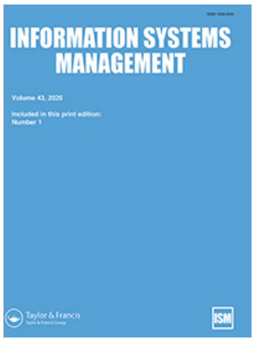

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Aligning Socio-Technical Systems: Rethinking AI Adoption and Digital Transformation in SMEs

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ABSTRACT
This study examines how SMEs adopt AI using a qualitative design informed by Socio-Technical Systems Theory. The findings indicate that AI adoption is shaped by the interaction of technical constraints, organizational routines, and external pressures such as client expectations and policy uncertainty. Leadership engagement, data infrastructure, and workforce dynamics play a central role in influencing implementation progress. The study provides practical guidance for supporting more context-sensitive and adaptive approaches to AI-enabled transformation in SMEs.

KEYWORDS
Artificial intelligence; socio-technical systems theory; SMEs

Introduction

The rapid advancement of digital technologies has fundamentally disrupted and redefined contemporary business environments (Calderon-Monge & Ribeiro-Soriano, 2024; Guo et al., 2023; Hanelt et al., 2021; Lythreatis et al., 2022; Zaman et al., 2025). Recent studies indicate that digital transformation continues to accelerate in the post-pandemic era while creating heightened uncertainty for decision-makers (Meske et al., 2022; Orth et al., 2025; Schneider et al., 2023; Soto-Acosta, 2024). This transformation obliges firms to reconsider their operational models, strategic positioning, and approaches to customer engagement across virtually all sectors (Bhatti et al., 2024; Feroz et al., 2023; Gala & Mueller, 2024; Gartner et al., 2024; Kim et al., 2025; Maycotte et al., 2025; Pergelova et al., 2019; Vial, 2021).

Among these technologies, Artificial Intelligence (AI) has emerged as a uniquely transformative force by not only automating tasks but reshaping decision-making logics and organizational capabilities, automating complex decision-making, extracting actionable insights from vast data flows, and reconfiguring the nature of core business functions, including marketing analytics, financial forecasting, supply chain optimization, and talent management (Donaldson et al., 2025; Dwivedi et al., 2021; Meske et al., 2022; Murtinu & De Massis, 2025; Schwaeke et al., 2025; Sipior et al., 2024; Sonntag et al., 2024). For small and medium-sized enterprises (SMEs), these developments present both opportunities and challenges: while AI offers the potential to enhance competitiveness and operational agility, it also demands capabilities that many SMEs continue to struggle to mobilize.

Notably, the adoption of AI is not a one-off technological substitution but a process that continuously reshapes business models and inter-organizational relationships (Bharadwaj et al., 2013; Hanelt et al., 2021; Nawab, 2024; Radicic & Petković, 2023). With capabilities such as natural language processing, predictive analytics, and machine learning now embedded in daily operations from personalized customer service to real-time decision intelligence AI adoption is driving measurable improvements in efficiency, agility, and responsiveness across global markets (Akter et al., 2022; Bughin et al., 2018; Chaudhuri et al., 2024; Cyfert et al., 2025; Davenport & Ronanki, 2018; Pfaff et al., 2023).

However, the promised gains from AI are not universally realized, particularly for SMEs, which account for the vast majority of firms globally and are often considered engines of innovation and employment. Despite well-documented benefits such as enhanced operational efficiency, data-driven decision-making, cost reduction, and improved customer experiences (Cooper, 2025; Cyfert et al., 2025; Hoffman et al., 2025;; Maycotte et al., 2025; Torroba et al., 2025), the integration of AI into SMEs is fraught with

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distinctive barriers. These include severe resource constraints, limited in-house technical expertise, such as the absence of dedicated IT staff in smaller firms, fragmented data infrastructure, and pronounced cultural and organizational resistance to change (Almashawreh et al., 2024; Apostoaie et al., 2025; Arroyabe et al., 2024; Clemente-Almendros et al., 2024; Dubey et al., 2019; Kergroach, 2020; Lada et al., 2023). Furthermore, regulatory uncertainty, data privacy concerns, and unclear returns on investment exacerbate adoption hesitancy, especially in firms lacking formalized digital transformation strategies (Aghazadeh et al., 2024; Bhatti et al., 2024; Feroz et al., 2023; Maycotte et al., 2025; Nawab, 2024; Wamba-Taguimdje et al., 2020).

Crucially, most extant research has approached these challenges through established frameworks such as the Technology – Organization – Environment (TOE) model or Technology Acceptance Model (TAM), which treat technological, organizational, and environmental factors as discrete and additive rather than interactive and dynamic (Akter et al., 2019, 2022; Almashawreh et al., 2024; Chaudhuri et al., 2024; Cyfert et al., 2025; Gupta & Rathore, 2024; Nawab, 2024; Pfaff et al., 2023; ,). This static view struggles to explain how these elements continuously influence each other throughout implementation. For example, Cyfert et al. (2025) found that while TOE factors such as leadership competence and organizational culture influenced digital readiness, the model failed to explain how these elements continuously interacted during implementation phases, leading to partial or stalled adoption outcomes. As a result, there remains a fundamental gap in understanding digital transformation as a recursive rather than linear phenomenon.

Socio-Technical Systems Theory (STST) offers a promising but underutilized framework for addressing this gap. By viewing organizations as dynamic, recursively coupled systems of social and technical subsystems, STST illuminates how technological change is simultaneously constrained and enabled by organizational routines, informal structures, and environmental contingencies (Appelbaum, 1997; Bostrom & Heinen, 1977; Kergroach, 2020; Mumford, 2006; Pasmore et al., 2019; Trist & Bamforth, 1951, 2000). Despite its relevance, applications of STST to AI adoption in SMEs remain limited, with much of the literature defaulting to models that overlook emergent adaptation and misalignment. For instance, Sony and Naik (2020) demonstrate how Industry 4.0 adoption in manufacturing settings involves ongoing negotiation between worker autonomy and algorithmic control, highlighting the recursive adjustments central to STST that are largely ignored in traditional frameworks (Sony & Naik, 2020; Yu et al., 2023).

To respond to this gap, this study explores how technological, organizational, and contextual factors interact to shape AI adoption trajectories in SMEs. Accordingly, the central research question guiding this study is: How do recursive interactions between technical, organizational, and environmental subsystems shape the processes and outcomes of AI adoption in SMEs?

By employing STST as the guiding lens, this research advances a processual and contextually grounded understanding of digital transformation in SMEs. Specifically, the study demonstrates how recursive interactions between technical and social subsystems generate both opportunities and persistent misalignments throughout the course of AI adoption. For example, SMEs often introduce AI-enabled tools to streamline workflows, only to encounter unintended consequences such as duplicated efforts or disrupted decision-making chains, revealing how even well-intended interventions can produce new forms of organizational friction. Theorizing digital transformation as an emergent, negotiated process rather than a sequence of isolated barriers and enablers, this work yields new insight into the dynamics of innovation, resistance, and adaptation unique to the SME context.

This study makes three key contributions. First, it extends STST to the under-examined context of SME AI adoption, highlighting the recursive and contingent interplay between technical, organizational, and environmental subsystems. Second, it empirically demonstrates that digital transformation in SMEs unfolds through ongoing negotiation, improvisation, and adaptation, challenging linear and static models of technological change. Third, it addresses a recent call from scholars for governance and capability-focused perspectives on AI (Meske et al., 2022; Orth et al., 2025; Schneider et al., 2023), providing actionable implications for SME leaders and policymakers, offering context-sensitive strategies to foster effective, resilient, and sustainable AI adoption in diverse organizational environments.

The remainder of the paper is structured as follows. First, we contextualize AI and outline the theoretical and contextual background. Next, we present our methodological approach and analytical procedures, underpinned by a grounded theory approach. Subsequent sections detail our empirical findings and introduce a process model of AI adoption. We conclude by articulating the study's theoretical contributions, discussing practical and policy implications, and identifying directions for future research.

Theoretical background

AI adoption in SMEs

The adoption of AI in SMEs is now widely recognized as a multidimensional phenomenon shaped by the interplay of technological, organizational, and contextual mechanisms (Almashawreh et al., 2024; Arroyabe et al., 2024; Cannas, 2023; Clemente-Almendros et al., 2024; Lada et al., 2023; Nawab, 2024). Recent research echoes this complexity by emphasizing capability development, governance, and early-stage innovation activities as critical to digital transformation outcomes (Orth et al., 2025; Schneider et al., 2023; Meske et al., 2022). To account for these dynamics, the literature has drawn upon a broad array of theoretical frameworks, including the TOE model, TAM, Dynamic Capabilities Theory, Resource-Based View (RBV), and Diffusion of Innovation (DOI) (Pfaff et al., 2023; Akter et al., 2022; Chaudhuri et al., 2024; Dwivedi et al., 2021; Torroba et al., 2025; Gupta & Rathore, 2024). These frameworks have illuminated how factors such as infrastructure, leadership, regulation, skills, and organizational culture shape the digital innovation process in SMEs.

For instance, TOE and TAM clarify the role of organizational readiness, perceived usefulness, and environmental pressures in shaping adoption intentions (Akter et al., 2022; Torroba et al., 2025; Gupta & Rathore, 2024), while RBV, DOI, and Dynamic Capabilities Theory explain how resources, innovation capability, and absorptive capacity enable or constrain transformation (Chaudhuri et al., 2024; Dwivedi et al., 2021; Pfaff et al., 2023). However, these frameworks primarily identify static barrier – enabler inventories rather than explaining how those factors evolve, interact, or occasionally conflict during implementation.

While these approaches have substantially advanced understanding of adoption determinants, recent research demonstrates that digital transformation in SMEs frequently unfolds through recursive and emergent processes that extend beyond static categorizations and variable-driven models (Bhatti et al., 2024; Cannas, 2023; Feroz et al., 2023; Hoffman et al., 2025; Nawab, 2024). This highlights a clear need to theorize AI adoption not only as a capability-building challenge but as a socially embedded change process shaped by ongoing negotiation and adaptation.

Socio-technical systems theory (STST) as an integrative lens

Socio-Technical Systems Theory (STST) offers such a perspective by conceptualizing organizations as dynamic configurations of interacting technical and social subsystems whose ongoing negotiation and adaptation fundamentally shape the outcomes of technological innovation (Bostrom & Heinen, 1977; Mumford, 2006; Pasmore et al., 2019; Trist & Bamforth, 1951). Rather than treating technology and organization as isolated variables, STST views innovation as an emergent, processual phenomenon in which changes to AI systems are intertwined with evolving work routines, governance mechanisms, data infrastructures, and decision-making practices (Akter et al., 2022; Cannas, 2023; Chaudhuri et al., 2024; Pfaff et al., 2023).

This systems lens is particularly salient in the SME context, where limited resources, flat hierarchies, informal decision-making, and sector-specific contingencies make the alignment between technical and social elements both more critical and more precarious (Bhatti et al., 2024; Cyfert et al., 2025; Hoffman et al., 2025; Nawab, 2024). Recent studies demonstrate how governance structures, explainability, and capability development shape the organizational acceptance of AI, particularly when resource constraints heighten risk (Meske et al., 2022; Schneider et al., 2023; Sonntag et al., 2024). Empirical research increasingly shows that AI adoption in SMEs is frequently shaped and sometimes undermined by persistent data silos, uncoordinated workflows, trust issues, and the episodic nature of leadership, all of which become visible through a socio-technical lens (Hoffman et al., 2025; Mumford, 2006; Pasmore et al., 2019).

Despite its explanatory power, the application of STST to SME AI adoption remains limited, with much of the literature defaulting to models that overlook emergent adaptation and misalignment (Sony & Naik, 2020; Yu et al., 2023). Where STST has been used, it has illuminated how mutual misalignment, adaptation, and improvisation shape innovation trajectories in context-specific ways (Appelbaum, 1997; Bostrom & Heinen, 1977; Trist & Bamforth, 1951). Accordingly, this study adopts Socio-Technical Systems Theory as a theoretical anchor to address persistent gaps in the field.

By moving beyond inventories of barriers and enablers, STST foregrounds the recursive, emergent, and nonlinear character of digital transformation in SMEs. This integrative systems perspective enables a more nuanced, context-sensitive account of AI adoption, one that explains how innovation, resistance, and adaptation continually unfold through the ongoing mutual shaping of technical and organizational arrangements in everyday SME practice.

Methodology

This study employs a qualitative research design, drawing on in-depth, semi-structured interviews as the principal data collection method to explore the dynamics of AI adoption in SMEs in the north of England. In total, interviews were conducted with senior leaders from 27 SMEs, representing a range of sectors and organizational contexts. To enhance contextual richness and strengthen triangulation, these interview data were supplemented by direct observation of business practices in several participating firms and by systematic review of relevant secondary sources, including over 30 company documents and industry reports. Data analysis was informed by an inductive, grounded approach, combining first- and second-order coding to systematically surface salient themes and relational dynamics. The analytical process was iterative and abductive, enabling us to capture the interplay between technical, organizational, and environmental conditions, and to develop a processual understanding consistent with STST (Gioia et al., 2013; Pattinson & Dawson, 2024; Strauss & Corbin, 1990). Integrating observational insights and secondary material allowed us to deepen our explanation of how socio-technical misalignments and organizational improvisation shape the trajectories and lived realities of AI adoption in SMEs.

Sample selection and description

The sample was constructed purposively to maximize theoretical and sectoral diversity. We targeted SME directors and senior technology leaders across a range of industries, including manufacturing, IT services and consulting, logistics, creative industries, hospitality, professional services, and more, who had direct experience with, or authority over, digital and AI-related decisions. Recruitment leveraged professional networks, SME-focused business organizations, and technology-sector events to reach relevant participants and facilitate snowball sampling. The final sample comprised 27 interviews with key informants, including Managing Directors, Chief Technology Officers, Heads of Innovation and Technology, IT Directors, and Project IT Managers, reflecting the centrality of executive leadership and technical expertise in shaping AI-related strategies (Table 1).

All participating firms conformed to the widely accepted SME definition: fewer than 250 employees for medium-sized, and fewer than 50 for small enterprises (see Table 1 for industry and role breakdown). To ensure a multifaceted perspective, our sample intentionally included SMEs at different stages of AI adoption from early-stage experimenters and prospective adopters to more advanced integrators. This allowed us to interrogate both the enablers and frictions affecting current and future adoption trajectories, and to surface variation rooted in industry context, organizational structure, and market environment.

Table 1. Respondents profile.

SME	Industry	Interviewee Role	Key AI/Tech Issues	Unique Context/Note
1	Manufacturing	Managing Director	Data integration, skills gap	Legacy production systems
2	Retail	Managing Director	Staff resistance, workflow changes	High staff turnover
3	Technology	IT Director	System scalability, AI integration	Competing in tech cluster
4	Construction	Managing Director	Workflow automation, cost concerns	Small in-house IT team
5	Food Processing	Head of Innovation and Technology	Data security, process optimization	Regulatory focus
6	Logistics	Managing Director	AI for route optimization, staff upskilling	High fuel cost pressure
7	Healthcare Services	Managing Director	Patient data privacy, cloud migration	Sector regulations
8	Professional Services	Managing Director	ROI uncertainty, sector benchmarking	Fee-for-service model
9	Creative Industries	Managing Director	Digital platform selection, tool adoption	Project-based work
10	Sport	Managing Director	Performance analytics, data privacy	Athlete monitoring
11	IT Services	IT Director	Cloud migration, cyber security	Service contracts
12	Tourism/Hospitality	Managing Director	Online booking AI, review analytics	Seasonal demand swings
13	Education/Edtech	Managing Director	Learning analytics, user privacy	Diverse learner base
14	Retail (E-commerce)	Head of Innovation and Technology	Customer personalization AI	Fast product cycles
15	Manufacturing (Auto)	Managing Director	Predictive maintenance, automation	Supplier-driven cycles
16	Agriculture/Agrifood	Managing Director	AI for yield prediction, IoT sensors	Weather-dependent
17	Consulting Services	Managing Director	Process automation, data analytics	B2B advisory
18	Telecom/ICT	Project IT Manager	Network AI, rapid tech shifts	High capex, fast obsolescence
19	IT Consulting	Managing Director	Client solutions, custom AI projects	Rapid project turnover
20	Marketing/Advertising	Managing Director	Campaign automation, data ethics	Client-driven projects
21	Media/Publishing	Managing Director	Content recommendation, platform bias	Shift to digital subscriptions
22	Real Estate	Managing Director	AI for lead scoring, virtual tours	Cyclical market trends
23	Retail	Managing Director	Inventory AI, sales forecasting	Perishable goods
24	Construction Services	Project IT Manager	Digital project management, compliance	Subcontractor coordination
25	Business Services	Managing Director	Workflow automation, CRM AI	B2B client base
26	IT Services	Managing Director	Ticketing AI, attendance analytics	Seasonal/event-driven demand
27	Logistics	IT Manager	Fleet management AI, optimization	High operational costs

Data collection

Interviews were conducted using a semi-structured protocol that combined a core set of open-ended questions with opportunities for follow-up probing and narrative elaboration (Appendix A). Participants received the interview guide in advance; participants were purposefully selected to ensure variation in firm size, industry, leadership structure, and digital maturity, supporting analytical generalization and a robust understanding of diverse adoption trajectories; however, interviewers were encouraged to pursue emerging lines of inquiry and adapt the dialogue to the respondent's expertise and organizational context. Each interview lasted between 45 and 65 minutes, was audio-recorded, and all 27 interviews were professionally transcribed in full. Field observations of selected firms (including site visits and shadowing of routine business activities) were used to capture everyday work practices, further contextualizing responses and enabling the triangulation of perspectives. Archival materials, such as organizational charts and internal communications, were also consulted to supplement and verify interview findings. Data collection continued until theoretical saturation was reached that is, no new themes or conceptual relationships emerged in later interviews per qualitative research best practice (Saunders & Townsend, 2016). The study received ethical approval from the Newcastle Business School Ethics Committee (Reference Number: 4517). All data collection was conducted on a voluntary basis with written informed consent. Participant identities were anonymized to ensure confidentiality throughout the research process.

Data analysis

Data analysis was conducted from August 2023 to July 2024. The research team adopted an iterative, multi-stage coding procedure, drawing on the Gioia methodology (Gioia et al., 2013) and grounded theory principles (Strauss & Corbin, 1990). Initial first-order codes were generated by close reading and open coding of interview transcripts, capturing informant-centric descriptions of digital transformation experiences and socio-technical challenges. These codes were then jointly reviewed and cross-checked by multiple researchers to ensure coding reliability, with consensus reached through iterative discussion and regular challenge sessions designed to surface differing interpretations.

Subsequent analysis involved grouping first-order codes into more abstract, theoretically informed second-order themes, examining the interaction of technical, organizational, and environmental dimensions in shaping the adoption process. This step surfaced key dynamics, such as improvisational adaptation, recursive misalignment, and the episodic role of leadership, which aligned closely with the tenets of Socio-Technical Systems Theory. Through ongoing comparison, the team distilled these second-order themes into a set of aggregate dimensions that captured the complexity and contingency of AI adoption in SMEs (see Figure 1 for the full data structure).

Throughout the process, analytical rigor was maintained through constant comparison, the integration of multiple data sources, and systematic, reflexive dialogue within the research team to challenge assumptions and ensure interpretive validity (Eisenhardt, 1989; Gioia, 2021). The lead researcher also maintained a positionality log to document evolving assumptions, contextual influences, and potential biases during interpretation. The outcome is a richly layered, contextually grounded understanding of how SMEs negotiate the socio-technical realities of AI-driven change.

Findings

Technical subsystem

Recurring technical challenges, including data fragmentation, costly customization, and bricolage-style integration, constitute an overarching socio-technical mechanism in which technical constraints reinforce uncertainty and dependence on improvisation rather than enabling linear transformation. AI-driven transformation in SMEs rarely unfolds as a straightforward upgrade of legacy systems; instead, it exposes the organizational "*bricolage*" and contingent improvisation endemic to resource-constrained contexts. As the Managing Director of a manufacturing firm (SME 1) explained, "*We're running production on systems that haven't changed in a decade trying to layer AI on top means lots of manual exporting and re-keying. You lose faith in the data fast.*"

Direct observation of these business practices corroborated such accounts, revealing everyday workarounds and patching routines as staff navigated fragmented digital and paper-based processes. This pervasive fragmentation of data an issue consistently raised across the majority of the 27 SMEs interviewed, spanning diverse sectors including manufacturing, food processing, IT services, and business services was further noted by the Head of Innovation in food processing (SME 5): "*Our data is everywhere spreadsheets, old machines, even some paper logs. Until that's fixed, AI is more of a dream than a reality.*"

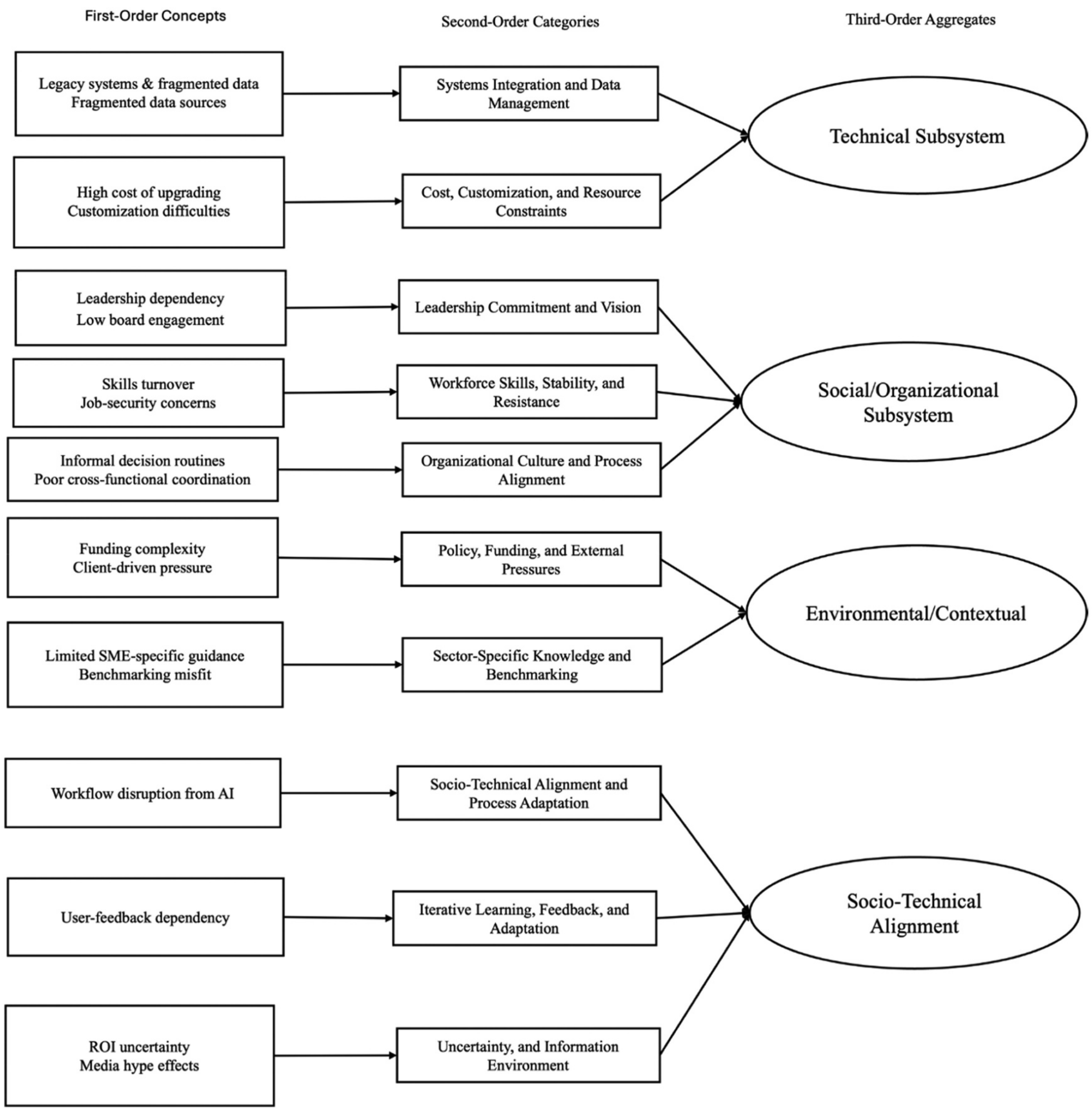

Figure 1. Data structure.

Rather than constituting isolated anecdotes, these experiences reflect a recurring theme that not only hampers analytics but also institutionalizes epistemic uncertainty: digital initiatives must continually negotiate the reliability and provenance of the data they seek to mobilize. Technical adaptation thus becomes inseparable from the ongoing repair of organizational knowledge infrastructures.

IT Directors (e.g., SME 11, IT services) describe integration as an act of continuous, context-specific improvisation: "*Every integration requires custom work. Vendors don't want to build for SMEs. We have to get creative, or give up on certain features*." Observations and industry documentation highlighted that these improvisational solutions were not one-off fixes but recurring necessities due to the lack of vendor support tailored for SMEs. This signals that technical alignment is less about technology per se than the organizational capacity for improvisational problem-solving often under severe resource constraints.

AI's celebrated scalability paradoxically amplifies SME vulnerability, as high entry and ongoing costs force continual triage between ambition and survivability. The IT Director in technology (SME 3) remarked, "*The off-the-shelf AI is designed for larger companies with deep pockets. We end up paying almost as much to make it fit our workflows as we would to build from scratch*."

In construction (SME 4), direct observation of project meetings and secondary analysis of financial records reinforced the acute trade-off between strategic investment and operational liquidity: "*It's not just the software cost, but the cost of training, downtime, consultants every hour spent on this is an hour we're not earning*."

Project IT Managers (e.g., SME 27, logistics) highlighted the volatility of customization: "*Every time we needed a tweak, the costs doubled. It's not built for businesses that need to change things month-to-month*." Documented project histories illustrated how digital transformation can become episodic, fragmented, and reversible, with firms "bouncing between pilots and patches, never reaching critical mass."

Social/organizational subsystem

Across cases, social dynamics including leadership dependence, skill instability, and informal decision-making reinforce a socio-technical mechanism in which digital progress remains fragile and contingent on individual commitment rather than institutionalized capability. Digital transformation trajectories are often fragile, hinging on the sustained intervention of a single leader. In logistics (SME 6), a Managing Director described this precarity: "*If I didn't drive this personally, we would still be arguing about the ROI of a website, let alone AI*." This personalist leadership can catalyze rapid change, but also embeds risk: "*When our last MD left, the AI project basically stalled overnight. The board lost interest, and middle management wouldn't touch it*" (Project IT Manager, SME 18, telecom/ICT). Review of organizational charts and board meeting minutes substantiated the centrality and fragility of digitally engaged leadership. The temporalities of digital change are thus punctuated by the contingencies of succession, with innovation easily stalled by leadership discontinuity. Moreover, the logic of "visionary leadership" often coexists uneasily with distributed inertia in flat organizational structures.

SMEs' efforts to build digital capacity are systematically destabilized by labor precarity and the recalcitrance of established routines. The Managing Director of hospitality (SME 12) observed, "*Every season we retrain on new systems, but by the time people are up to speed, half of them move on. Digital skills leak out the door*." This dynamic renders capacity-building a Sisyphean effort perpetually undermined by turnover, insecurity, and informal networks. Observation of training sessions and HR reports echoed this constant struggle for upskilling and retention. Resistance is rarely overt, but is instead manifested as skepticism, procedural drift, or covert workaround. As the Head of Innovation in retail e-commerce (SME 14) notes, "*There's open skepticism*: '*Are these bots going to take my job?' You have to work twice as hard to show AI is a support, not a threat*." The challenge is less a lack of training than a crisis of trust and perceived occupational value.

Attempts to institutionalize AI within SME workflows routinely collide with the sedimented logics of informal, relationship-driven decision-making a dynamic reported by a majority of interviewees across sectors. "*Here, most decisions are made over coffee, not through dashboards*," (Managing Director, SME 9, creative industries) encapsulates the deep entanglement of culture and routine. Documented process maps and meeting notes revealed how the drive for algorithmic standardization is often perceived as an existential threat to the SME's value proposition: "*Standardizing everything for an algorithm feels like we'd lose what makes us different*," (Managing Director, SME 25, business services). Cross-functional initiatives frequently falter not on technical grounds, but because they challenge tacit territorialities and longstanding patterns of organizational autonomy: "*Getting two teams to agree on how to change their workflow is sometimes harder than writing the code*" (IT Director, SME 3, technology).

Environmental/contextual factors

Environmental forces including policy complexity, market pressure, and limited knowledge operate as intertwined mechanisms that shape organizational interpretation and technical adaptation, often amplifying rather than resolving misalignment. The environment for SME digitalization is not merely external but constitutive structuring possibilities and foreclosing pathways. Funding regimes operate as both stimulus and choke point: "*Government funding is out there, but figuring it out is a full-time job by the time you've jumped through the hoops, the tech has moved on*," (Project IT Manager, SME 24, construction services).

Policy documents and funding guidelines reviewed in this study mirrored this bureaucratic complexity. The specter of client and market pressure is ever-present: "*Clients expect us to talk AI, even if we're just a ten-person firm. There's a sense of 'adopt or get left behind*'" (Managing Director, SME 25, business services).

Benchmarking, rather than facilitating learning, often distorts priorities: "*We try to benchmark against the big consultancies, but their solutions are built for scale. It's apples and oranges*" (Managing Director, SME 19, IT consulting). Thus, "best practices" become a source of misalignment translating organizational aspirations into expensive dead-ends.

The knowledge ecosystem for SME AI adoption is riven with absence and overgeneralization. "*There are endless white papers about AI for banks or retailers, but very little for a regional logistics SME with a dozen trucks*," (Managing Director, SME 6, logistics).

When adaptation is attempted, transferability is an illusion: "*We copied a scheduling AI from a bigger firm, but our workflows are just different enough that it caused more confusion than improvement*" (Project IT Manager, SME 27, logistics).

Observation of failed implementation attempts and review of industry guidance highlighted that sectoral learning is improvisational and recursive, characterized by a continual search for context-sensitive solutions in a landscape of generic advice.

Socio-technical alignment

Progress toward alignment emerges through recursive adjustments across technical, organizational, and environmental subsystems, illustrating that adaptation is iterative and negotiated rather than a predictable or linear outcome. AI implementation is a process of continual negotiation between technical affordances and organizational realities. Rather than resolving existing misalignments, technology frequently exacerbates latent contradictions: "*We automated parts of project management, but because roles weren't clarified, people kept duplicating effort some on the tool, some by hand*," (Managing Director, SME 9, creative industries).

Algorithmic interventions disrupt power relations, as observed by the Head of Innovation in food processing (SME 5): "*Algorithms were suggesting decisions that used to be made by supervisors some staff saw this as losing autonomy, and others as a relief.*" Socio-technical change thus unfolds as a series of emergent, contested adjustments more improvisational than planned.

Where progress occurs, it is iterative, reflexive, and provisional. The IT Director in IT services (SME 11) stressed, "*We only made headway when we started piloting small, getting end-user feedback fast, then tweaking. Our biggest learning came from what didn't work right away.*"

Organizational learning is driven less by formal strategy than by cycles of failure, improvisation, and incremental adaptation: "*The first three months of any new tool are bumpy. Adaptation happens through constant feedback there's no plug-and-play*" (Managing Director, SME 8, professional services).

Review of pilot project documentation and internal feedback loops further illuminated the trial-and-error nature of digital change. The environment of SME digital transformation is saturated with uncertainty, epistemic, financial, and symbolic. "*It's not just whether the numbers add up; there's so much hype and so little clarity that boards become paralyzed*," (Project IT Manager, SME 18, telecom/ICT).

The Managing Director in sport (SME 10) concluded, "*Everyone is selling AI as a silver bullet, but we've learned to be wary that sometimes the return on investment just isn't there for a business our size.*" Decision-making is thus as much about managing narrative and expectation as about evaluating tangible benefit, with hype cycles introducing both opportunities for experimentation and conditions for strategic paralysis.

We clarify the theoretical integration by showing how recurring socio-technical mechanisms across subsystems converge into a single recursive alignment process, consolidating themes previously presented in parallel. Figure 2 synthesizes the findings by proving how the technical, organizational, and environmental subsystems interact recursively to shape the process of socio-technical alignment in AI adoption within SMEs.

Building on the separate themes discussed earlier, such as technical bricolage, episodic leadership, and

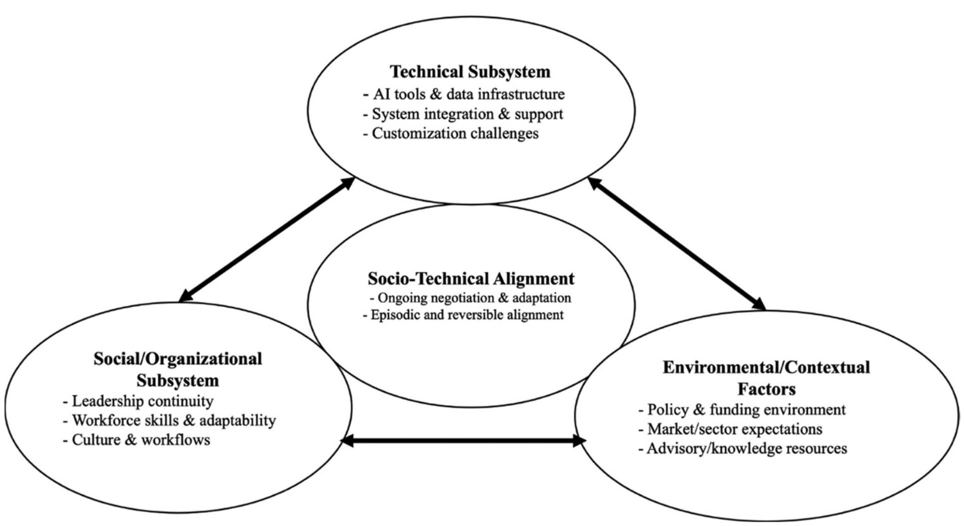

Figure 2. Recursive model of AI adoption in SMEs: the interplay of technical, organizational, and environmental subsystems.

environmental contingencies, this framework clarifies that AI adoption is not the product of isolated drivers or linear progress, but emerges from the ongoing negotiation and dynamic interplay among these interconnected subsystems.

For example, fragmented data infrastructures not only pose direct obstacles but also reinforce established organizational routines and amplify the need for leadership intervention. Likewise, environmental pressures, such as regulatory changes or market expectations, filter through organizational sensemaking and technical adaptation, further reinforcing or destabilizing alignment efforts.

The figure shows that the process of socio-technical alignment is cyclical and contingent: misalignments or breakdowns in one subsystem provoke compensatory responses and improvisations in others, driving a continuous cycle of adaptation and recalibration.

Crucially, this recursive dynamic explains why AI adoption in SMEs is often partial, provisional, and subject to reversal or re-negotiation as new actors, technologies, and environmental scripts emerge. By explicitly connecting these subsystems into a single, integrated model, Figure 2 demonstrates that socio-technical alignment serves as the central mechanism linking all preceding themes to the broader challenge of AI-enabled transformation in SMEs. This integrated perspective provides a clearer, more holistic account of how barriers and enablers identified in earlier themes are continually reshaped and redefined through the everyday practices of digital innovation.

Discussion

Theory development and reflection on the theoretical gap

This study explores the recursive and contingent dynamics that underpin AI adoption in SMEs, revealing that digital transformation is not a linear sequence of steps but rather an interpenetration of technical, organizational, and environmental logics (Feroz et al., 2023; Vial, 2021). Deploying STST as an analytical lens surfaces several distinctive insights that challenge and complicate mainstream accounts (Appelbaum, 1997; Bostrom & Heinen, 1977; Mumford, 2006). Unlike prevailing models that parse technical and organizational barriers into discrete, addressable categories (Cyfert et al., 2025; Pfaff et al., 2023), our findings foreground their mutual constitution. Reflecting participants' experiences, digital change was repeatedly described as "*a constant battle to keep things working together*" (IT Manager, SME 27), illustrating that alignment is not episodic "*fixes*" but a lived, ongoing struggle to make systems usable.

This shifts the focus from identifying discrete "*factors*" to explaining the underlying socio-technical mechanisms that continually reproduce misalignment in practice. For example, technical limitations such as fragmented legacy data systems were found to directly reinforce and be reinforced by organizational routines and informal workarounds, as staff devised creative, non-standardized solutions to compensate for digital shortfalls. Conversely, efforts to introduce standardized AI workflows frequently activated cultural resistance and process drift, prompting further technical improvisation. As the Head of Innovation at SME 5 put it, "*Every improvement exposes something else that doesn't really fit*," capturing how adaptation generates new forms of misalignment.

These patterns demonstrate that everyday adaptation is not a residual barrier to be "*overcome*," but a primary mode through which AI adoption unfolds within SMEs. In this way, the interplay between technical affordances and organizational practices continually shaped the lived reality of AI integration in SMEs, making the boundaries between "*barrier*" and "*enabler*" both porous and dynamically negotiated.

Efforts to embed AI in legacy environments did not simply confront "resistance to change" or "*skills gaps*," but activated patterns of organizational bricolage, workaround, and epistemic uncertainty that reproduced themselves with each attempted integration. Technical adaptation in SMEs thus emerged as a process of context-specific improvisation and ongoing repair, rather than straightforward implementation, reflecting the persistent fragmentation of data and the instability of knowledge infrastructures. Participants frequently expressed skepticism about data reliability "*We never really know what numbers we can trust*" (Managing Director, SME 12) showing how uncertainty becomes a socio-technical condition rather than a solvable problem.

This reframes digital transformation as continuous re-problematization rather than maturation, where progress is conditional, provisional, and frequently reversible. The rhythms and discontinuities of leadership intervention fundamentally shape digital change in SMEs. Contrary to assumptions of gradual digital "*maturity*," our data reveal that digital trajectories are episodic, marked by intense surges of innovation contingent on the active presence of a committed leader, and periods of inertia or reversal following their departure (Dubey et al., 2019; Feroz et al., 2023). As the Project IT Manager at SME 18 stated: "*When our champion left, it felt like everything digital just collapsed a bit*."

Rather than treating leadership as a static readiness component, our analysis positions it as a temporal force structuring the momentum and direction of socio-technical alignment. The social life of digital initiatives, therefore, is characterized by path dependence, organizational memory, and the latent possibility of abrupt discontinuity (Mumford, 2006). Moreover, workforce precarity, persistent turnover, and the entrenchment of informal, relationship-driven routines systematically destabilize capacity-building efforts and amplify the challenge of institutionalizing digital change.

Environmental factors, far from acting as a passive context, structure the very dilemmas and contradictions through which digital strategies unfold (Kergroach, 2020). The pursuit of government funding, navigation of regulatory uncertainty, and pressures to "keep up" with client expectations are not exogenous constraints but are enacted and reinterpreted through the situated practices of SME actors. Attempts to translate "best practice" from larger firms often result in misfit rather than convergence. One participant noted, "We're told to copy what the big firms do … but our world just isn't built that way" (Managing Director, SME 19), emphasizing environmental misalignment as a generative tension.

Consequently, external forces co-produce the misalignments SMEs must negotiate, making environmental complexity a core part of the recursive alignment mechanism rather than a backdrop to it. Sectoral knowledge, in this sense, is not simply "*lacking*," but structurally under-produced, leaving SMEs to experiment at the margins of formal guidance (Cyfert et al., 2025; Pfaff et al., 2023). Decision-making is shaped as much by narrative and symbolic expectations propelled by media and vendor hype cycles as by hard financial calculation, producing environments of epistemic, financial, and symbolic uncertainty.

STST provides a generative framework for apprehending these dynamics (Appelbaum, 1997; Bostrom & Heinen, 1977; Mumford, 2006). The process of joint optimization, rather than an endpoint to be reached, appears as a continuous, unfinished negotiation among technical affordances, social logics, and environmental scripts (Trist & Bamforth, 1951). Participants' stories illuminate this directly: "It's never done very time we think AI is working, the business changes again" (Managing Director, SME 8).

Our findings extend STST by demonstrating that misalignment is not a transitional stage but an enduring condition that drives ongoing cycles of adaptation and recalibration. Far from being reducible to an implementation problem, "*failure*" or "*partial adoption*" frequently signals the persistence of deep-seated tensions between the formal demands of AI systems and the tacit, relational infrastructure of everyday work (Pasmore et al., 2019). Digital transformation therefore emerges as a recursive, socio-technical learning process one characterized by improvisation, instability, and unresolved contradictions rather than convergence toward stability.

Contributions to research and theoretical implications

These insights recast SME digitalization as a situated, improvisational, and deeply social process, irreducible to any inventory of barriers or enablers (Cannas, 2023; Nawab, 2024). We contribute to theory by refining core concepts within STST, demonstrating that alignment is not a target state but an inherently episodic and reversible condition shaped by leadership discontinuities, data instability, and environmental pressures. Accordingly, the study advances STST from a model oriented toward joint optimization to one that conceptualizes socio-technical alignment in SMEs as a contingent outcome continually re-negotiated through practice.

First, this research extends STST by theorizing recursive socio-technical alignment as a defining mechanism in SME AI adoption where misalignment is not a temporary hurdle but a productive and persistent driver of adaptation. This advances understanding beyond static readiness and maturity perspectives by highlighting the dynamic mutual constitution of technical, organizational, and environmental elements.

Second, we deepen theoretical insight into socio-technical improvisation, showing that progress in SMEs is produced less by addressing predefined gaps and more by navigating, repurposing, and at times leveraging frictions that emerge during AI integration (Dubey et al., 2019). In this way, the study clarifies that breakdowns are not signs of failure but core triggers of learning and transformation in resource-constrained environments.

Third, we demonstrate that the temporal structure of digital transformation is episodic and discontinuous, driven by fluctuations in leadership engagement, workforce stability, and market expectations thereby adapting the concept of joint optimization to reflect ongoing renegotiation rather than convergence.

These contributions indicate that SME digital transformation is characterized by "*episodic alignment (temporary synchronisation)*" and "*productive misalignment (beneficial system tension)*," offering a theoretical refinement that explains why partial, provisional, and reversible progress is the norm rather than the exception.

Finally, the practical work of digital transformation is reframed: it involves not just technical upgrading, but also the ongoing negotiation of meaning, authority, and organizational identity in the face of pervasive uncertainty and change.

Limitations and future research direction

While this study provides a nuanced, theory-driven account of AI adoption in SMEs, several limitations merit acknowledgment. First, the research is based on qualitative interviews with a purposive sample of SME directors and technology leaders; thus, the findings may not fully capture the heterogeneity of SME experiences, particularly across different regions, industries, or organizational sizes. Second, the cross-sectional nature of the data constrains our ability to observe the evolution of socio-technical alignment and adaptation over time. To build on these insights, future research should pursue longitudinal and processual designs that trace the dynamic evolution of AI adoption and socio-technical alignment within SMEs. Comparative case studies across sectors, regions, and national ecosystems are needed to elucidate how contextual factors shape patterns of adaptation, resistance, and organizational learning. Mixed-methods and network-analytic approaches could further illuminate the interplay of resistance, trust-building, and improvisational strategies at multiple organizational levels. Moreover, future research should unpack the micro-foundations of socio-technical adaptation, such as the role of informal communication, learning routines, and inter-organizational collaboration in sustaining digital transformation. There is also a need to investigate the impact of emerging policy frameworks, evolving regulatory environments, and external shocks (e.g., economic crises or disruptive technological change) on the recursive processes of AI-enabled transformation in SMEs.

Practical implications

For SME leaders, these findings highlight the necessity of cultivating not only technical capabilities but also organizational resilience, digital skills, and adaptive learning cultures. Leadership should be viewed not simply as a driver of change, but as a critical mediator who brokers meaning across technical and social domains, builds trust, sustains momentum amid uncertainty, and fosters distributed agency. Practical steps include appointing cross-functional "AI champions" to sustain progress during leadership transitions, scheduling early pilot cycles that involve frontline employees in feedback loops, and co-designing workflows with end users to reduce resistance and prevent duplicated effort. Providing clear narratives about how AI supports rather than threatens roles can help mitigate anxieties around job displacement, especially in high-turnover sectors. To operationalize improvisation as a capability, leaders can structure transformation as a series of micro-pilots, each testing a narrow workflow change with rapid feedback loops. Modular experimentation, introducing discrete AI components that can be reconfigured without costly system-wide disruption, helps SMEs learn from failure while preserving continuity. Peer-learning groups across similar-sized firms can accelerate the transfer of contextual knowledge and reduce duplication of effort.

For example, SMEs in this study that implemented weekly "AI show-and-tell" sessions, where employees demonstrated improvements and raised issues, reported faster alignment and fewer workarounds. Similarly, firms that invested in small-scale data quality initiatives before major system deployments avoided extended rework and loss of confidence in insights.

For policymakers, the study underscores the limitations of one-size-fits-all digitalization initiatives. Effective policy must account for the recursive, context-specific, and improvisational realities of SMEs, and address persistent barriers such as data fragmentation, regulatory uncertainty, and skill shortages. Practical interventions include low-bureaucracy funding mechanisms tied to phased experimentation rather than large up-front technology commitments, sector-specific advisory services staffed by practitioners familiar with SME workflows, and data infrastructure support programs that focus on foundational readiness (e.g., interoperability standards and secure data sharing).

Support mechanisms should extend beyond funding to include advisory networks, regulatory clarity, tailored sectoral guidance, and platforms for peer learning and collaborative problem-solving. Publicly supported digital sandboxes, shared analytics resources, and facilitated communities of practice can help SMEs collectively test AI tools and develop situated solutions more effectively than working in isolation.

Recognizing the persistent fragility and path-dependence of SME transformation, policy design should prioritize flexibility, knowledge sharing, capacity building, and the co-production of actionable practices with SME stakeholders. Such policies would shift digital transformation from a compliance exercise to a collaborative and ongoing capability-building process.

Conclusion

This research demonstrates that AI adoption in SMEs is not a linear progression toward digital maturity but a recursive and episodic socio-technical process in which misalignment continually reemerges and drives ongoing adaptation. By extending Socio-Technical Systems Theory to conceptualize alignment as inherently unstable and negotiated, we highlight how leadership discontinuity, data fragmentation, and environmental pressures shape transformation pathways. Progress depends not only on technology investment but on cultivating organizational learning, experimentation, and shared sensemaking. For policymakers and practitioners, the findings point to the importance of flexible support mechanisms, sector-tailored guidance, and capacity-building approaches that reflect the realities of SME contexts.

Author contributions

CRediT: **Albert Amanollahnejad:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Validation, Visualization, Writing – original draft, Writing – review & editing; **Samuel Fosso-Wamba:** Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Software, Supervision, Validation, Visualization, Writing – review & editing; **Muhammad Salman Shabbir:** Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Validation, Visualization, Writing – review & editing; **Ashkan Pakseresht:** Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – review & editing.

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