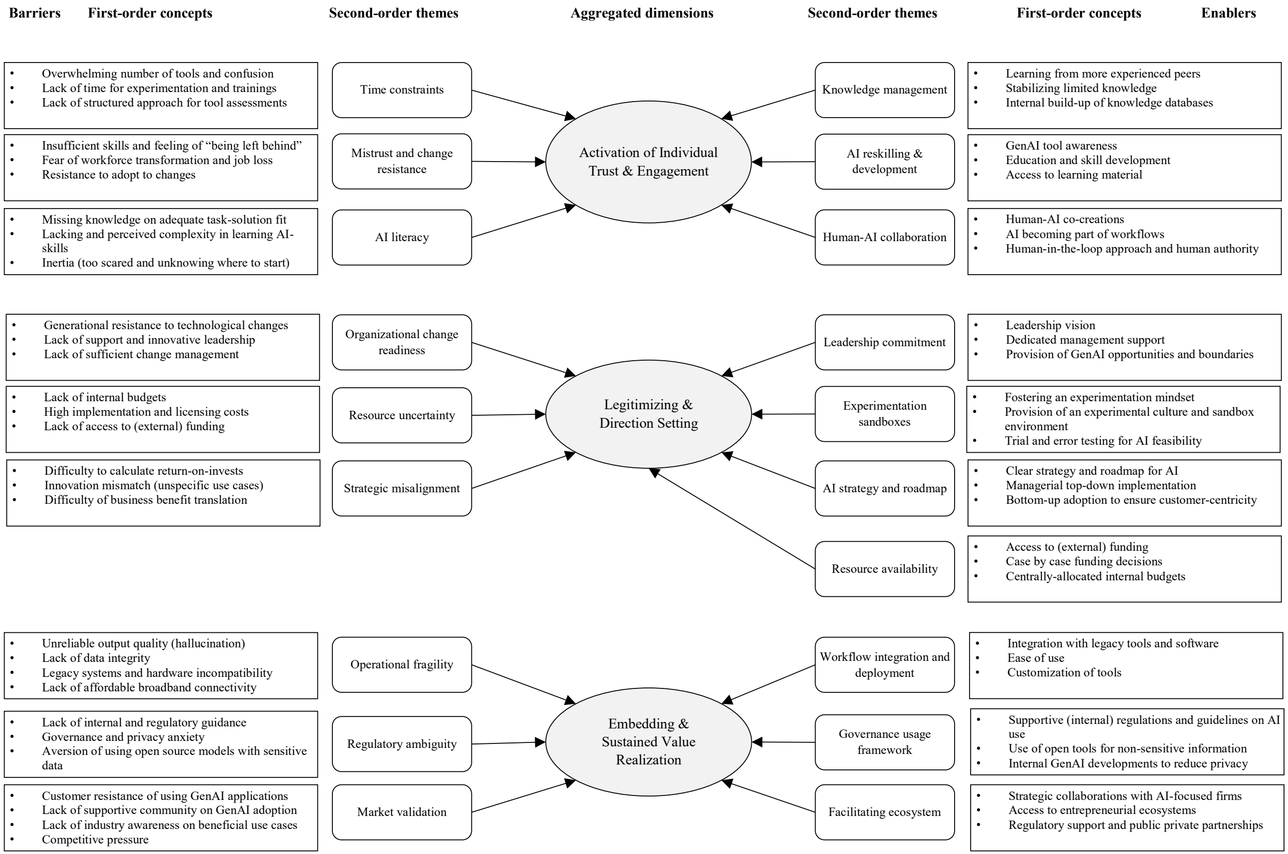

Figure 1. Gioia *et al*. (2013) informed process model of GenAI enactment in SMEs. Source: Authors' own work

configurations of enabling and constraining mechanisms instead of a linear adoption sequence. These configurations capture the dynamic interplay between technological affordances, organizational readiness, and environmental pressures across the adoption process. Based on the 31 semi-structured interviews (478 coded statements), the following phases emerged: (1) *Activation of Individual Trust and Engagement*, (2) *Legitimizing and Direction Setting*, and (3) *Embedding and Sustained Value Realization*. The phases, depicted in Figure 1, illustrate dominant organizing processes, through which SME adoption unfolds and may co-exist, overlap, or even iterate over time. The division of Figure 1 into enabling and constraining conditions illustrates the dynamic tension between factors that facilitate and inhibit technology adoption. Furthermore, to strengthen empirical validity, interview quotations across the phases were systematically triangulated with organizational artifacts (e.g. usage guidelines, process workflows) to corroborate how stated enablers and barriers manifested in SME practices.

4.1 Phase 1: Activation of individual trust and engagement

Adoption is activated and shaped through individual trust and experimental engagement, serving as an entry condition for GenAI use. This phase reflects the extent to which individuals possess confidence, competence, and the willingness to engage with GenAI in their work environment.

From a TOE perspective, this phase is characterized by technological and individual conditions, where tool accessibility, ease of use, and prompt capabilities enable low-barrier experimentation, while organizational structures remain emergent. Activation of trust and engagement occurs when individual factors such as AI literacy, time availability for experimentation, and psychological safety are deliberately activated. As one participant noted: "*Awareness and education is already half the battle (. . .) knowledge of the prompts and the how-to is another" [Interview 7]*. Constraining conditions leading to adoption breakdowns include fear of AI displacement (both on individual and organizational level), mistrust of AI outputs, questioning GenAI's value, and resistance to unfamiliar technologies. As another respondent mentioned: *"There is mistrust, this negative narrative (. . .) that AI will take your job. . .you cannot take fear away from people (...) be transparent" [Interview 1]*.

This phase aligns with an improvisational form of bricolage (Baker and Nelson, 2005; Karanasios *et al*., 2025) where employees combine available tools, such as free-tier tools, shared prompt libraries that facilitate low-cost experimentation. Artifact evidence, such as prompt libraries and hackathon briefs, demonstrates that early-stage engagement is structured around low-cost experimentation. These artifacts provide evidence that experimentation sandboxes serve as practical mechanisms in which trust and capabilities are developed, further reinforcing their role as key enablers in this phase.

Together, these results indicate that GenAI adoption is activated through the interplay of accessible technological affordances, deliberate cultivation of individual trust, and willingness to engage. The transition to the next phase is triggered when individual-level experimentation accumulates into visible, recurring patterns, evidenced through artifacts such as shared prompt libraries and hackathon outputs. This in turn prompts a shift from informal, fragmented use toward deliberate organizational direction-setting.

However, the absence of subsequent organizational legitimization produces fragmented, idiosyncratic use patterns leading to adoption breakdowns and non-scalability.

4.2 Phase 2: legitimizing and direction setting

Organizations legitimize work practices when leadership articulates a clear vision and sets the direction of AI and its use cases. In doing so, organizations transition beyond fragmented experimentation toward coordinated adoption efforts.

From a TOE perspective, this phase is dominated by organizational conditions, such as leadership vision, strategic roadmap development, governance frameworks, and deliberate signaling of intent to convert fragmented experiments into legitimate organizational practices. Technological conditions become secondary, focusing on tool selection, licensing, and integration. Environmental conditions begin to surface through emerging regulatory and institutional signals (e.g. EU AI Act, GDPR) that inform governance design.

One respondent described integrating GenAI into strategy: *"You need to transform from viewing AI as a side project to it becoming something that is part of your strategy (. . .) Leadership creates both opportunities and boundaries (. . .) [then] prove the value of AI to those on the ground." [Interview 6]*.

Yet, constraints may emerge that lead to adoption breakdowns, particularly when leadership is perceived as non-supportive, absent, or having weak change management mechanisms. This is evident in statements such as: *"AI is not something that you do a course on, and then you're up to date, it is a continuous process that you have to take people through (...) get those things right and have a roadmap that is clear (...) and the adoption rate of this tech will go through the roof." [Interview 3]*.

Where phase 1 activates individual engagement, this phase emphasizes a leadership-led change process that formalizes and directs adoption. This transition is characterized by selective bricolage, whereby organizations evaluate which informal practices from phase 1 to retain, formalize, or discard. Thereby, they convert experimentation into governed and repeatable legitimate practices.

This is further supported by organizational artifacts such as internal AI usage guidelines, which formalize acceptable use practices and governance structures. These artifacts demonstrate legitimacy through formalization, reinforcing governance and strategic clarity as key enablers, while their absence acts as a barrier in this phase.

The transition to the next phase is triggered when formalized practices produce observable and replicable value outcomes, signaling a shift from legitimized intent to operational relevance. This marks the inflection point at which organizational legitimacy translates into embedded adoption.

4.3 Phase 3: embedding and sustained value realization

In the third phase, systems are established to embed, stabilize, and scale GenAI into operations for sustained value realization.

From a TOE perspective, this phase is characterized by technological and environmental conditions, where infrastructural reliability (e.g. data quality, system integration) and regulatory factors (e.g. compliance with regulations such as EU AI Act and GDPR) determine whether GenAI transitions from legitimized practice to sustained value. Organizational conditions serve as the integrating mechanism, ensuring alignment and integration between governance structure, process workflows, and capability development.

At this stage, adoption becomes institutionalized through workflow integration, supported by governance structures, dealing with regulatory ambiguities, and aligned with operational and strategic objectives. Embedding occurs when GenAI use is integrated into work processes and linked to tangible outcomes such as efficiency gains, time saving, cost reduction, improved decision-making, and productivity improvements. *"By using GenAI, you get something in real time (. . .) [something that usually] cost you 200 euros to write (. . .) you will now get in five minutes." [Interview 2]*. These outcomes signal the transition from exploratory use to embedded practice.

However, sustained adoption is constrained by operational fragility, including data quality issues, tool inaccuracy, poor quality output, and infrastructural limitations. These constraints reduce trust in outputs and limit GenAI embeddedness. As one respondent cautioned: *"You cannot just blindly trust the output, because sometimes it produces things that sound very plausible but are not right (. . .) we use it as support, not as a final decision-maker." [Interview 11]*. Such limitations signal the importance of a robust digital backbone for sustained GenAI adoption.

These findings further reveal the completion of bricolage trajectory, where improvised practices from phase 1, selectively formalized in phase 2, are either absorbed into governed workflows or persist as accumulated technical debt, surfacing as operational fragility.

Governance mechanisms further legitimize embedded use through clarifying responsible AI practices and reducing perceived regulatory risk. As one respondent stated: *"You need to build an AI [usage] framework and bring all the team members together and state, this is how we should potentially use it [GenAI tools] (. . .) this framework serves as a guideline for responsible use within our business processes and organization."* [Interview 4].

This is further evidenced by organizational artifacts such as strategic roadmaps, AI usage guidelines, and process workflows, which illustrate how GenAI transitions from isolated use cases to integrated practices. These artifacts provide insights into sustained embedding being dependent on the alignment of infrastructure, governance, and capability development. However, misalignment across these TOE dimensions, could lead to stalled or partial adoption.

Across all three phases, the results, supported by triangulated artifact evidence, reveal that GenAI adoption in SMEs is enacted through an iterative process shaped by perceived enablers and barriers, and how these conditions are operationalized. This highlights that adoption unfolds through the dynamic reconfiguration of technological, organizational, and environmental conditions, while alignment across these dimensions is important for sustained and embedded value realization.

5. Discussion

We began this study by asking: *How do small and medium-sized businesses enact the adoption of generative artificial intelligence?* and *How do enablers and barriers, across the technological, organizational, and environmental dimensions, interact to shape the phases of this enactment process?* Rather than treating GenAI adoption as a linear diffusion process, our results reveal that SMEs across differing regulatory landscapes tend to enact adoption through three interrelated, non-linear phases: (1) *Activation of Individual Trust and Engagement*, (2) *Legitimizing and Direction Setting*, and (3) *Embedding and Sustained Value Realization.*

Our findings suggest that adoption outcomes are not a primary function of technological capability alone. Instead, they rely on the interplay between individual-level activation, organizational-level legitimacy, and environmental-level stabilization factors. This reinforces the core premise of the TOE framework, which posits that adoption outcomes are shaped by the combined influence of technological, organizational, and environmental conditions instead of any single dimension in isolation (Farmakis *et al.*, 2025; Tornatzky and Fleischer, 1990).

To interpret these enactment dynamics, we draw on the TOE framework by demonstrating a multi-level understanding of how the structural conditions are enacted and stabilized across phases of adoption (Siljeur *et al.*, 2025; Tornatzky and Fleischer, 1990; Wang *et al.*, 2025).

While TOE explains the macro-level conditions shaping adoption, bricolage is introduced as a complementary micro-level mechanism that explains how SMEs navigate these conditions in practice. Consistent with this view, the enactment process further identifies how these conditions are activated through micro-level experimentation and "making do" practices (Baker and Nelson, 2005), which shape how adoption unfolds in resource-constrained environments. In this context, bricolage therefore complements the TOE perspective by illustrating how adoption conditions are activated, legitimized, and embedded through iterative experimentation to sustained adoption.

5.1 Why GenAI adoption is activated at the individual level

The first phase reveals that GenAI adoption is activated through individual trust and engagement, rather than organizational instruction. This finding is prominent in SMEs, where structures are lean, roles overlap, and employees are usually close to the operational problems and have direct autonomy to experiment with new tools (e.g. Dörr *et al.*, 2023). Individual trust in GenAI outputs coupled with basic AI literacy and time for experimentation become preconditions for individual engagement activation. From a TOE perspective, this phase is predominantly shaped by technological conditions, while organizational conditions remain weak.

This insight mirrors long-standing technology acceptance research, which emphasizes that perceived ease of use and usefulness can drive early adoption independently of organizational strategy and environmental conditioning (M. Al-Okaily, 2025a, b; Venkatesh *et al.*, 2003). Yet, while early enthusiasm accelerates experimentation, trust plays a more crucial role than in prior technologies, given the probabilistic and generative nature of outputs. Mistrust, fear of displacement, and the unreliability of GenAI outputs may prevent engagement even when tools are available. However, these factors often require an individualized and interpretivist lens as they unfold in various facets. For instance, fear of displacement may manifest as concerns over work transformation, individual job losses, or organizational redundancies, particularly when larger corporations possess greater resources to pursue technological advancements. Consequently, individual-level psychological readiness functions as an activation mechanism, explaining why GenAI adoption often begins informally and unevenly within SMEs.

The informal character of phase 1 engagement thereby reflects what Baker and Nelson (2005) describe as bricolage, being both an asset and liability. As an asset, it facilitates low-cost experimentation and generates contextually situated knowledge about GenAI affordances. As a liability, it produces fragmented, idiosyncratic use patterns that remain invisible to management and difficult to scale. This could create conditions for adoption breakdown.

Accordingly, this suggests that early-stage technological and organizational conditions alone are insufficient for adoption and require the individual's willingness to experiment and engage. Consistent with findings by Neumann *et al.* (2024) and Bankins *et al.* (2024), the enactment process therefore clarifies why early-stage adoption generally emerges bottom-up in SMEs and why organizational strategies follow, instead of precede, individual experimentation and engagement.

5.2 How organizational direction legitimizes experimentation

Our findings reveal that while individual engagement and experimentation activate GenAI adoption, it does not alone lead to sustained adoption. The second phase illustrates the organizational leadership role in legitimizing and coordinating GenAI use through signaling strategic intent, setting boundaries, and showing commitment.

From a TOE perspective, this phase is characterized by organizational conditions, where leadership vision, governance usage frameworks, and strategic alignment convert fragmented experiments into legitimate organizational practices. Technological and environmental conditions play a supporting role in this phase.

This insight aligns with established literature, which emphasizes the role digital leadership plays in legitimizing AI initiatives, reducing internal resistance, actively promoting and fostering buy-in, investing in employee development, and embedding AI in operational decision-making through data-driven practices (Jöhnk *et al.*, 2021; Siljeur *et al.*, 2025). Drawing on Wang *et al.* (2025), who empirically demonstrate that digital leadership moderates a positive relationship between data-driven decision-making and both organizational creativity and sustainable competitive advantage, and in line with Chaudhuri *et al.* (2024), our findings suggest that when leadership frames GenAI as part of the organizational strategy and simultaneously fosters data-driven practices (e.g. tracking output quality, evaluating use case systematically, and linking GenAI outputs to observable organizational outcomes), this amplifies the conversion of individual experimentation into organizational-level capability.

These findings are further supported by Raisch and Krakowski (2021), which illustrate that AI value materializes when organizations invest in complementary managerial and organizational capabilities rather than treating AI as a plug-and-play solution.

Viewed through a bricolage lens, phase 2 represents an important organizational decision point regarding informal tool combinations generated in phase 1. In this phase, leaders apply selective bricolage, where organizations determine which experimental practices to retain, formalize, or discard, thereby meta-structuring the organizational dimension of TOE.

From a TOE perspective, organizational conditions shape the direction setting of adoption, while the enactment perspective reveals how leadership commitment translates bottom-up experimentation into shared and coordinated organizational practices. The technological and organizational conditions serve as enablers of digital integration, while digital leadership moderates how that integration is converted into data-driven organizational capabilities.

5.3 Why embedding and sustaining value realization remains fragile

Our findings reveal that even when GenAI is legitimized, embedding and sustaining value remain fragile. Sustained adoption requires the consideration of aligning workflow integration, governance structures, infrastructural reliability, and to validate external market conditions.

This phase emphasizes the importance of technological and environmental conditions illustrated in the TOE, particularly infrastructure and regulatory environment readiness (Siljeur *et al.*, 2025). In light of growing global pressure on SMEs to align technological adoption with broader corporate responsibility, governance frameworks for GenAI use are likely to intersect with wider regulatory expectations concerning environmental and social priorities. Accordingly, a proactive sustainability strategy may moderate the relationship between AI-driven supply chain integration and firms' innovative and collaborative capabilities, particularly in shaping how SMEs govern the use of open-source models versus proprietary data (Chouaibi *et al.*, 2022; Leipziger *et al.*, 2025; Wang and Zhang, 2025). Such AI-driven innovation capabilities may further strengthen information-driven strategic resilience (Wang and Zhang, 2026), thereby helping to mitigate operational fragility. Therefore, organizations need to develop capacities that enable the translation of AI-enabled information flows into adaptive responses under conditions of volatility. In this regard, progressing from exploratory GenAI use to its embedded integration – mediated by strategic resilience – may support SMEs in navigating uncertainties associated with GenAI outputs.

However, our findings on the enactment process revealed that these conditions become prominent only after the individual activation and organizational legitimization has occurred. This means that SMEs generally encounter infrastructure and environmental constraints only after GenAI adoption has begun, which explains why promising initiatives may be abandoned later. Thereby, emphasizing that GenAI adoption is not a one-time decision but requires ongoing nurturing for stabilization and constant iterations in changing regulatory environments.

5.4 Enactment as a socio-technical process

Taken together, these findings suggest that GenAI adoption is a socio-technical enactment process shaped by the dynamic interplay between technological, organizational, and environmental conditions over time. This study reinforces the TOE framework as the explanatory lens, demonstrating that adoption unfolds through shifting configurations of these conditions across phases, rather than through static antecedents. At the same time, bricolage complements TOE by explaining how these conditions are enacted at the micro-level, particularly during early-stage activation, where SMEs rely on "making do" practices to initiate adoption under resource constraints. This pairing of a macro-level structural lens with a micro-level lens mirrors Coleman's (1990) boat, a framework management scholars increasingly draw on to bridge macro- with micro-levels of explanation (Cowen *et al.*, 2022). Phase 1 operates at the micro-level of individual action, phase 2 reflects organizational structure formation around that action and phase 3 aggregates both into the macro-level outcome of sustained adoption.

This novel perspective thereby helps to explain the variation in findings on GenAI adoption outcomes across SMEs and reveals why adoption success cannot be claimed through technology access or leadership support alone. Instead, adoption is reflected in how TOE conditions are progressively enacted across phases, extending the TOE framework from static drivers to a dynamic process. In doing so, the model addresses a recurring gap in cross-boundary management research, where aggregation of micro-level practice into macro-level outcomes is often assumed rather than theorized (Cowen *et al.*, 2022).

6. Conclusion

Applying a qualitative research design, the findings demonstrate that GenAI adoption in SMEs is enacted across three phases: (1) Activation of Individual Trust and Engagement, (2) Legitimizing and Direction Setting, and (3) Embedding and Sustained Value Realization. While the activation phase addresses individual receptiveness toward GenAI, thereby positioning individual engagement as core infrastructure of GenAI adoption, the legitimization phase is primarily driven by the organization. In doing so, SMEs ensure sufficient managerial attention and resource allocation to operationalize individual-led experimentation. Yet, to create value and embed generative systems in a sustainable manner, a hybrid interplay among individuals, the organization, environmental actors, and technology is required.

Moreover, the study highlights how TOE accounts for the structural conditions of GenAI adoption and how these conditions are progressively enacted across a dynamic, three-phase adoption process in SMEs. This moves the framework beyond the static, factor-based models that have characterized much of the existing AI adoption literature in SMEs. Bricolage, in turn, illuminates the “making do” practices that co-evolve with the three phases, revealing how SMEs practically navigate TOE conditions under resource constraints. Together, these contributions trace the path from individual-level activation to organizational-level outcomes, bridging macro- and micro-perspectives of GenAI adoption in SMEs.

6.1 Theoretical implications

The study advances two theoretical contributions. First, the study extends the TOE framework (Tornatzky and Fleischer, 1990) from a static-factor model to a dynamic, processual account of GenAI adoption enactment in SMEs. By conceptualizing a three-phase process, we theorize GenAI enactment beyond static adoption mechanisms, acknowledging generative technological capabilities and their changing influences on socio-technological interactions. Thereby, we expand research on sequential adoption of traditional AI (Gursoy *et al.*, 2019; Hansen *et al.*, 2024) and highlight the foundational importance of employee-level activation before organizational legitimization. Individual use and experimentation can position SMEs at the starting point for GenAI adoption and build trust and readiness for change toward such systems. Such activation further requires alignment with organizational grounding, emphasizing the need for sequential multi-actor considerations when enacting GenAI in SMEs. While the TOE framework has traditionally emphasized organizational and environmental readiness as the primary drivers of adoption, our findings demonstrate the activating role of individual-level conditions such as trust, AI literacy, and psychological safety. Viewing individuals as central to technology adoption, particularly when novel technologies stimulate individuals’ cognition, we demonstrate that activation and engagement operate as core enabling conditions that influence how individuals enact generative technologies in daily routines. Without individuals’ receptiveness toward generative tools and an enabling environment, GenAI tools and infrastructure may remain underutilized, and governance mechanisms may be perceived as hindrances rather than enablers. This shifts the individual level from a supportive role to a primary actor in the adoption process and reframes individual engagement as infrastructure rather than a consequence.

Second, the study complements TOE with bricolage to explain how structural conditions are operationalized through micro-level "making do" practices in resource-constrained SME contexts. While TOE identifies the macro-structural conditions shaping adoption, it does not explain the mechanisms through which those conditions are enacted in practice (Baker and Nelson, 2005; Karanasios *et al.*, 2025). Our findings reveal a bricolage trajectory that co-evolves with the adoption phases. In phase 1, employees improvise with freely available tools and shared prompt libraries to enact the technological dimension of TOE under resource constraints. In phase 2, organizations apply selective bricolage, determining which informal practices to formalize or discard as governance structures emerge. In phase 3, bricolage practices are either absorbed into governed workflows or persist as accumulated technical debt, surfacing as operational fragility. This dual role, operating as an enabling asset during activation and a constraining liability when improvised practices accumulate as technical debt, explains why TOE conditions alone are insufficient to account for adoption outcomes in resource-constrained SME contexts. Together, TOE and bricolage provide a complementary explanatory framework that accounts for macro-structural conditions shaping GenAI adoption and the micro-level practices through which those conditions are enacted.

6.2 Practical implications

This paper holds several important implications for SMEs, enabling them in experimenting with and institutionalizing GenAI.

Consistent with phase 1, adoption strategies in SMEs should prioritize psychological readiness before committing to substantial technological investments. This involves building trust in GenAI outputs, providing basic AI literacy, and creating clearly bounded "safe-to-fail" experimentation spaces. In practice, SMEs can operationalize this by defining low-risk domains for GenAI use (e.g. internal communication drafts, document summaries), appointing a GenAI champion to curate a shared prompt library and facilitate brief internal knowledge-sharing sessions, organizing lightweight hackathon-style exercises within pre-allocated experimentation time, and tracking simple indicators of engagement and trust (e.g. recurring use cases, employee comfort levels). These low-cost scaffolding mechanisms harness bricolage by encouraging employees to draw on existing tools and knowledge while generating situated learning that subsequently informs organizational direction setting in phase 2.

Building on phase 1, SME leaders should manage GenAI adoption in phase 2 as a socio-technical change process rather than an IT transformation. Hybrid adoption, which combines leadership commitment and top-down direction with bottom-up employee trust, engagement, and experimentation, is most likely to institutionalize adoption. Therefore, leaders should establish guardrails through AI usage frameworks, while legitimizing experimentation through use cases. In practice, SMEs can begin with "minimum viable governance frameworks" that define acceptable use (e.g. use of public tools for non-sensitive organizational data, human-in-the-loop validation practices), as evidenced by the analyzed organizational artifacts. Governance is thus positioned as enabling infrastructure: it reduces uncertainty, signals strategic commitment, and converts fragmented bottom-up experimentation into coordinated organizational capability. Therefore, governance should be treated as enabling infrastructure rather than external compliance.

Building on phases 1 and 2, GenAI initiatives in SMEs should be anchored in explicit use case value realization to sustain adoption beyond experimentation. Reflecting phase 3 of the enactment process, absent a clear link between GenAI and measurable outcomes, adoption is unlikely to progress from exploratory use to embedded practice. In practice, SMEs can implement simple experimentation roadmaps for each prioritized use case that specify the targeted workflow, expected benefits, and clear criteria for scaling, modifying, or discontinuing each use case. Use-case tracking mechanisms, such as a shared log documenting time savings, cost reductions, or quality improvements attributable to specific GenAI tools, can be integrated into process workflows and strategy roadmaps, as shared by the analyzed organizational artifacts. These artifacts help translate experimentation into observable business value, provide an evidence base for scaling decisions, and support continuous adjustment as technological and regulatory conditions evolve.

6.3 Limitations and future research

While this study provides a processual view of GenAI enactment in SMEs and emphasizes the foundational role of individual-led adoption, it also has limitations and presents opportunities for future research. First, the qualitative research design prioritized depth over quantitative generalizability across varying regulatory landscapes. Future research could therefore empirically test the proposed process and adoption patterns. Second, the cross-sectional nature of the data limits insights into how adoption patterns evolve. The three phases are analytically derived from retrospective interview accounts rather than from longitudinal observations of organizational change over time. Accordingly, the triggers that transition the SME from individual activation to organizational legitimization, and from legitimization to embedded practice, are inferred instead of directly observed. A longitudinal study tracking SMEs could examine transitions between the enactment phases. In particular, assessing an activation-level threshold that triggers subsequent legitimization could prove promising for advancing the discourse on GenAI enactment. Third, the multi-country design introduces language and interpretive validity constraints. While transcription and analysis were conducted with care, the study did not employ cross-cultural validation procedures. Last, while our sample spanned multiple countries, industry-specific studies would further elucidate GenAI adoption mechanisms.

Appendix 1

Table A1. Overview sample characteristics

#	Role	Industry sector	Firm size (# employees)	Country
1	CEO	Strategy and ICT consulting	21	South Africa
2	Managing Director	Marketing	12	France
3	CEO	Strategy and change management consulting	3	South Africa
4	Managing Partner	Marketing	7	South Africa
5	Managing Director	Mining technologies	40	South Africa
6	Managing Director	Strategy and ICT consulting	3	France
7	CEO	Education and marketing consulting	13	South Africa
8	Managing Director	Legal	20	South Africa
9	CFO	Telemedicine	50	Germany
10	CIO/CDO	Electronics	250	Germany
11	CEO	Legal	12	Germany
12	Implementation Manager	Education technology	46	Germany
13	Co-founder and Director	Tourism	13	Vietnam
14	Co-CEO	Electronics	40	Germany
15	Team Lead Digitization	Production	200	Germany
16	CEO	HR consulting	8	Germany
17	CEO	Healthcare	30	Germany

(*continued*)

Table A1. Continued

#	Role	Industry sector	Firm size (# employees)	Country
18	CEO	Transformation and leadership consulting	1	Germany
19	Successor to CEO	Landscaping and gardening	75	Germany
20	Managing Director	Real estate	19	Germany
21	Managing Director	Production	110	Germany
22	Managing Director	Winery and Gin distillery	18	South Africa
23	Managing Director	Winery	16	South Africa
24	Customer Success Officer	Software	15	South Africa
25	Managing Director	Agriculture	4	South Africa
26	Managing Director	Development finance consulting	10	South Africa
27	Managing Director	Mining consulting	8	South Africa
28	Principle Investment Partner	Private equity	200	South Africa
29	COO/CFO	Startup consulting	23	Germany
30	Managing Director	HR consulting	5	South Africa
31	Managing Director	ICT	14	South Africa

Note(s): CDO = Chief Digitization Officer, CEO = Chief Executive Officer, CFO = Chief Financial Officer, CIO = Chief Information Officer, COO = Chief Operating Officer, HR = Human Resource, ICT = Information and Communication Technology

Appendix 2

Table A2. Interview guideline – English version

Section	Question
Background information	
	Q1: Can you briefly describe your organization (industry, size, location)?
	Q2: Can you briefly describe your role in technology or innovation decisions?
Technology context	
	Q3: What GenAI tools or apps are currently in use within your organization (e.g., ChatGPT, Midjourney, GitHub Copilot)?
	Q4: What features or functionality influenced your decision to adopt these tools?
	Q5: What specific use cases have you applied GenAI to?
	Q6: What challenges have you encountered using these tools?
	Q7: What other technologies have supported the adoption of GenAI (e.g. CRM, ERP, cloud platforms, APIs)?
Organizational context	
	Q8: Who in your organization is driving or championing GenAI adoption? Is there formal leadership or a dedicated team?
	Q9: What internal resources have enabled GenAI adoption?
	Q10: How is GenAI adoption aligned with your organization's strategic goals?
	Q11: Has the adoption of GenAI led to changes in roles, workflows, or organizational culture?
Environmental context	
	Q12: How have external actors influenced your decision to adopt GenAI (e.g. customers, competitors, suppliers, regulators)?
	Q13: What external barriers have you encountered?

(*continued*)

Table A2. Continued

Section	Question
	Q14: What external enablers have helped in adoption? Q15: Are you aware of any AI-specific regulations, ethical guidelines, or privacy laws that affect your use of GenAI?
Organizational maturity and usage patterns	
	Q16: How is GenAI used across your organization (isolated pilots, coordinated across teams, enterprise-wide approach)? Q17: Has your organization developed any internal GenAI guidelines or frameworks? If yes, are these widely adopted and understood? Q18: Have you implemented any formal learning opportunities related to GenAI (e.g. internal training, knowledge hubs, workshops)? Q19: To what extent have external partners supported your GenAI journey (e.g. entrepreneurial ecosystems, AI coaches, academic institutions, consultants)? Q20: What measurable benefits have you observed from GenAI usage?

Note(s): The development of questions is stimulated by the work of Hughes *et al*. (2026), Mikalef and Gupta (2021), and Wael AL-khatib (2023), to conduct interviews in German, the interview guideline was translated using deepl.ai. Subsequently, the translation was validated by German native speakers, proficient in English, within the team of authors

Table A3. Interview guideline – German version

Section	Question
Basisinformationen und hintergrund	
	Q1: Können Sie Ihre Organisation kurz beschreiben (Industrie, Unternehmensgröße, Ort)? Q2: Können Sie Ihre Rolle in Technologie- oder Innovationsentscheidungen kurz beschreiben?
Technologischer kontext	
	Q3: Welche GenAI-Tools oder -Apps werden derzeit in Ihrer Organisation verwendet (z.B. ChatGPT, Midjourney, GitHub Copilot)? Q4: Welche Funktionen oder Eigenschaften haben Ihre Entscheidung zur Nutzung dieser Tools beeinflusst? Q5: Für welche konkreten Anwendungsfälle wird GenAI eingesetzt? Q6: Mit welchen Herausforderungen waren Sie bei der Nutzung dieser Tools konfrontiert? Q7: Welche weiteren Technologien haben die Einführung von GenAI unterstützt (z.B. CRM, ERP, cloud platforms, APIs)?
Organisatorischer kontext	
	Q8: Wer treibt in Ihrer Organisation die Einführung von GenAI voran? Gibt es eine formale Leitung oder ein dediziertes Team? Q9: Welche internen Ressourcen haben die GenAI-Adoption ermöglicht? Q10: Wie ist die GenAI-Adoption mit den strategischen Zielen Ihrer Organisation abgestimmt? Q11: Hat die Einführung von GenAI zu Veränderungen bei Rollen, Arbeitsabläufen oder der Unternehmenskultur geführt?
Externer kontext	
	Q12: Wie haben externe Akteure Ihre Entscheidung zur Einführung von GenAI beeinflusst (z. B. Kunden, Wettbewerber, Lieferanten, Regulierungsbehörden)? Q13: Mit welchen externen Hürden waren Sie konfrontiert? Q14: Welche externen Faktoren haben die Adoption unterstützt?

(*continued*)

Table A3. Continued

Section	Question
	Q15: Sind Ihnen KI-spezifische Vorschriften, ethische Leitlinien oder Datenschutzgesetze bekannt, die Ihre Nutzung von GenAI betreffen?
Organisationale reife und nutzungsmuster	
	Q16: Wie wird GenAI in Ihrer Organisation eingesetzt? (z.B. isolierte Pilotprojekte, koordinierte Teams, unternehmensweite Nutzung)?
	Q17: Hat Ihre Organisation interne Richtlinien oder Rahmenwerke für GenAI entwickelt? Wenn ja, werden diese breit angewendet und verstanden?
	Q18: Haben Sie formelle Lernangebote im Zusammenhang mit GenAI eingeführt (z. B. interne Schulungen, Wissenszentren, Workshops)?
	Q19: In welchem Umfang haben externe Partner Ihre GenAI-Reise unterstützt (z. B. unternehmerische Ökosysteme, KI-Coaches, Hochschulen, Berater)?
	Q20: Welche messbaren Vorteile haben Sie durch den Einsatz von GenAI beobachtet?

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