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Review

Artificial Intelligence Adoption in SMEs: Survey Based on TOE–DOI Framework, Primary Methodology and Challenges

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Abstract: Despite the transformative potential of artificial intelligence (AI), small and medium-sized enterprises (SMEs) continue to face significant challenges in its effective adoption. While prior studies have emphasized strategic benefits and readiness models, there remains a lack of operational guidance tailored to SME realities—particularly regarding implementation barriers, resource constraints, and emerging demands for responsible AI use. This study presents an analysis of AI adoption in SMEs by integrating the technology–organization–environment (TOE) framework with selected attributes from the diffusion of innovations (DOI) theory to examine adoption dynamics through a dual structural and perceptual lens. Empirical insights from sectoral and regional contexts are also incorporated. Ten critical challenges are identified and analyzed across the TOE dimensions, ranging from data access and skill shortages to cultural resistance, infrastructure limitations, and weak governance practices. Notably, the framework is expanded to incorporate responsible AI governance and democratized access to generative AI—particularly open-weight large language models (LLMs) such as LLaMA, DeepSeek-R1, Mistral, and FALCON—as emerging technological and ethical imperatives. Each challenge is paired with actionable, context-sensitive solutions. The paper is a structured, literature-based conceptual analysis enriched by empirical case study insights. As a key contribution, it introduces a structured, six-phase roadmap methodology to guide SMEs through AI adoption—offering step-by-step recommendations aligned with technological, organizational, and strategic readiness. While this roadmap is conceptual and has yet to be validated through field data, it sets a foundation for future diagnostic tools and practical assessments. The resulting study bridges theoretical insight and implementation strategy—empowering inclusive, responsible, and scalable AI transformation in SMEs. By offering both analytical clarity and practical relevance, this study contributes to a more grounded understanding of AI integration and calls for policies, ecosystems, and leadership models that support SMEs in adopting AI not merely as a tool, but as a strategic enabler of sustainable and inclusive innovation.

Keywords: artificial intelligence (AI); small and medium-sized enterprises (SMEs); technology–organization–environment (TOE) framework; diffusion of innovations (DOI); digital transformation; AI adoption challenges; innovation management

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1. Introduction

Small and medium-sized enterprises (SMEs) constitute the backbone of the global economy, representing approximately 90% of all businesses and more than 50% of employment worldwide [1]. Their critical role is reflected in their contributions to gross domestic product (GDP), productivity, innovation, job creation, export growth, and inclusive economic development [2]. To remain competitive in an increasingly digital and globalized environment, SMEs must overcome size-related limitations by enhancing operational efficiency and accelerating their capacity to adapt to technological and social change [3,4]. Among emerging technologies, artificial intelligence (AI) is widely recognized as the most transformative. AI refers to the development of intelligent systems—primarily software—that can perform tasks requiring human-like intelligence, such as learning, reasoning, and decision-making. Despite its potential to drive productivity, innovation, and customer engagement, AI adoption among SMEs remains limited and often unsuccessful, particularly in developing regions [5,6]. Although research acknowledges that SMEs can benefit from AI as much as large firms [7], SMEs face multiple and specific obstacles that cause early-stage adoption to be hindered by continuing practical constraints and challenges [8–11]; advancing our knowledge of these obstacles is both urgent and necessary.

This descriptive research has two main research objectives: (1) To understand the financial, technical, and organizational challenges that SMEs experience during AI implementation; (2) To provide an advisable executive summary aimed at facilitating the implementation of AI by SMEs based on the most recent (5-years old) empirical analysis and case studies. Our research objectives are founded in three key reasons: (1) Most existing studies focus on large firms whose abundant technical, financial, and human resources differ substantially from those of SMEs [12]. In contrast, SMEs—while resource-constrained—are typically more agile, closer to their customers, and less burdened by bureaucracy [13]. (2) Although digital maturity has been linked to better AI readiness [14], AI introduces unique challenges—such as system complexity, skill gaps, and uncertainty around returns—that are not fully addressed in general digital transformation literature [15,16]. (3) The early implementation phase of AI—where failure is most common—is still underexplored in academic SMEs literature [17].

Aiming towards this goal, this study presents an analysis on AI adoption in SME integrating the technology–organization–environment (TOE) framework developed by Tornatzky and Fleischer (1990), [18], complemented by selected constructs from the diffusion of innovations (DOI) theory [19], following recent integration efforts proposed by [20]. The TOE framework analyzes technology adoption across three interrelated dimensions: technological readiness, organizational capacity, and environmental influence [21–24]. It has received strong empirical and theoretical support in the SME context [25,26], and has been applied in diverse geographic and sectoral settings—including the European Union [27], India [28], Saudi Arabia [29], Ghana [30], Jordan [24], and Egypt [31]. More than its solid foundation, its value lies in its ability to surface the real-world challenges SMEs face during AI adoption.

The remainder of this paper is structured as follows. Section 2 reviews the potential benefits of AI for businesses and the unique characteristics of SMEs that influence adoption. Section 3 introduces the TOE framework and explains the rationale for integrating selected elements of the DOI theory to analyze SME-specific adoption dynamics. From the analyzing of the TOE–DOI framework, we derive a structured set of challenges and corresponding solutions. Section 4 shows an empirical view, focusing on recent empirical studies in diverse regional and sectoral contexts to enhance the practical foundation. Section 5 examines ten key challenges facing SMEs in the AI adoption process, offering targeted solutions within the TOE dimensions. Section 6 introduces a primary roadmap methodology that establishes a structured methodology for the effective adoption of AI. Section 7 synthesizes the main lessons learned, study limitations, and future research, Section 8 concludes with final reflections and recommendations for future research.

2. AI's Benefits for Business and Peculiarities for SMEs

According to the literature, efficiency, productivity, enhanced safety, innovation, and better-quality outputs are among the expected AI's benefits for businesses. Ref. [32] categorizes benefits into four groups: (1) growth and profits (expansion of commercial objectives and networks, scalability, productivity, and consequent profits); (2) performance, ease, and convenience (enhancements in performance, accuracy, speed, time, and cost savings); (3) safety (real-time monitoring, robotic assistance in dangerous occupational tasks); and (4) sustainability (optimal resource utilization; energy savings; transparency; equality).

Most of the benefits of AI for business arise through the next four pillars, which can transform business operations and position them more solidly in the market, strengthening competitive advantages: automation, personalization of customer service, decision-making processes and predictive analytics, and rapid innovation [33]. The literature supports the benefits provided by AI that could be captured by large companies and SMEs [7]. In general terms, this is true. However, in practice, the nature of SMEs adds concerns and opportunities that are not present in MNEs. This section describes both.

(a) Automation of routine tasks

Automation of routine tasks is one of the most immediate and cost-effective applications of AI for SMEs. By automating repetitive activities such as inventory management, invoicing, customer service, and task scheduling, businesses can significantly reduce operational costs, minimize human error, and enhance overall efficiency. Automation also contributes to better accuracy, faster response times, and higher levels of customer satisfaction by ensuring timely service delivery.

As ref. [34] explains, automation can augment production and efficiency by (a) the substitution of capital for labor, with the displacement of workers from the tasks that are being automated and (b) by the improvement of tandem worker-AI. Beyond basic tasks, AI also enables the automation of higher-order processes that traditionally relied on human judgment—particularly in data-intensive or knowledge-driven sectors. It is important to distinguish between two forms of automation: robotic process automation (RPA), which focuses on rule-based, repetitive tasks with low complexity and quick return on investment; and intelligent automation, which leverages AI to perform more complex, adaptive tasks. Automation further contributes to improved accuracy, faster response times, and higher levels of customer satisfaction by ensuring timely service delivery. For instance, on E-Commerce, ref. [35] finds that AI-powered chatbots and virtual assistants have reduced customer response times by 40 percent and lowered operational costs by 20–30 percent while improving customer satisfaction. In healthcare, automation through AI is facilitating early diagnosis and monitoring, to improving overall patient access and quality and efficiency of care [36]. For SMEs, automatization creates both an opportunity and concerns. Ref. [37] signal opportunities in personalized customer service and tailored products and services to individual customer needs. Although the latter unlocks deeper value, it also introduces new challenges, such as the potential exclusion of employees from decision-making processes. Thus, it is necessary to streamline operations and has the responsibility of carefully managing the human implications of automation. For example, when machine learning is unsupervised and carried out in circumstances where intuitive and empathic intelligence prevails, it will be necessary (a) to look for solutions that mitigate the loss of human employment, and (b) to begin preparing human labor for tasks that machines cannot yet perform (high complexity and empathetic–emotional value) [38]. Brand perception, and long-term loyalty, are areas where human emotional intelligence is paramount. In many SMEs, human interaction—characterized by empathy, emotional nuance, and personal touch—remains a cornerstone of a satisfying service experience [39]. AI's lack of emotional intelligence, impersonal tone, or perceived manipulation can erode service quality and diminish customer trust. This tension between automation and human interaction in service delivery calls for a deeper understanding of how AI affects traditional service marketing principles. Strategies are needed to mitigate these downsides, such as hybrid models that combine AI efficiency with human empathy [40].

(b) Enhanced personalized customer service and the role of human interaction

AI provides powerful opportunities for improving personalized customer relationships, allowing organizations to customize products, services, and marketing to customer preferences. This can improve consumer satisfaction, engagement, and corporate performance. AI-powered virtual assistants and chatbots are improving customer support in many sectors such as e-commerce (for instance, Amazon); retail (for instance, customized marketing campaigns and offers); travel and hospitality; financial services; banking and insurance; healthcare, etc., [41]. Customer transactions, account queries, personalized financial planning, personalized treatment strategies that increase patient care or early detection of disease, and real-time support and assistance to suit consumer requests are some examples. Chatbots can answer questions about products, orders, and troubleshooting, and deliver accurate and personalized responses quickly, ensuring a smooth customer service experience. Customer satisfaction increases when clients wait less for human support. However, virtual assistants learn from consumers' interactions and preferences to enhance personalization. They can read natural language requests for more advanced and customized help. Siri, Alexa, and Google Assistant can schedule reminders, make reservations, and answer complex queries based on user preferences [42]. For SMEs, AI also provides powerful opportunities for improving personalized customer relationships, which are essential to foster loyalty and differentiate themselves in competitive markets [43]. For instance, ref. [44] demonstrate how AI can facilitate seamless engagement across multiple digital channels by analyzing customer feedback and sentiment in real time, allowing businesses to make timely improvements and address concerns promptly. Chatbots, virtual assistants, etc., enable SMEs to deliver more agile, tailored, and around-the-clock services. These tools reduce staff workload, boost efficiency, and allow businesses to provide unique experiences to individual customers. Nonetheless, these systems are not without drawbacks. When AI interactions fail to meet user expectations, the resulting dissatisfaction can negatively impact customer trust.

(c) Predictive analytics integrated with human knowledge

Predictive AI involves using AI tools to identify patterns, anticipate behaviors, and forecast upcoming events. Normally, with data-driven decision-making, AI can analyze data from various sources to provide SMEs with valuable insights for making informed decisions about production planning and inventory management [37]. Businesses can use predictive AI in the domains of strategic planning, resource allocation, and problem-solving. Using big data analytics, AI can predict potential future outcomes, causation, risk exposure, and equipment failures before they occur, as well as identifying bottlenecks, optimizing workflows, and allocating resources more effectively, etc. The example of financial services is conclusive [45]. AI can also improve control, identifying defects and anomalies in real time, leading to higher product quality and reduced waste. For instance, applied to agriculture, AI improves farm monitoring and aids in the mapping of agricultural zones, soil management, crop husbandry, irrigation disease, yield estimation, and harvesting [46]. Moreover, AI can improve the use of resources such as energy, materials, and personnel, leading to cost savings and improved efficiency [47]. In SMEs, predictive analytics represents one of the most impactful applications of AI, to schedule maintenance proactively and avoid costly downtime. As a result, SMEs become more agile and responsive to shifting market dynamics, consumer behavior, and competitive pressures. By leveraging advanced data analysis, SMEs can make informed decisions, improve objectivity, and foster a culture of continuous improvement—aligning offerings with consumer preferences [32]. Despite these benefits, challenges persist—particularly for SMEs. Data availability and quality remain major barriers. Additionally, the complexity and lack of interpretability of AI models, coupled with ethical concerns such as data bias and privacy risks, complicate the real-world deployment of predictive AI [48].

(d) Innovative product and service development

Innovation is a cornerstone of business growth, and AI is a powerful enabler of this transformation. By integrating AI into product design and optimizing production processes, enterprises can develop more advanced offerings, address evolving customer demands, and accelerate time to market. For SMEs, AI opens new possibilities to reimagine their market role and unlock creativity and efficiency, making innovation a strategic imperative.

New Product Development: AI can assist in the design and development of new products by analyzing market trends and customer preferences, leading to faster innovation cycles [37].

However, innovation, especially disruptive innovation such as AI, often entails high failure rates and uncertain short-term returns [49]. While failure can be a valuable source of learning, many SMEs lack the financial and organizational buffers that allow larger firms (MNEs) to absorb such risks [14].

In general, SMEs face distinct constraints compared to larger enterprises, including limited absorptive capacity, narrower margins, and resource scarcity [50]. This underscores the importance of adopting a tailored approach that accounts for SME-specific challenges and innovation dynamics.

Therefore, while AI offers tremendous innovation potential for SMEs, its successful implementation requires a structured and context-sensitive framework. To address this, the following section introduces the TOE framework, complemented by selected elements from the DOI theory.

3. Critical Analysis of AI Adoption in SMEs: Internal and External Factors Through the TOE–DOI Framework

This section provides a critical analysis of the internal and external factors that influence the adoption of AI in SMEs, using the TOE framework as the main analytical structure. To enhance this analysis, selected constructs from the diffusion of innovations DOI theory are integrated into the TOE model to better capture the perceptual and human-centered dimensions of adoption.

The section begins by introducing the TOE and DOI frameworks, discussing their individual relevance, and the rationale for combining them to analyze AI adoption in SMEs. This conceptual foundation is developed in Section 3.1, which presents the theoretical integration and its suitability for SME contexts.

Following this, the three core dimensions of the TOE framework are examined in detail: technical, organizational, and environmental. Section 3.2 explores technological determinants, including compatibility, complexity, and infrastructure readiness. Section 3.3 discusses organizational factors such as leadership, skills, financial capacity, and cultural readiness. Section 3.4 analyzes environmental influences, including competitive pressure, regulatory environments, and public–private ecosystem support. Section 3.5 introduces a short discussion of the empirical findings on SMEs and AI adoption, including a table with examples from the literature on empirical studies on the different dimensions of the TOE mode.

Together, these analyses provide a comprehensive understanding of the structural and perceptual barriers and enablers shaping AI adoption in SMEs.

3.1. TOE Plus DOI Framework Relevant to SMEs

This study is directed at the business community, where the goal of AI adoption is not adoption for its own sake, but rather the generation of net long-term value. This value must take into account the full cost of implementing and using AI technologies. Although conceptual gains from AI, such as improved productivity, efficiency, and innovation, are widely acknowledged, they are not easily measurable. This article does not attempt to quantify net gains directly, but rather focuses on the factors that enable or hinder the adoption and integration of AI into business strategy. Post-adoption performance issues and unrealized gains are therefore beyond the scope of this study.

The second key issue is generalizability. The net value of the adoption of AI is context-dependent: it does not apply equally across all firms, but is shaped by firm-specific characteristics [51]. To address this, the study distinguishes between SMEs and large enterprises. Although SMEs themselves form a heterogeneous group, they tend to face common constraints such as limited financial capacity, infrastructure gaps, and knowledge shortages [52–55].

Given that AI adoption affects data, processes, strategy, and people, a dual perspective is required: one that includes both a process-oriented and an organization-oriented lens. The **Diffusion of Innovations (DOI)** theory, developed by Rogers [19], takes a process-based user-centered approach and emphasizes perception-based attributes such as relative advantage, complexity, compatibility, trialability, and observability. Although DOI provides insight into how individuals and organizations perceive innovations, it lacks consideration of environmental and structural factors [56].

Complementing this, the **technology–organization–environment (TOE)** framework, developed by Tornatzky and Fleischer, [18] , offers a broader organizational view by categorizing adoption factors into three core dimensions: technological readiness, organizational capacity, and environmental influences. TOE has received strong empirical support in the context of business technology adoption [23,24,57,58]. It is particularly relevant for SMEs, where the dynamic interplay of internal capabilities and external conditions determines the success of digital innovation.

Several studies have affirmed that TOE factors are not static; they vary according to the type of technology and organizational setting [59]. The size of the company, in particular, has been identified as a key moderating variable in the adoption of technology [60]. The TOE framework thus provides a holistic view to understand how firms adopt innovations and has proven effective in multiple settings, including digital transformation [61], data analytics [62], and e-commerce [63–66].

Despite its strengths, TOE presents two limitations. First, it does not capture the cognitive biases or individual characteristics of decision-makers, a critical issue in SMEs, where leadership is often centralized. Second, it overlooks how perceptions of innovation characteristics influence adoption [25,64]. To address these gaps, several authors have proposed the integration of DOI attributes into the TOE model.

This integration enriches the TOE framework by incorporating individual-level DOI insights. While TOE explains organizational and environmental readiness, DOI addresses how users evaluate innovations, focusing on perceived ease of use, usefulness, trialability, and observability. This combined approach is particularly suitable for SMEs, where adoption decisions are often informal, perception-driven, and highly context-specific.

To reflect emerging challenges, including ethical compliance and regulatory adaptation, we further expand the TOE–DOI model to include dimensions of responsible and inclusive AI governance, particularly relevant for SMEs navigating complex digital ecosystems. In light of increasing policy attention and stakeholder expectations, AI adoption today must address not only feasibility and usability, but also fairness, transparency, data protection, and human rights.

As emphasized by [67], responsible AI involves embedding ethical values in both the development and the implementation processes. These concerns intersect the organizational dimension (e.g., leadership accountability, employee awareness, and governance protocols) and the environmental dimension (e.g., regulatory compliance and societal expectations). However, such concerns are still underrepresented in SME adoption studies. By incorporating responsible AI governance into our analytical lens, this paper extends the TOE–DOI framework to address this increasingly important facet of digital maturity.

Empirical research increasingly validates the relevance of this integrated TOE–DOI model in the SME context. Applications have been documented in different regions, including the European Union [27], India [28], Saudi Arabia [29], and Ghana [30], as well as in e-commerce settings in Jordan [24] and Egypt [31]. These studies highlight the flexibility and applicability of the framework in sectors and national settings.

Figure 1 presents the TOE–DOI Dimensions, factors and attributes for AI Adoption in SMEs. It illustrates how technological, organizational, and environmental enablers interact dynamically with innovation perception attributes (e.g., complexity, observability). This visual synthesis emphasizes the nature of AI adoption, highlighting internal readiness, external pressures, and perceived innovation characteristics as critical levers throughout each stage.

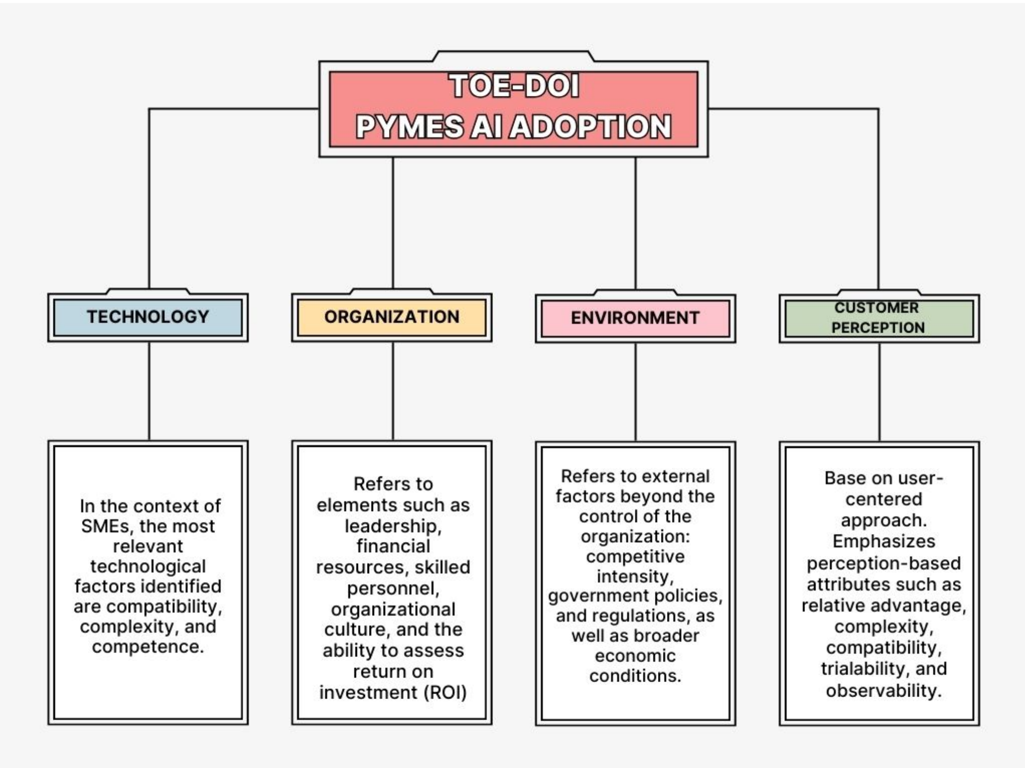

Figure 1. Illustrative TOE–DOI Dimensions, factors, and attributes for AI adoption in SMEs.

3.2. Technological Determinant

Among the technological factors that can limit or enable AI adoption in organizations, several have been extensively studied. These include comparative advantage, compatibility, complexity, testability, traceability, ease of use, perceived usefulness, intensity of information, and uncertainty [62,68]. In the context of SMEs, the most relevant technological factors identified are compatibility, complexity, and competence.

Compatibility refers to the degree to which AI solutions align with existing systems (hardware, software, technological frameworks, and digital resources) and how well they integrate with current production processes [59,62]. The positive impact of compatibility on the adoption of AI in SMEs has been supported in various studies [6]. However, it is important to emphasize that we are talking about the perceived compatibility of AI within a specific organizational context. When perceived compatibility is low, businesses are faced with two difficult choices: adapting the AI system or reengineering their internal processes. Both scenarios involve high costs and time-consuming transitions [11,69].

Complexity tolerance—the degree to which an organization perceives itself ready to handle the technological sophistication of AI—is one of the most critical barriers to adoption. Research has shown that higher perceived complexity negatively impacts AI adoption decisions [70,71]. As a result, it is essential for SMEs to develop strategies that strengthen internal confidence and reduce fear or resistance associated with AI complexity [62]. If managers believe that the adoption of AI will require excessive effort or disruption, their support for such initiatives is likely to diminish [59].

Competence is defined here as the degree to which the existing technological resources of an SME are adequately prepared to support the adoption of AI [59,72]. It is considered a fundamental determinant of successful AI integration, particularly in the SME sector [6]. Competence encompasses three critical dimensions: tangible resources, intangible resources, and data. Tangible resources refer to infrastructure components such as servers, middleware, storage, hardware, and networking [73]. Intangible resources include absorptive capacity—measured through prior technological experience [74], internal knowledge [75], and the presence of innovation strategies or digital transformation roadmaps [76]. Both types of resource play a vital role in enabling and maintaining AI integration.

Finally, data competence forms the third pillar of technological preparedness. Data directly influences the effectiveness of AI and the level of trust in its outputs. The main challenges for SMEs often stem from inadequate data availability, poor data quality, and insufficient protection measures [77]. As emphasized by [78], robust data governance and management practices must become a strategic priority for SMEs looking to adopt AI technologies effectively.

3.3. Organizational Determinant

The organizational factor of the TOE framework refers to internal characteristics that facilitate or hinder the adoption and implementation of AI. This includes elements such as leadership, financial resources, skilled personnel, organizational culture, and the ability to assess return on investment (ROI) [79].

Leadership plays a central role. TOE highlights the importance of top management support in creating a favorable environment and mobilizing organizational resources for AI adoption [80]. Here, leadership is defined as the degree to which managers believe and support the potential of AI technologies. Previous research identifies this support as a critical success factor [26,59,79,81]. Key leadership responsibilities in AI adoption include the following: (a) securing and efficiently allocating resources [26,79]; (b) preparing the organization culturally through the capacities of its personnel; and (c) aligning AI initiatives with corporate strategy while communicating benefits to internal and external stakeholders [72,82]. This role is more effective when top managers have technical knowledge of AI, understanding AI concepts and their applications [60,83] and/or have prior technological experience [74,75].

Financial resources represent another critical element. AI systems typically involve higher direct and indirect costs than traditional technologies. Implementation costs include software and hardware acquisition, training programs, and access to specialized expertise. Financial constraints—defined as the difficulty in accessing the capital necessary to support the adoption of AI—can significantly hinder implementation [14]. These limitations have been consistently identified as one of the main barriers for SMEs [32].

Human resource competence is also vital. AI adoption requires not only technical expertise but also non-technical skills to support organizational transformation. Many SMEs lack employees with the qualifications and experience needed to work effectively with AI systems [84,85]. The ease or difficulty of AI adaptation often depends on whether existing human resources are able to absorb AI-related responsibilities without major structural or role-based adjustments [76,86].

Cultural readiness and change management are equally important. Assessing ROI in AI adoption is often difficult, particularly when outcomes are long-term or intangible [29]. Moreover, the integration of AI often introduces profound cultural shifts. Constructive learning environments, open communication, and committed leadership are essential to reduce uncertainty and resistance. Employees may fear displacement or an inability to adapt to changes related to AI [9]. Leaders who embrace AI as a core strategic competence, adopt inclusive communication, and foster shared learning environments can inspire trust and commitment throughout the workforce. This leadership helps employees see AI as an opportunity rather than a threat, motivating them to acquire new skills and actively participate in transformation [81,87]. A strong culture of innovation and support helps reduce fear and psychological stress during AI transitions.

3.4. Environmental Determinant

The environmental dimension of the TOE framework refers to external factors beyond the control of the organization that may exert pressure or offer support for the adoption of new technologies [59,88]. These factors typically include competitive intensity, government policies, and regulations, as well as broader economic conditions.

Competitive pressure is one of the most frequently cited environmental motivators for the adoption of technology. As competition intensifies, businesses—particularly SMEs—may adopt AI to improve operational efficiency, improve customer experiences, or develop data-driven business models to gain a strategic advantage [89].

Government policy and institutional support also play a critical role. Public interventions, including well-designed AI strategies, can help SMEs overcome barriers related to financial and technical resource limitations. Effective policy formulation, as discussed by [90], can offer a supportive framework for adoption, particularly when aligned with national innovation agendas. Incentives such as tax credits, infrastructure funding, advisory support, and targeted grants can reduce financial risk and promote experimentation, even in cases where AI investments may not produce immediate returns [91].

However, **regulatory uncertainty and restrictive legislation** can pose serious challenges. The absence of clear and coherent regulatory frameworks—or their overly rigid implementation—can discourage firms from engaging with AI technologies. When legal obligations are ambiguous or inconsistently enforced, businesses may delay or completely avoid AI initiatives due to perceived compliance risks.

A particularly important aspect is **data protection and AI-specific regulation**. Compliance with data privacy laws and AI governance requirements is now central to how firms design, implement, and manage AI-driven systems. Adherence to these frameworks not only reduces legal risk, but also strengthens stakeholder trust and social legitimacy. Therefore, ensuring ethical and responsible use of AI becomes a dual priority—one that satisfies both legal compliance and strategic communication.

3.5. Empirical Findings on SMEs and AI Adoption

Despite AI gaining the attention of researchers and SMEs managers, empirical evidence regarding AI's adoption is still insufficient. The lack of data (quality and quantity) and the conceptual and empirical frameworks that connect SMEs and technology are the main explanations. However, among the scarce evidence, empirical findings confirm the validity of the independent variables in the TOE framework. In fact, the TOE framework itself has already been empirically tested and is recognized as one of the strongest theoretical tools to explain technology adoption in SMEs [21,92,93]. Empirical evidence also confirms that the TOE variables most closely related to the characteristics that distinguish structural and perceptually SMEs from large enterprises are the most influential: specifically, limited IT infrastructure, talent shortages and restricted access to capital, and complexity aversion and compatibility in perceptual differences. As a result, in practice, SMEs favor simpler, off-the-shelf AI solutions, such as chatbots, with adoption objectives focused on operational efficiency and customer service automation. It is emphasized that SMEs, which adopt AI more reactively and with limited scope, require customized frameworks, modular solutions, specific policy incentives, capacity-building initiatives, and supplier partnerships, among others.

These findings strongly align and reinforce the TOE–DOI-based challenge–solution matrix presented in this study. Furthermore, the review provides practical information for policymakers and ecosystem actors looking to foster the equitable diffusion of AI across all organizational sizes and sectors.

Table 1 presents examples from the literature on empirical studies on the different dimensions of the TOE model. We use the following nomenclature in the table. T1 = Compatibility (Technology factor 1), T2 = Complexity (Technology factor 2), 02 = Cost and Financial resources (Organizational factor 2), 04 = Skilled personnel (Organizational factor 4), E1 = Competitive intensity (Environmental factor 1).

Table 1. Examples from the literature on empirical studies on the different dimensions of the TOE model.

Dimension	Factor	Description
T1	Compatibility	Compatibility has significant positive effect in SMEs AI adoption [94–99]
T2	Complexity	Complexity may be a fundamental barrier in the AI adoption [62,66,70,71,94,97]
O2	Cost & Financial resources	Cost is one of the mainly factors with significant negative effect [41,100,101]
O4	Skilled personnel	Skills shortage & AI adoption present a significant negative relationship in automation of processes, products/processes, interaction with clients, and data analytics [58,74,102–105].
E1	Competitive intensity	Competitive intensity in markets presents a significant positive relationship to AI adoption [97,106–108]

4. Empirical Insights from Sectorial and Regional Studies

To enhance the practical foundation of the proposed challenge–solution framework, this section synthesizes findings from recent empirical studies in diverse sectorial and regional and contexts. It is organized into twelve sets, including eleven studies and a final table reflecting the summary.

4.1. AI Adoption in Manufacturing and Retails SMEs

This subsection focuses on manufacturing and retailing for SMEs with two case of analysis, AI-driven smart manufacturing, and AI and IoT integration in retail and manufacturing SMEs.

4.1.1. AI-Driven Smart Manufacturing: Technological and Organizational Lessons from Customization Models [109]

Wan et al. [109] provide a comprehensive review of AI-driven smart manufacturing systems, focusing on custom manufacturing factories that integrate AI with the Internet of Things (IoT), cyber-physical systems (CPS), and cloud computing. Although the study does not focus solely on SMEs, it offers valuable insight into the structural and implementation challenges SMEs may face when trying to adopt such advanced systems. Technologically, the study emphasizes that AI-enabled manufacturing relies heavily on data fusion, distributed decision-making, and predictive analytics, capabilities that often exceed the technical maturity of typical SMEs (TOE: Technological). Organizationally, successful implementation requires strong coordination across supply chains, cross-functional collaboration, and highly skilled staff, factors that align with the DOI constructs of complexity, observability, and trialability.

Wan et al. [109] highlight practical adoption hurdles such as fragmented data architectures, cybersecurity risks, and lack of standardization, which resonate with many of the barriers. For SMEs, these challenges are magnified due to budget constraints and limited IT infrastructure. The paper also notes that while large firms can internally develop smart factory capabilities, SMEs often depend on external partnerships or modular platforms, reinforcing the importance of ecosystems and scalable cloud-based solutions discussed throughout this study.

Quantitatively, the review cites improvements of up to 20–30% in operational efficiency, defect reduction, and time-to-market among early adopters of AI-driven customized manufacturing. These performance outcomes reinforce the ROI potential of AI adoption when technological and organizational readiness align. In general, this study supports the call for phased low-risk AI deployment in SMEs, such as through simulation tools, AI-as-a-Service models, or open source toolkits, validating both the scalability and strategic alignment principles embedded in our proposed framework.

4.1.2. AI and IoT Integration in Retail and Manufacturing SMEs: Operational Efficiencies and Strategic Challenges [110]

Haider and Faisal [110] present a comprehensive analysis of how the synergy between AI and the IoT transforms operational strategies in retail and manufacturing SMEs. Their findings align with several dimensions of the TOE–DOI framework, particularly within the technological and organizational domains. In the retail sector, the deployment of IoT sensors and AI algorithms facilitates personalized customer experiences and predictive inventory management. Quantitative results highlight improvements such as up to 20% increases in sales through AI-driven personalization and significant reductions in stock shortages and overstocking. In manufacturing, the integration of AI-enabled predictive maintenance and real-time quality control using IoT data reduced downtime by up to 30% and defect rates by 25%, reflecting measurable ROI and operational efficiency.

Despite these benefits, the study underscores key adoption challenges: high initial infrastructure costs (TOE: Technological), a shortage of skilled personnel (TOE: Organizational), and persistent cybersecurity concerns (TOE: Environmental). Notably, the authors advocate for cloud-based and edge computing solutions to reduce latency and improve scalability, which mirrors the challenge–solution logic proposed in this paper. The study further reinforces the importance of modular and democratized AI deployments, contributing empirical validation to the strategic actions outlined in Section 4. Their sectoral insights, grounded in performance metrics, enhance the external validity of the proposed framework by illustrating successful implementation pathways alongside critical adoption barriers.

4.2. AI Synergies and Revenue Growth in European SMEs

Ardito et al. [111] present robust econometric evidence on the impact of AI adoption on revenue growth among 11,429 European SMEs, using data from Flash Eurobarometer 486. Their findings reveal that AI adoption, especially when complemented by Big Data Analytics and the IoT, significantly increases the probability of revenue growth by at least 30%. Specifically, the combined adoption of AI with IoT or BDA led to a 21% increase in the likelihood of high-growth scenarios. This reinforces the view, consistent with our TOE–DOI framework, that technological readiness must be coupled with complementary infrastructure and organizational capabilities to produce strategic returns.

The study also illustrates the value of modular and combinatory adoption strategies, where SMEs that take advantage of multiple digital assets achieve synergistic results. From a practical point of view, these results support the actionable pathway in our framework that encourages SMEs to adopt scalable, integrated technology stacks rather than isolated tools. Furthermore, Ardito et al.'s [111] findings validate the role of external ecosystem support and digital service platforms as critical enablers in overcoming capability gaps. By linking AI adoption with clear economic performance indicators, this study strengthens the external validity of our challenge–solution model and exemplifies how customized digital strategies can lead to measurable SME growth in national and sectoral contexts.

4.2.1. AI Adoption in European SMEs and the Role of Internal Capabilities [27]

Arroyabe et al. (2024) [27] conducted an empirical analysis involving 12,108 SMEs across the European Union, utilizing data from the Flash Eurobarometer and advanced analytics techniques (regression, ANN, tree regression). Their findings underscore that internal capabilities—particularly digital and innovation capabilities—are far more influential for AI adoption than external environmental support alone. Quantitative indicators show that digital capabilities (e.g., use of IoT, cloud, robotics) exhibit a significantly stronger correlation with AI integration outcomes than business environment factors. For example, SMEs with high digital capability scores had up to a 52% higher likelihood of successful AI adoption. Innovation capabilities also showed a positive impact, especially when digital maturity was moderate, revealing synergistic effects.

In contrast, environmental support variables (such as access to funding or skilled labor) had a weaker and less consistent influence, reinforcing the need to emphasize internal readiness and complementary innovation processes. This aligns with the technological and organizational dimensions of the TOE framework and emphasizes the DOI principle of innovation compatibility. The study validates the importance of customized interventions that focus on strengthening SME-specific digital and innovative capabilities while designing ecosystem support to complement, rather than replace, internal drivers.

4.2.2. A Comprehensive Systematic Literature Review [112]

This systematic review provides valuable information on the challenges that SMEs face when adopting AI, specifically within the industrial sector. Based on a PRISMA-guided analysis of 71 studies, the review identifies 27 distinct challenges and organizes them using the PESTEL framework. These findings directly align with the TOE–DOI lens applied in this article, particularly highlighting technological and organizational barriers such as lack of digital maturity, data availability and quality, and insufficient AI knowledge. In particular, more than 90% of SMEs reported having no AI applications in place, and knowledge gaps were cited in 35 of the studies analyzed, emphasizing the critical role of internal readiness (TOE: Organizational).

In terms of technological readiness, poor IT infrastructure and fragmented data practices were frequently mentioned, while social challenges such as management skepticism and low acceptance of AI surfaced as major inhibitors. Quantitative indicators such as low ROI visibility and high risk of failure were also emphasized, especially in cases where AI implementation lacked strategic alignment or adequate planning. This review reinforces the complexity and interdependence of SME-specific constraints, underscoring the urgent need for tailored support structures to bridge the adoption gap between SME and AI.

4.2.3. AI and Robotics as Innovation Drivers in European SMEs [113]

Segarra-Blasco et al. [113] provide a large-scale empirical study using data from the Flash Eurobarometer 486 survey, covering over 16,000 SMEs in Europe. Their analysis explores the adoption of artificial intelligence (AI) and robotics and their association with different types of innovation outcomes, including product, process, organizational, and marketing innovations. The study applies a two-stage residual inclusion model and confirms that start-ups and scale-ups are significantly more likely to adopt AI and robots, aligning with the emphasis of our TOE–DOI framework on organizational readiness and dynamism as key enablers. Quantitative indicators reveal that 6.9% of SMEs adopted AI and 8.3% adopted robots, with adoption strongly correlated with internationalization, firm size, digital infrastructure and country-level information and communication technology skills.

Importantly, AI adoption is associated more significantly with product, process and organizational innovations, while robot adoption is closely linked to product and process improvements. The findings highlight clear sectoral differences: manufacturing firms use these technologies for specialized innovation tasks, while service sector SMEs integrate them more broadly. These insights strengthen the external validity of our challenge-solution framework, particularly with respect to the technological and environmental dimensions of the TOE model, and demonstrate the role of digital complementarity in shaping innovation trajectories.

4.3. Nordic Countries Study for AI Adoption in Manufacturing and Retail SMEs

Peretz-Andersson et al. [114] investigate how AI implementation unfolds within manufacturing SMEs in Nordic countries using a resource orchestration lens. Their qualitative study reveals how firms must strategically coordinate, develop, and leverage internal and external resources to extract value from AI technologies. Technologically, the SMEs examined struggled with limited data maturity, outdated legacy systems, and integration challenges, aligning closely with the technological barriers outlined in the TOE framework. Organizationally, success was linked to proactive leadership and internal champions who could bridge technical and operational divides. In addition, employee resistance and lack of digital skills were reported as key inhibitors, mapping to DOI attributes such as perceived complexity and lack of trialability.

A critical contribution of the study lies in its emphasis on dynamic capability building: firms that succeeded in AI implementation actively reconfigured internal processes and cultivated strategic partnerships with technology providers. Environmentally, government support and regional innovation networks played an enabling role, especially when cross-organizational collaboration was required.

Although the study is qualitative, it includes proxy performance outcomes such as increased production efficiency, reduced waste, and shorter lead times, illustrating tangible business benefits. These findings reinforce the importance of tailoring AI strategies to sector-specific resource constraints and support the adaptability of the TOE–DOI framework to high-precision, capital-intensive SME contexts such as manufacturing.

4.4. AI Adoption and Digital Competencies in Spanish SMEs

Huseyn et al. [85] present a robust empirical investigation of the adoption of AI among Spanish SMEs, highlighting the decisive role of digital competencies and skill development. Based on a representative sample of 836 SMEs and a logistic regression analysis enhanced by Generative Adversarial Networks (GANs), the study identifies key enablers mapped to the organizational and technological dimensions of the TOE framework. Firms led by university-educated managers, staffed with information technology specialists and engaged in internal IT training initiatives showed significantly higher AI adoption rates.

In addition, the adoption of ERP systems and marketing analytics tools—indicators of digital maturity—is positively correlated with the integration of AI, reinforcing the notion that cumulative digital capacity accelerates the adoption of innovation. In particular, SMEs collaborating with universities and research centers had a six-fold increase in the likelihood of adoption of AI, underscoring the environmental enablers emphasized in the TOE model. Quantitative indicators such as a 94.3% sensitivity and 85.7% overall model accuracy strengthen the reliability of these insights. This study offers both theoretical reinforcement and practical validation for our framework by illustrating how targeted capacity building and ecosystem collaboration can overcome the adoption inertia in resource-constrained contexts.

4.5. Insights from Italian SMEs: Organizational Readiness and Strategic Implementation

Proietti and Magnani [115] provide an in-depth examination of AI adoption in 36 Italian SMEs in 14 industries, highlighting substantial gaps in digital maturity and AI integration. The study identifies that the vast majority of these companies operate at low or very low levels of digital maturity, with fewer than 14% demonstrating active use of AI technologies. Key barriers include high perceived costs, lack of internal expertise, unclear strategic relevance, and limited understanding of generative AI capabilities. In particular, only 11% of the respondents reported familiarity with or use of generative AI tools.

To address these challenges, the authors propose a structured implementation framework that emphasizes iterative goal setting, cultural readiness, external support, and technical enablers. The study also highlights that tailored proof-of-concept projects and cloud-based AI services can help SMEs overcome infrastructure and data limitations. The findings support the organizational and technological dimensions of the TOE framework, particularly regarding digital skills, managerial commitment, and phased adoption strategies, and reinforce the need for simplified, human-centered solutions to promote adoption.

Quantitative findings (e.g., 70% of firms had never used generative AI; 50% lacked investment plans) underscore the urgency of action and further support the inclusion of regional insights to tailor policy and support mechanisms.

4.6. AI-Driven Business Model Innovation for Sustainability: Evidence from U.S. SMEs

Shaik et al. [3] examine how AI-driven business model innovation (AIDBMI) enables small- and medium-sized enterprises (SMEs) in the United States to transition toward carbon-neutral operations. Drawing on data from 326 SMEs and analyzed using structural equation modelling partial least squares structural equation modeling (PLS-SEM), the study finds that AI significantly facilitates the integration of sustainable business practices by enhancing both technological (e.g., green technology innovation) and strategic (e.g., strategic intent and architecture) enablers. Key technological factors include the deployment of AI in optimizing energy use, managing renewable energy integration, and supporting circular supply chains—mapped directly to the TOE–Technological domain. Organizationally, the success of AIDBMI depends on the firm's innovation capability, alignment of sustainability goals, and internal structures—corresponding to TOE–Organizational and DOI–Compatibility dimensions. Strategic enablers such as sustainability-focused leadership and employee engagement emerged as critical success factors.

Quantitatively, the model explains 82.8% of the variance in carbon-neutral business performance, and shows that AIDBMI mediates the impact of green innovation capability and strategic architecture on sustainability outcomes. The study reinforces this paper's challenge–solution framework by validating how AI supports environmental and economic performance through innovation in business models. It also highlights government policy as a moderating environmental factor, emphasizing the importance of external support for SMEs aiming for net-zero goals.

4.7. AI-Driven Bank Digitalization and SME Financing in China

Zhang et al. [116] investigate how AI and big data are transforming SME financing in China through digital bank models. Their study presents a theoretical model that compares three types of financial institutions: traditional large banks, regional banks, and internet banks. The findings suggest that internet banks—leveraging AI-driven risk assessment and digital loan technologies—are better positioned to meet the financing needs of digitally mature SMEs. Meanwhile, regional banks retain advantages for SMEs with low digital footprints, due to their relational lending capabilities and access to internal business information.

This case highlights how the effectiveness of AI applications in the financial sector depends on technological readiness (TOE: Technological), SME digital maturity (TOE: Organizational), and the institutional banking environment (TOE: Environmental). Although the paper does not offer firm-level performance metrics, it underscores the importance of strategic digital alignment between SMEs and financial institutions to unlock AI's potential to improve credit access and reduce financing restrictions. The findings reinforce the challenge of aligning external financial ecosystems with the adoption capacity of SMEs, especially in rapidly digitizing economies.

4.8. Digital Readiness as a Foundation for AI Adoption in Emerging Market SMEs in India

Pingali et al. [5] provide a multi-study, mixed-method investigation into the digital readiness of SMEs operating in emerging markets, with a focus on India. Although the study does not address AI adoption directly, it offers foundational insights highly relevant to understanding the preconditions for effective AI integration in resource-constrained contexts. The authors conceptualize "digital readiness" as a higher-order construct composed of three dimensions: technological sensemaking, agility, and implementation capacity. These dimensions align well with the TOE framework's technological and organizational pillars, while also reflecting DOI principles such as trialability, complexity, and compatibility.

Using qualitative interviews with 50 SME leaders and follow-up surveys from 324 SMEs across two empirical studies, the authors develop a validated 20-item scale for assessing digital readiness. Quantitative findings reveal strong predictive power of digital readiness on three critical performance outcomes: new product development ($R^2 = 0.42$), operational efficiency ($R^2 = 0.18$), and overall business performance ($R^2 = 0.17$). Notably, leadership style (e.g., millennial leadership), strategic focus (e.g., operational efficiency, rural outreach), and external market dynamics (e.g., platform availability and institutional support) emerged as major enablers.

These insights are highly consistent with the challenge-solution framework of this paper. They reinforce the need for foundational digital maturity as a prerequisite for advanced AI adoption and provide empirical grounding for the role of contextual factors, such as infrastructure, market structure, and institutional trust, in shaping adoption trajectories. The study's use of agility and technological sensemaking also supports the inclusion of DOI-oriented attributes such as observability and reinvention in strategic readiness assessments.

Overall, Pingali et al.'s [5] framework enhances the external validity of our proposed TOE–DOI model by emphasizing how strategic alignment, digital agility, and environmental enablers can shape AI adoption in SMEs, particularly in volatile or under-resourced economies.

4.9. Saudi Arabia: Sustainable Business Performance Through AI Adoption

Badghish and Soomro (2024) present an empirical investigation of AI adoption among SMEs in Saudi Arabia through the lens of the TOE framework [97]. Their study, based on a survey of SMEs across six sectors, quantitatively validates key TOE constructs such as relative advantage, compatibility, sustainable human capital, market/customer demand, and government support as significant drivers of AI adoption. Notably, the research distinguishes between operational and economic performance as outcome measures, revealing that AI adoption positively impacts both dimensions.

Furthermore, firm size emerged as a moderator: medium-sized enterprises experienced a stronger relationship between AI adoption and performance outcomes than smaller firms. These findings reinforce the relevance of TOE dimensions—especially technological compatibility and external support—in shaping AI adoption pathways. The inclusion of performance indicators such as profitability, operational efficiency, and workforce readiness enhances the practical applicability of the TOE–DOI challenge–solution framework in emerging markets such as Saudi Arabia.

4.10. AI and Financial Inclusion in African SMEs: A Fintech-Driven Perspective

In their regional analysis of AI-driven financial inclusion, Omokhoa et al. [117] examine the transformative role of AI and fintech in supporting the growth of SMEs within the African financial services sector. Drawing on the Nigerian and broader context of sub-Saharan Africa, the study highlights how the integration of AI—when combined with digital wallets, alternative credit scoring models, and mobile-based fintech platforms—has reduced access barriers for small companies to finance. From a TOE perspective, the technological enablers included AI-based mobile lending tools and cloud-based financial platforms, which address structural weaknesses in traditional banking infrastructure. Organizationally, SMEs that successfully adopted these tools demonstrated agile leadership and openness to platform-based innovation, although skill shortages and limited digital literacy remained persistent inhibitors. Environmentally, regulatory uncertainty and underdeveloped data protection frameworks were noted as external barriers to scaling AI-based financial services.

Quantitatively, the paper reports a significant increase in SME access to microloans and reductions in operational costs, though long-term profitability impacts remain underexplored. The authors recommend targeted policy interventions and investment in AI literacy to support inclusion efforts. This case study underscores how the adoption of AI in emerging economies intersects with broader goals such as financial inclusion and the survival of small businesses, extending the relevance of the TOE–DOI framework to contexts where digital infrastructure and regulatory ecosystems are still evolving.

4.11. AI Adoption and Sustainable Performance in Developing Economies: Evidence from Pakistani SMEs

A comprehensive study by Soomro et al. [118] provides empirical evidence on how AI adoption influences the sustainable performance of SMEs in Pakistan. Using a hybrid methodological approach that combines partial least squares structural equation modeling (PLS-SEM) and artificial neural networks, the study analyzed data from 305 SMEs in sectors such as retail, agriculture, manufacturing and services. The research adopts a TOE–DOI perspective, evaluating factors such as top management support, employee capability, vendor support, and environmental pressures. In particular, top management support ($\beta = 0.27$), employee capacity ($\beta = 0.25$), and customer pressure ($\beta = 0.16$) were found to have significant positive effects on AI adoption, while the availability of financial resources did not show a significant effect. From a DOI lens, perceived relative advantage ($\beta = 0.18$) emerged as a key enabler, while perceived complexity also positively influenced adoption ($\beta = 0.12$), contrary to common assumptions. Importantly, the study demonstrates that AI adoption improves the economic ($\beta = 0.64$), social ($\beta = 0.57$), and environmental performance ($\beta = 0.56$) of SMEs—quantitative evidence that reinforces AI's role as a transformative tool for sustainability.

These findings substantiate the challenge–solution framework proposed in this article by confirming the importance of organizational readiness, capability building, and vendor ecosystems in supporting scalable AI implementation across SMEs in developing economies.

4.12. AI Marketing and SME Performance in Emerging Economies: Evidence from Ghana SMEs

Abrokwah-Larbi and Awuku-Larbi [100] provide empirical evidence from Ghana on how AI in Marketing (AIM) significantly improves the performance of small businesses in four key dimensions: financial, customer, internal business process, and learning and growth. Drawing on the Resource-Based View (RBV), their study surveyed 225 SMEs and applied structural equation modeling to assess the impact of AIM determinants, including IoT, collaborative decision-making systems, virtual and augmented reality, and personalization. The findings revealed strong positive effects, with AIM explaining up to 61% of variance in learning and growth performance and 58% in internal processes.

These results reinforce the emphasis of the TOE–DOI framework on organizational and technological readiness, while also showing that even in resource-constrained emerging economies, strategic alignment of AIM capabilities can produce tangible performance benefits. The study also highlights specific barriers such as resource limitations and skill gaps, echoing the challenges identified in Section 4, and suggests that personalization and CDMS are particularly effective levers for SMEs seeking growth and innovation.

4.13. Summary Table to Complement the Cases Analysis

To complement the in-depth case studies presented earlier and enhance the generalizability of our proposed challenge–solution framework, Table 2 provides a synthesized overview of recent empirical studies examining AI adoption in SMEs. The studies span various geographic regions, including Europe, Asia, Africa, and the Americas, and cover a diverse range of sectors such as manufacturing, finance, retail, and sustainability-focused companies. This comparative summary draws attention to the specific technological, organizational and environmental dimensions emphasized by the TOE–DOI framework, while also illustrating how enablers and barriers manifest themselves across different economic and regulatory landscapes.

Each row in the table highlights key insights derived from regional and sectoral studies, including practical outcomes such as increased productivity, increased revenue growth, or improvements in sustainability. Several entries incorporate quantitative performance indicators, such as variance explained in strategic models or percentage gains in efficiency, thus reinforcing the external validity and applicability of the proposed framework. The table also captures the variation in adoption strategies, ranging from modular deployment and ecosystem collaboration to skills development and leadership-driven transformation. This comparative layer is intended to guide policymakers, practitioners, and researchers in designing more context-sensitive and scalable approaches to AI integration in SMEs.

Table 2. Summary of empirical AI adoption studies in SMEs with quantitative indicators.

Region/ Count.	Sector	Key Insights	Performance Indicators (KPIs)	Source
Global	Smart Manufacturing	AI-enabled smart factories. Barriers include fragmented IT, cost, and complexity.	Up to 30% increase in operational efficiency	Wan et al. (2020) [109]
Global	Retail & Manufac.	AI + IoT improved sales, inventory, and maintenance.	20% sales increase, 30% downtime reduction	Haider & Faisal (2024) [110]
Europe	Multi-sector	AI + IoT + BDA synergy boosts revenue through modular strategies.	21% increase in high-growth likelihood	Ardito et al. (2024) [111]
Europe	General SMEs	Digital and innovation capabilities strongly influence AI success.	52% higher AI adoption in digitally mature firms	Arroyabe et al. (2024) [27]
Europe	Industrial	Lack of digital maturity and alignment blocks adoption.	90% without AI apps; qualitative challenge frequency	Oldemeyer et al. (2024) [112]
Europe	General SMEs	AI/robotics adoption enhances multi-type innovation.	6.9% AI adoption, 8.3% robotics adoption	Segarra-Blasco et al. (2025) [113]
Nordics	Manufac-turing	Resource orchestration key; regional networks support.	Qualitative: reduced waste, lead time, improved efficiency	Peretz-Andersson et al. (2024) [114]
Spain	General SMEs	Digital maturity and university collaboration increase uptake.	6x AI adoption increase via R&D links; model accuracy 85.7%	Huseyn et al. (2024) [85]
Italy	General SMEs	Most firms lack maturity; PoCs and cloud tools help.	Only 14% use AI; 50% have no investment plans	Proietti et al. (2025) [115]
USA	Sustaina-bility	Gen-AI supports carbon-neutral innovation	82.8% variance in carbon-neutral performance explained	Shaik et al. (2024) [3]
China	Finance	Internet banks outperform traditional ones for digital SMEs.	Improved loan access, no specific KPIs reported	Zhang et al. (2022) [116]
India	Multi-sector (E-SMEs)	Digital readiness linked to strategic agility	Strong correlation with product and operational gains	Pingali et al. (2023) [5]
Saudi Arabia	Retail	Cultural and leadership factors drive success.	Operational + economic outcomes (no % reported)	Badghish & Soomro (2024) [97]
Africa	Finance Services	AI-fintech enhances inclusion and cuts costs.	Increased loan access, reduced operating costs	Omokhoa et al. (2024) [117]
Pakistan	Multi-sector	Organizational factors outweigh financial ones in adoption.	Economic ($\beta = 0.64$), Social ($\beta = 0.57$), Environmental ($\beta = 0.56$)	Soomro et al. (2025) [118]
Ghana	General SMEs	AI in marketing drives internal and growth outcomes.	61% variance in learning, 58% in internal process performance	Abrokwah-Larbi et al. (2024) [100]

5. Challenges and Actionable Pathways for AI Adoption in SMEs

Building on the theoretical foundation established through the integrated TOE–DOI framework, this section transitions from conceptual analysis to practical application, identifying ten key challenges that SMEs often face during the process of adopting AI. These challenges are analyzed in alignment with the three dimensions of the TOE framework, technical, organizational, and environmental, and incorporate both structural constraints and perception-based dynamics.

Each subsection that follows presents one challenge, articulates its core implications for SMEs, and offers targeted, evidence-based solutions. The analysis draws on the SME context, where resource limitations, agility, and leadership centralization influence adoption decisions. The final Section 5.11 provides a consolidated mapping of all challenges and their associated responses across the TOE dimensions to offer a strategic overview.

Table 3 summarizes the ten AI adoption challenges and the corresponding high-level interventions that SMEs can implement to overcome them.

Table 3. Overview of AI adoption challenges and actionable solutions in SMEs.

Challenge	Core Challenge	Strategic Solution	TOE Dimension
1. Knowledge and Expertise Gaps	Lack of internal technical capabilities to manage AI	Internal training, low-code tools, external partnerships	Technological/ Organizational
2. Scalability Constraints	High risk and complexity of scaling AI solutions	Modular deployment, agile methods, cloud platforms	Technological
3. Financial Limitations	High upfront and ongoing costs for AI systems	Flexible financing, pilot testing, government incentives	Organizational
4. Data Deficiency	Insufficient, unstructured, or poor-quality data	Data governance, real-time collection, cleaning, API integration	Technological
5. Infrastructure and Integration Issues	Incompatible legacy systems and lack of AI-ready infrastructure	Cloud-based tools, APIs, AI computation centers	Technological
6. Cultural Resistance to Change	Organizational fear, inertia, and lack of innovation mindset	Inclusive leadership, innovation culture, pilot-driven learning	Organizational
7. Human–AI Productivity Misalignment	Anxiety about automation and job displacement	Augmentation approaches (co-intelligence, centaur models)	Organizational
8. Weak Public–Private Collaboration	Limited access to shared knowledge, funding, or platforms	Innovation ecosystems, public–private partnerships, shared spaces	Environmental
9. Limited Access to advanced AI such as Gen-AI	Barriers to using state-of-the-art AI such as Gen-AI	Plug-and-play Gen-AI tools, augmentation use cases, strategic embedding, toward open-weight LLM adoption	Technological/ Organizational
10. Lack of Responsible AI Governance	Absence of ethical practices and transparency in AI deployment	Lightweight governance, transparency, stakeholder engagement, data protection	Organizational/ Environmental

5.1. Closing the Knowledge Gap and Technical Expertise

This subsection addresses one of the most fundamental barriers to AI adoption in SMEs: the lack of internal knowledge and technical capabilities. Within the TOE framework, this challenge cuts across both technological and organizational dimensions. Technologically, SMEs often lack familiarity with data infrastructure, machine learning, and AI tools. Organizationally, they frequently operate without in-house expertise or structured training programs to close this gap.

This deficiency can lead to ineffective decision-making, failed implementation attempts, and under-utilization of the potential of AI. For SMEs, where resources and specialization are typically limited, targeted solutions are needed to empower staff and reduce dependency on high-level technical talent.

As noted in [97], one of the main organizational constraints that affects the implementation of AI in small businesses is the shortage of skilled personnel, especially in data-driven roles. Ref. [112] emphasize that limited technical expertise and lack of internal champions are among the most cited barriers in the reviewed studies. Similarly, ref. [100] identify training deficiencies as a primary obstacle to realizing AI benefits in marketing-oriented SMEs in emerging economies. On a broader level, ref. [115] argue that without appropriate training and awareness programs, even well-intentioned AI pilots are likely to perform poorly or completely stall.

These findings underscore the importance of investing in customized capacity-building strategies. Blended approaches, including continuous learning platforms, collaborations with research institutions, and low-code AI tools, can significantly improve SMEs' ability to absorb and apply AI technologies over time.

To overcome this challenge, SMEs can implement the following actionable strategies:

A. Develop Internal Capabilities through Training. Invest in continuous role-specific training for employees in areas such as data analysis, AI fundamentals, and algorithmic thinking. Training should be modular and accessible, allowing gradual learning and practical application in daily operations.

B. Leverage Low-Code and Pre-Trained AI Tools. Adopt user-friendly, cloud-based platforms offering pre-configured AI models. These reduce the technical entry barrier and enable SMEs to gain value from AI without requiring advanced programming or data science skills.

C. Build Strategic External Partnerships. Collaborate with universities, research centers, AI consulting firms, and technology providers. These partnerships provide access to expert guidance, reduce learning curves, and help SMEs co-develop solutions tailored to their business context.

D. Engage in Open Innovation Networks. Participate in innovation ecosystems and industry alliances to exchange knowledge, gain exposure to best practices, and remain informed about AI trends and tools suitable for SME environments.

In summary, closing the knowledge and skill gap is essential for SMEs to effectively integrate AI into their business strategy. By combining internal training, accessible tools, and external collaboration, SMEs can build the capabilities needed to adopt AI in a sustainable and scalable way, strengthening both technological readiness and organizational maturity.

5.2. Designing Scalable AI Solutions for Sustainable Growth

This subsection addresses the scalability challenge within the technological dimension of the TOE framework. Many SMEs struggle to implement AI solutions that can grow with their business due to resource constraints, infrastructure limitations, and the perceived complexity of large-scale AI deployment.

Scalability is critical to ensure that early AI investments deliver long-term value. Without scalable design, SMEs may face high sunk costs, low adaptability, and limited return on investment. Therefore, SMEs must adopt strategies that allow for controlled experimentation while maintaining flexibility to expand as their capabilities evolve.

As noted in [112], small-scale pilots often initiate the adoption of AI, but lack clear frameworks to scale these projects. Ref. [119] emphasize that cloud-based Gen-AI platforms and modular tools enable scalable low-cost experimentation that aligns well with SME capabilities. Ref. [115] highlight that modular AI architectures, combined with agile methodologies, are crucial to balance innovation speed with risk management in resource-constrained environments. Regionally, ref. [27] show that access to flexible infrastructure, such as edge computing and AI computation centers, significantly affects scalability potential in European SMEs. These findings underscore the importance of scalable design not only from a technical perspective but also as a strategic imperative for sustainable digital growth.

To respond to this challenge, the following actionable strategies are recommended:

A. **Adopt Modular Implementation Approaches**
Begin with small-scale, manageable AI projects that are aligned with specific business needs. This reduces upfront risk while providing opportunities to validate performance and refine processes prior to full-scale deployment.

B. **Utilize Agile Methodologies**
Employ agile project management techniques that support iterative development and regular feedback. This increases responsiveness to business changes and helps align AI solutions with evolving operational priorities.

C. **Leverage Scalable Cloud Platforms**
Use cloud-based infrastructures that enable on-demand computing power and storage. This allows SMEs to scale AI applications gradually, reducing the need for heavy capital investments in IT hardware.

D. **Ensure Future Integration Compatibility**
Select AI tools and architectures that are interoperable and adaptable to future technologies or systems. This forward-thinking approach avoids vendor lock-in and allows easier expansion and system upgrades.

In summary, SMEs can overcome scalability constraints by implementing modular AI projects, adopting agile workflows, and leveraging cloud infrastructures. These strategies ensure that the adoption of AI remains flexible, cost-effective, and aligned with the firm's growth trajectory and technological evolution.

5.3. Overcoming Financial Barriers to Enable AI Adoption

This subsection addresses the financial resource constraints facing SMEs, categorized under the organizational dimension of the TOE framework. High initial investments, ongoing maintenance costs, and uncertainty about returns often hinder SMEs from adopting AI technologies. These limitations can delay strategic digital transformation and increase risk aversion commonly found in resource-constrained environments.

As noted in [97], limited access to financial capital remains one of the main organizational obstacles in the successful implementation of AI in SMEs. Similarly, ref. [100] emphasize that in emerging economies, budgetary constraints significantly reduce AI readiness and limit experimentation with new technologies. Ref. [115] identify the upfront costs of infrastructure modernization and integration as deterrents, particularly in traditional sectors such as manufacturing. Moreover, ref. [112] argue that uncertainty about AI's return on investment (ROI) contributes to delayed decision-making, especially when SMEs lack internal strategic foresight or financial risk tolerance. Together, these findings reinforce the need for flexible financing models, government-backed incentives, and phased adoption strategies that reduce the perceived and real financial burden on SMEs.

To mitigate this challenge, SMEs should adopt a combination of financial strategies and risk-minimizing implementation models. These include the following:

A. **Explore Flexible Financing Mechanisms**
SMEs can access external financing options such as public grants, low-interest innovation loans, and tax incentives. Shared-resource models (e.g., AI-as-a-Service or pay-as-you-go platforms) also lower entry costs and reduce upfront capital expenditure.

B. **Implement Pilot Tests to Reduce Risk**
Pilot projects allow SMEs to test AI solutions in limited controlled environments before making full-scale investments. This phased approach provides early evidence of ROI and builds organizational confidence while minimizing financial exposure.

C. Adopt Cloud-Based and Scalable Solutions
Using cloud infrastructure allows SMEs to avoid high infrastructure costs. Pay-per-use models allow businesses to expand computing resources in line with their growth and adoption pace, reducing the need for costly on-premise systems.

D. Foster Public–Private Collaboration
Partnering with governmental agencies, technology vendors, and innovation hubs can open access to subsidies, co-investment schemes, and technical expertise. These alliances reduce the burden of individual investment and create supportive adoption ecosystems.

In summary, overcoming financial limitations requires SMEs to adopt strategic funding approaches, reduce upfront risks through pilots, and leverage scalable, low-cost technological infrastructures. Collaborative ecosystems further amplify these efforts, making AI adoption more viable, sustainable, and aligned with organizational capacity.

5.4. Ensuring Data Availability, Quality, and Governance for AI Success

This subsection addresses one of the most critical technological challenges in AI adoption for SMEs: the lack of sufficient, high-quality, and well-integrated data. Within the technological dimension of the TOE framework, data is a foundational input to develop and deploy effective AI systems. However, many SMEs face limitations in data availability, integration, and governance that compromise AI performance, reliability, and ethical use.

As highlighted by [112], inadequate data infrastructures and fragmented legacy systems are the key technological barriers for SMEs to implement AI. Ref. [115] emphasize that poor data standardization and lack of interoperability often delay the development and decision-making of AI models. Furthermore, ref. [119] argue that without access to robust and well-governed data streams, SMEs cannot benefit from generative AI tools or real-time analytics. From a governance perspective, ref. [67] underscore that data quality and transparency are not only technical requirements but also ethical imperatives to ensure responsible AI results, especially in environments with increasing regulatory scrutiny. Taken together, these findings suggest that SME AI readiness must be rooted in comprehensive data strategies, including collection, cleaning, integration, and governance protocols.

To overcome this challenge, SMEs should adopt a strategic approach built around five interrelated actions:

A. Establish Robust Data Collection Systems
Identify key internal and external data sources and implement continuous real-time data collection mechanisms. This improves the quantity and relevance of the data for model training and decision-making.

B. Improve Data Quality through Cleaning and Validation
Invest in systematic data cleaning processes, removing duplicates, correcting errors, and filling gaps, to ensure the integrity and usability of datasets. High-quality data are essential to generate accurate and reliable AI output.

C. Facilitate Data Integration across Systems
Use APIs and cloud platforms to unify data from disparate systems, including legacy platforms. Integrated data ecosystems prevent information silos and support scalable AI solutions that align with firm operations.

D. Leverage Data Enrichment and Analytics Tools
Apply data mining, augmentation, and visualization tools to expand the scope and depth of available data. This enhances the insight generation capacity of AI models and supports more informed business decisions.

E. Implement Strong Data Governance Practices
Define and enforce policies on data access, privacy, storage, and compliance. Align

governance with national and international regulations (e.g., GDPR) to ensure ethical, transparent, and secure data usage.

In summary, SMEs must view data not only as a technical requirement but also as a strategic asset. By building structured data pipelines, improving quality, enabling integration, and ensuring governance, SMEs can significantly enhance their AI readiness and secure long-term value from AI adoption.

5.5. Building Future-Ready Infrastructure and Integration Pathways

This subsection addresses the technological infrastructure and system compatibility barriers that fall under the technological dimension of the TOE framework. Many SMEs struggle with legacy systems, fragmented digital architectures, and limited capacity to adopt AI solutions that require modern, scalable environments. These limitations hinder seamless integration and the long-term scalability of AI initiatives.

Ref. [112] identify infrastructure limitations and interoperability as the main inhibitors of AI adoption among SMEs. Ref. [97] similarly emphasize technological readiness, including updated IT infrastructure, as a foundational component under the TOE framework. From a regional lens, ref. [27] show that infrastructure and cloud availability significantly impact AI adoption in European SMEs. In emerging economies such as India, ref. [28] highlight the unstable internet and low cloud penetration as key infrastructure bottlenecks. Sector-specific studies, such as ref. [115], confirm that fragmented legacy systems are particularly acute in manufacturing and retail SMEs.

To address these gaps, shared infrastructure models, such as public-private AI computation centers and cloud-based integration platforms, have been proposed as cost-effective and scalable solutions [119]. These platforms offer SMEs flexible access to advanced AI capabilities without requiring extensive capital investments in on-premise infrastructure.

To overcome this challenge, SMEs should focus on building flexible and modular infrastructures that support interoperability, gradual deployment, and external collaboration. The following strategies are recommended:

- **A. Adopt Cloud-Based AI Platforms** Leverage scalable cloud infrastructure to reduce initial investment and ensure on-demand access to computing resources.
- **B. Collaborate with Public–Private AI Centers** Partner with national or regional AI innovation hubs to access shared infrastructure, expert support and high-performance computing tools.
- **C. Use APIs for System Interoperability**
  Deploy APIs to bridge legacy systems and new AI tools, allowing SMEs to avoid full system overhauls while improving compatibility.
- **D. Invest in Modular Digital Infrastructure**
  Design infrastructure upgrades in modular phases to support future AI applications without disrupting current operations.

In summary, investing in future-ready and interoperable digital infrastructure is essential for SMEs to unlock the full potential of AI and ensure long-term scalability and integration success.

5.6. Cultivating an Innovation-Driven Culture to Support AI Adoption

This subsection addresses the cultural and organizational barriers to AI adoption within SMEs, falling under the organizational dimension of the TOE framework. A major challenge in this context is the resistance to change that can emerge from rigid hierarchies, limited exposure to digital tools, and fear of job displacement, factors that slow or prevent AI adoption. As noted in [112], cultural inertia and lack of digital maturity are among the most persistent organizational challenges that impede the diffusion of AI in small companies. In support, refs. [3,97] emphasize that fostering innovation-driven environments, supported by leadership and strategic alignment, is essential for SMEs to realize the full benefits of AI integration.

Regionally, ref. [27] show that in the European context, a lack of innovation culture and slow organizational learning are key inhibitors of AI readiness in SMEs. Similarly, in Saudi Arabia, ref. [29] highlight that resistance to change and low managerial awareness are major barriers to technology assimilation. In India, ref. [28] find that weak organizational openness and conservative leadership styles contribute to reluctance to experimentation and AI learning. These findings underscore the need for inclusive leadership-driven innovation cultures that empower employees to participate in digital transformation.

To foster a culture that embraces innovation and technological transformation, SMEs must create conditions that promote experimentation, collaboration, and inclusive participation. The following strategies can help build such a culture:

A. **Promote an Innovation Mindset Internally**
Encourage creativity, openness to new ideas, and willingness to experiment. Support innovation champions within the organization and reward proactive behavior that contributes to digital initiatives.

B. **Implement AI through Gradual, Pilot-Driven Approaches**
Use small-scale pilot projects to introduce AI incrementally, allowing employees to gain confidence, understand its value and see its alignment with long-term goals without overwhelming disruption.

C. **Create Internal Spaces for Learning and Experimentation**
Establish safe environments for trial-and-error, where staff can test ideas and learn new tools without fear of failure. This fosters continuous learning and reduces resistance to change.

D. **Encourage Open Innovation and External Collaboration**
Engage employees, clients, partners, and external experts in co-creation. Opening innovation processes to diverse stakeholders increases idea generation and fosters a sense of shared ownership over change.

E. **Lead Change Management with Transparency and Inclusion**
Clearly communicate the purpose, benefits, and implications of AI adoption. Address concerns directly, involve staff in solution design, and promote social responsibility along with economic efficiency.

In summary, cultivating an innovation-driven culture is essential to overcome internal resistance and ensure that AI adoption is embraced throughout the organization. By promoting creativity, collaboration, and inclusivity, along with transparent change management, SMEs can align technological transformation with the engagement of human capital and long-term organizational resilience.

5.7. Enhancing Human–AI Collaboration to Improve Organizational Productivity

This subsection addresses productivity-related challenges under the organizational dimension of the TOE framework. In a highly competitive and dynamic environment, SMEs must take advantage of AI to increase productivity without compromising employment or organizational cohesion. However, many businesses face the dilemma of choosing between automation, which can displace workers, and augmentation, which aims to improve human capabilities through technology.

Augmentation offers a strategic path forward. As argued by [92], AI-driven increase leads to productivity growth by allowing machines to complement—rather than replace—human labor. Unlike automation, which focuses on full task substitution, augmentation emphasizes synergy: machines contribute processing and scale, while humans provide judgment, creativity, and contextual understanding.

The concept of **co-intelligence**, introduced by [120], reinforces this model. Co-intelligence is based on active collaboration between humans and machines, where tasks are divided to capitalize on the respective strengths of each. This collaborative approach empowers employees to remain central in decision-making while leveraging AI to improve speed and accuracy.

Recent empirical findings support this approach. Ref. [97] emphasize the need for human-centered strategies in the adoption of AI in small businesses, advocating for the upgrading of the workforce and the integration of collaborative technologies to drive sustainable performance. Furthermore, ref. [112] identify employee participation and capability development as central to successful adoption of AI in SMEs, confirming that augmentation, rather than full automation, offers a more sustainable and inclusive productivity strategy.

Other human–AI models, such as the **Centaur** and **Cyborg** metaphors, further illustrate augmentation [120]:

- **Centaur teams** represent human–machine pairings that jointly perform tasks to outperform either work alone.
- **Cyborg workers** use embedded or connected AI systems to amplify their own capabilities in real-time, increasing performance and adaptability.

These paradigms support the idea that AI should not replace people, but rather enhance human performance, innovation, and satisfaction.

Actionable Strategies to adopt an augmentation-focused approach include:

A. **Design AI systems that complement—not replace—human roles**
Focus on tools that support decision-making, improve accuracy, or automate repetitive tasks while leaving critical thinking and judgment to employees.
B. **Invest in employee upskilling for AI collaboration**
Provide training on how to work effectively with AI tools and interpret AI-generated outputs to empower employees in augmented workflows.
C. **Promote a co-intelligence mindset across the organization**
Encourage leadership and teams to frame AI not as a substitute, but as a partner in productivity and innovation.
D. **Experiment with augmentation models such as Centaur and Cyborg approaches**
Pilot use cases where human–AI synergy can be observed, measured, and refined, especially in customer service, product development, or strategic planning.

In summary, shifting from automation to augmentation enables SMEs to improve productivity in a more inclusive and sustainable manner. By fostering human–AI collaboration, SMEs can protect jobs, increase engagement, and position themselves for long-term competitive advantage in the digital economy.

As the internal capabilities of SMEs mature, additional challenges emerge at the interface between the organization and its external ecosystem—particularly in the areas of public–private collaboration, generative AI integration, and responsible governance.

5.8. Strengthening Public–Private Collaboration to Support AI Adoption

This subsection addresses the challenge of insufficient public–private collaboration, situated within the environmental dimension of the TOE framework. Despite growing interest in AI, small companies often lack access to well-structured and inclusive ecosystems that connect them to public institutions, tech providers, and knowledge centers. This disconnect can hinder the diffusion of AI knowledge, tools, and funding, especially in regions where digital infrastructure and innovation policies are underdeveloped. As [97] highlights, government incentives, cross-sector alliances, and institutional frameworks are critical enablers to overcome environmental barriers to AI adoption. Their findings reinforce the need for coordinated action between governments, academia and industry to bridge the resource and knowledge gaps facing SMEs.

To overcome this barrier, a multi-stakeholder approach is needed to build a supportive environment where SMEs can access the expertise, infrastructure, and capital required for sustainable AI adoption.

Key strategies to strengthen public–private collaboration include the following:

A. **Develop Inclusive Innovation Ecosystems**
Foster structured partnerships among governments, technology providers, universities, and research centers. These ecosystems should offer shared resources, such as cloud access, computing infrastructure, training programs, and co-investment platforms.

B. **Establish Collaborative Spaces for SMEs and Tech Stakeholders**
Create physical and virtual environments, such as AI hubs, open innovation labs and online platforms, where SMEs can co-develop AI solutions, share experiences, and get advice from technical experts and researchers.

C. **Implement Tailored Financial Incentives**
Design public funding mechanisms such as grants, tax credits, and subsidized loans specifically targeted at SMEs seeking AI adoption. Encourage private sector co-financing through equity partnerships or innovation vouchers.

D. **Promote Knowledge Exchange and Joint Capacity Building**
Launch joint research initiatives, AI-focused training programs, and cross-sector mentorships that connect SMEs with academic and corporate expertise. These initiatives can reduce skill gaps and accelerate learning.

E. **Introduce Adaptive and Innovation-Friendly Regulation**
Simplify regulatory procedures and promote standards that support experimentation and reduce compliance burdens. This fosters a more agile environment for testing and adopting AI technologies.

In summary, public–private collaboration is a critical enabler of AI adoption in SMEs, yet current efforts often lack structure, accessibility, and strategic alignment. By building integrated, resource-rich ecosystems supported by financial incentives, shared knowledge, and flexible regulation, stakeholders can unlock the full potential of AI for SMEs and drive inclusive innovation at scale.

5.9. Strategically Leveraging Generative AI to Democratize Capabilities and Drive Innovation: Toward Open-Weight LLM Adoption

This subsection addresses the dual challenge and transformative opportunity of strategically integrating generative artificial intelligence (Gen-AI) into SME operations. Located within both the technological and organizational dimensions of the TOE framework, this challenge concerns not only access to cutting-edge tools but also the strategic alignment, governance, and scalability of those tools within SME contexts.

Gen-AI is revolutionizing access to intelligent automation, enabling SMEs to perform tasks previously reserved for large enterprises. As demonstrated by [119], tools such as Microsoft Copilot, Jasper, and Canva allow smaller firms to automate content creation, enhance customer interaction, and support strategic planning—all with minimal infrastructure and low financial barriers. These tools democratize innovation, allowing SMEs to overcome longstanding resource constraints. Similarly, ref. [3] emphasize the role of Gen-AI as a driver of transformation of the business model and alignment of sustainability.

Recent developments in the AI industry have also increased deployment flexibility—crucial for SMEs. Although many begin by accessing Gen-AI via third-party APIs (e.g., OpenAI or Google Cloud), some eventually require full control over infrastructure for cost, compliance, or customization reasons. As adoption matures, SMEs may seek to host models on private cloud instances or even on-premise servers.

The rapid emergence of high-performing open-weight LLMs, such as LLama, DeepSeek-R1, Mistral, or Falcon families, is reshaping the landscape of AI adoption. These models now offer small businesses a viable alternative to closed systems, matching proprietary performance while providing greater transparency, adaptability, control, and sustainability [121]. Open-weight models empower SMEs to fine-tune and deploy AI tools aligned with their infrastructure, compliance, and budgetary needs, making them particularly attractive for long-term integration.

However, many SMEs continue to adopt Gen-AI in fragmented or exploratory ways, without embedding it into core strategic processes or innovation pipelines. Organizational readiness, ethical concerns, and the lack of digital governance practices often result in under-utilization and operational misalignment.

To unlock Gen-AI's full potential, SMEs should adopt a structured and intentional approach. The following actions are recommended:

A. **Adopt Accessible, Low-Code Gen-AI Platforms**
Begin with intuitive, commercially available Gen-AI tools that support content creation, communication, ideation, and task automation. Low-code platforms such as `Jasper`, `Notion AI`, `Copy.ai`, `ChatGPT`, and `Canva Magic Write` offer SMEs immediate entry points to experiment with AI without needing specialized technical skills. These tools require minimal onboarding, typically follow a free-mium pricing model, and can be embedded into existing workflows.

B. **Enhance Workforce Capabilities through Augmentation**
Use Gen-AI to augment, not replace, human capabilities. Empower employees across departments (for example, marketing, customer service, R&D) to harness Gen-AI to write reports, generate insights, answer internal queries, or accelerate ideation. This augmentation model reinforces a *co-intelligence approach* where AI assists, but human judgment remains central.
To accelerate adoption, SMEs can introduce 'AI pilots' within departments to pilot tools and coach others. Platforms such as `ChatGPT` for Business, `Microsoft Copilot`, or `Google Workspace AI` integrate directly with standard office software, making the augmentation process seamless. In parallel, free and paid learning modules on platforms such as LinkedIn Learning, Coursera, or Google's AI Academy help build internal capability.

C. **Align Gen-AI with Strategic and Innovation Goals**
Integrate Gen-AI into broader strategic planning and innovation processes. Rather than treating AI as a side experiment, SMEs should embed Gen-AI into their OKRs (Objectives and Key Results), innovation roadmaps, and performance KPIs. Use cases may include trend analysis, scenario simulation, customer journey visualization, and stakeholder communication support.
For example, SMEs can use Gen-AI to draft strategic memos, synthesize competitor reports, or explore "what-if" analyses related to product launches or market entry. Alignment with strategic goals ensures that AI investments are not just technically sound, but also business-relevant. Decision support functions such as executive briefings, sales forecasting, or risk scenario modeling are particularly impactful.

D. **Leverage Small Open-Weight LLMs for Flexible and Scalable Deployment**
For SMEs with intermediate or advanced digital maturity, small open-weight LLMs

(e.g., `Mistral-7B`, `LLaMA 3`, `DeepSeek-R1`, `Phi-2`) present an attractive alternative to API-based tools. These models offer higher transparency, control over fine-tuning, and deployment cost-efficiency—particularly relevant for privacy-sensitive industries or firms with unique use cases.
Modular deployments can begin in containerized environments using tools such as `Docker`, `Kubernetes`, and libraries such as `Hugging Face Transformers`, `LangChain`, or `vLLM`. These support inference at the edge or on affordable GPU cloud services (e.g., `Paperspace`, `RunPod`, or `Replicate`).
SMEs can gradually scale from local pilots to fully integrated Gen-AI pipelines, ensuring that each step aligns with internal governance, data sovereignty, and customization needs. Use cases such as internal knowledge bases, structured summarization, or semantic search are ideal starting points for in-house LLM hosting.

E. **Accessible Catalog of Practical Applications: A Strategic Ecosystem Imperative**
SMEs would benefit significantly from access to a curated and regularly updated catalog of Generative AI applications, particularly those based on LLMs, that showcase real-world use cases and documented productivity improvements. Such a catalog should include sector-specific and cross-functional case studies, benchmarks, deployment guides, and integration templates—providing SMEs with actionable insights on how GenAI can enhance efficiency, reduce costs, and unlock new forms of innovation.
At present, no widely recognized repository exists that systematically compiles and contextualizes successful GenAI applications tailored for SMEs. This absence creates a significant barrier, as many SMEs lack the internal capacity to explore the breadth of AI solutions or to translate abstract capabilities into operational use cases. A well-designed catalog would act as a practical bridge—demystifying AI by showing how similar-sized firms have applied it for marketing automation, customer support, internal documentation, compliance analysis, or knowledge management.
Establishing and maintaining such a catalog should be viewed as an ecosystem-level priority for policy actors, industry alliances, and AI providers. Without this, SMEs will continue to face limited access to replicable adoption pathways—hampering both innovation scalability and cross-sector learning.
Illustrative Case Example: A mid-sized logistics SME in Spain integrated Mistral-7B via Hugging Face and FastAPI to automate client email summarization and route planning queries. This reduced human workload by approximately 40% and achieved a 12% increase in customer satisfaction within six weeks. Hosting was implemented through a GPU instance on Paperspace, reducing infrastructure costs by 35% compared to equivalent proprietary API services.
As needs evolve, transitioning to open-weight LLMs [122], such as DeepSeek-R1, LLaMA, Mistral, or Falcon, offers SMEs greater autonomy and transparency. These models allow for self-hosting, fine-tuning, or deployment on private infrastructure, making them suitable for SMEs operating under strict compliance, cost, or customization requirements. This flexibility enables more sustainable, ethically guided, and strategically aligned AI adoption.

F. **Scale Strategically from Pilots to Core Functions**
Begin with low-risk, high-frequency use cases—such as drafting marketing copy, summarizing meeting notes, automating internal documentation, or creating customer FAQs—where Gen-AI can deliver immediate efficiency gains with minimal risk. These entry points allow SMEs to experiment with generative technologies, build organizational confidence, and fine-tune deployment practices in a contained environment.
As internal trust and technical familiarity increase, expand AI applications to more complex and value-adding business functions, including customer service automation

(e.g., chatbot integration), sales intelligence, supply chain prediction, or even product design ideation. Each expansion phase should be guided by clearly defined success metrics (e.g., response time reduction, conversion uplift, error rate minimization) and paired with stakeholder feedback loops.

Strategic scaling requires a governance layer that ensures alignment with business priorities, ethical safeguards, and compliance constraints. This may involve forming an internal AI task force, defining data usage policies, and setting thresholds for human-in-the-loop oversight.

Example Pathway:

- *Phase 1—Exploration:* Deploy Gen-AI for internal document drafting and idea generation.
- *Phase 2—Operational Integration:* Extend Gen-AI to handle customer emails, generate marketing briefs, or automate routine analysis.
- *Phase 3—Strategic Embedding:* Integrate Gen-AI into CRM systems, product development workflows, or knowledge management platforms.

A phased, feedback-driven rollout mitigates risk, nurtures AI maturity across the organization, and enables SMEs to evolve from exploratory use to strategic integration—maximizing return on investment and long-term competitiveness.

G. Addressing Practical Integration and Mitigation of LLM Risks

While open-weight LLMs offer SMEs greater autonomy, transparency, and cost control compared to closed platforms, their deployment introduces non-trivial risks that must be strategically managed. Common technical challenges include prompt injection attacks, model hallucination (i.e., generation of false or misleading outputs), and the propagation of encoded biases. These risks are further compounded by SMEs' typically limited in-house AI expertise and constrained cybersecurity budgets.

In practice, SMEs must weigh the flexibility of self-hosting against the operational overhead it entails—such as provisioning GPU-based infrastructure, managing version control, ensuring uptime, and enforcing data security protocols. Without sufficient safeguards, improperly configured LLMs can produce unreliable results or expose sensitive business data to unintended uses.

Recommended Mitigations and Integration Strategies:

- **Lightweight Guardrails:** Implement tools for content moderation, such as prompt sanitization, response length limits, and input validation layers. Libraries such as `Guardrails.ai`, `LangChain safety chains`, or `Rebuff` offer plug-and-play solutions to mitigate harmful output and misuse.
- **Use of Containerized Frameworks:** Leverage containerized deployments (e.g., Docker with Hugging Face Transformers + FastAPI) to simplify integration and enforce isolation. This reduces the complexity of managing dependencies and accelerates reproducibility.
- **Monitoring and Feedback Loops:** Incorporate human-in-the-loop (HITL) oversight for critical tasks and establish monitoring tools (e.g., logging, real-time review dashboards) to capture hallucination incidents or drift in model behavior over time.
- **Shared Maintenance Communities:** Rely on open communities and maintained libraries (e.g., `OpenLLM`, `LLMGuard`, or Hugging Face Model Hub) that offer security patches, pretrained safety layers, and updated weights. These ecosystems provide a valuable lifeline for SMEs without dedicated AI teams.
- **Prioritized Use Cases:** Limit LLM deployment to high-ROI, low-risk applications—such as internal knowledge search, summarization, and document generation—before expanding to customer-facing or compliance-critical contexts.

– **Ethical and Compliance Guidelines:** Develop internal guidelines addressing transparency, data provenance, and consent in GenAI applications. These should reflect emerging standards (e.g., EU AI Act (https://artificialintelligenceact.eu/, accessed on 12 May 2025), ISO/IEC 42001 (https://www.iso.org/standard/81230.html, accessed on 12 May 2025)) and foster a culture of responsible use.

Ultimately, adopting open-weight LLMs is not merely a technical decision but a governance challenge. For SMEs, combining lightweight safety protocols with community-supported tooling and a clear risk assessment process is essential to avoid harm, preserve trust, and build sustainable AI capabilities.

H. Establish Ethical Governance and Usage Guidelines

Introduce lightweight but effective ethical governance structures tailored to the size and capabilities of SMEs. These frameworks should include principles of transparency, fairness, accountability, and security in the use of Generative AI (Gen-AI), particularly large language models (LLMs). Clear documentation of how Gen-AI tools are used internally (e.g., for content creation or decision support) and externally (e.g., customer interactions) helps build trust with employees, clients, and regulatory bodies.

Transparency guidelines should ensure that Gen-AI-generated content is identifiable, especially in customer-facing contexts. This includes labeling AI-generated responses or content to avoid misleading stakeholders. Bias mitigation practices must be implemented to reduce the risk of replicating harmful stereotypes or skewed outputs in automated content. This can be achieved using prompt calibration, fairness-aware fine-tuning, and output filtering tools.

SMEs should also establish internal policies outlining appropriate use cases, limitations of Gen-AI tools, employee responsibilities, and data protection protocols. These policies should align with emerging legal frameworks such as the EU AI Act or ISO/IEC 42001, ensuring compliance with data privacy, accountability, and algorithmic impact assessment norms.

To promote accountability, SMEs can assign a responsible AI lead or committee—even if informally composed—who periodically reviews Gen-AI use, tracks incidents (e.g., hallucinations, misuse), and updates governance practices as technologies evolve. Training staff on these principles reinforces an ethical culture and reduces misuse risk.

Ultimately, ethical governance is not an overhead but a strategic enabler—providing guardrails that reduce legal exposure, foster user confidence, and ensure Gen-AI serves as a sustainable and trusted innovation driver.

In summary, strategically integrating Generative AI—particularly open-weight large language models—offers SMEs an unprecedented opportunity to enhance productivity, foster innovation, and democratize advanced digital capabilities. However, realizing this potential requires more than access to technology: it demands a structured, risk-aware, and goal-aligned adoption approach. SMEs must evolve from ad-hoc experimentation to intentional, phased deployment—supported by curated application catalogs, workforce augmentation, modular infrastructures, and robust governance practices.

The growing availability of customizable, open-source models such as DeepSeek-R1, Mistral, and LLaMA gives SMEs the flexibility to deploy AI solutions aligned with their compliance needs, budget constraints, and operational contexts. Yet, this flexibility also introduces new risks—ranging from hallucination and bias to infrastructure and security overhead. Addressing these challenges calls for lightweight safety layers, ethical guidelines, community-supported tooling, and ecosystem-wide support to bridge capability gaps.

Ultimately, Gen-AI adoption in SMEs is not simply a technical transformation—it is a strategic shift that must be embedded in core processes, guided by ethical governance, and reinforced through real-world use cases. The path forward is not to scale Gen-AI rapidly, but to scale it wisely—anchored in usability, accountability, and long-term value creation.

5.10. Embedding Responsible AI Practices and Human-Centered Governance

This subsection addresses the growing challenge of embedding responsible AI practices into SME operations—an issue increasingly critical within the organizational and environmental dimensions of the TOE framework. As regulatory frameworks evolve and stakeholder expectations increase, AI adoption must go beyond technical performance to uphold principles such as fairness, transparency, accountability, and inclusion [67].

Recent studies emphasize that most SMEs lack the internal structures, awareness, or ability to apply these principles consistently [67,112]. AI is often adopted reactively or without ethical safeguards, creating risks related to compliance, trust, and long-term value alignment. Ref. [67] recommend lightweight but effective governance mechanisms that SMEs can implement to ensure ethical deployment. These include risk assessment protocols, explainability practices, and stakeholder engagement strategies - all of which are essential to align Gen-AI tools with broader business and social values.

This governance gap exposes SMEs to reputational, operational, and compliance risks, especially as governments introduce AI-specific regulations and consumers increasingly demand ethical and transparent digital practices.

Therefore, responsible adoption of AI should not be seen as a barrier, but as a strategic enabler of trust, innovation, and market legitimacy in the evolving digital economy.

To foster responsible and human-centered AI in SMEs, the following practices are recommended:

A. **Integrate Ethical Considerations into AI Planning**
Begin AI projects with structured reflection on potential impacts, such as bias, discrimination, or data misuse. Embed human rights principles into AI decision-making from the outset, even in pilot projects.

B. **Establish Lightweight Governance Structures**
While SMEs may lack formal ethics boards, simple mechanisms, such as designating an AI responsibility lead or incorporating stakeholder reviews, can support ethical oversight and build internal accountability.

C. **Promote Transparency and Explainability**
Ensure that AI-generated outputs (e.g., decisions, recommendations) are explainable to nontechnical users and customers. Use interfaces that allow humans to override, question, or validate AI suggestions.

D. **Strengthen Data Protection and Consent Protocols**
Adhere to national and international data privacy laws. Where possible, ensure that AI systems use consent-based anonymized data and that data handling policies are clearly communicated.

E. **Engage Stakeholders in Responsible Innovation**
Involve employees, users, and partners in discussions about AI risks, values, and priorities. This participatory approach fosters shared responsibility and aligns AI solutions with organizational values.

In summary, SMEs must view responsible AI as a core component of digital transformation, not an afterthought. By embedding ethical awareness, lightweight governance, and transparent practices into their AI journey, SMEs can improve trust, ensure regulatory compliance, and futureproof their innovation strategies.

5.11. Mapping AI Adoption Challenges and Solutions Within the TOE Framework

To consolidate the ten challenges and corresponding strategies presented in this section, this final subsection offers a challenge mapping matrix across the three dimensions of the TOE framework. Technological, Organizational, and Environmental.

This matrix (Table 4) aims to provide a practical synthesis for policymakers, SME leaders, and researchers by identifying where barriers occur and which levers are most effective to mitigate them. It reinforces the core thesis that AI adoption in SMEs is not a purely technical endeavor, but a multidimensional process that intersects technology readiness, internal capabilities, leadership, culture, and external institutional support.

By visualizing this mapping, we also highlight the systemic and interdependent nature of AI adoption: Each solution does not operate in isolation, but contributes to enabling success across dimensions. This integrated view is also consistent with the hybrid TOE–DOI framework adopted in this study.

Table 4. TOE framework: mapping AI adoption challenges and actionable pathways in SMEs.

TOE Dimension	Challenge	Key Actionable Solutions
Technological	Lack of data quality and access	Data governance, real-time data collection, cleaning, integration with APIs
	Infrastructure and system misalignment	Cloud platforms, modular architectures, public–private AI centers
	Scalability and complexity of AI tools	Modular deployment, agile methodology, scalable cloud services
	Generative AI underutilization and lack of strategic alignment	Low-code Gen-AI tools,toward open-weight LLM adoption augmentation use cases, phased integration, innovation alignment
Organizational	Skills shortage and knowledge gap	Internal training, external partnerships, accessible platforms, open innovation
	Cultural resistance and lack of innovation mindset	Pilot projects, transparent leadership, learning environments, inclusive change management
	Lack of structured methodology for AI adoption	Six-phase roadmap/methodology: assess, define strategy, select tools, pilot, train, monitor
	Financial resource constraints	Flexible financing, pilot-based risk management, public incentives, cloud services
	Human–AI misalignment in productivity goals Augmentation-focused adoption, co-intelligence models, upskilling, role redefinition	
	Limited responsible AI governance and ethical practices	Lightweight AI ethics protocols, transparency, employee awareness, stakeholder inclusion
Environmental	Limited public–private collaboration and policy support	Innovation ecosystems, collaborative hubs, AI grants, capacity-building programs

6. Structured Pimary Methodology for Effective AI Adoption in SMEs

This section introduce a primary roadmap structured methodology for effective AI Adoption as a way of stages and key activities. It addresses the organizational challenge of lacking a clear methodology for AI adoption, a barrier within the organizational dimension of the TOE framework. Many SMEs begin the adoption of AI without a structured approach, leading to fragmented efforts, inefficient resource allocation, and misalignment between business objectives and AI capabilities.

We propose an initial structured methodology designed to guide SMEs through effective AI adoption, as a formal step-by-step approach to reduce risk, manage change and ensure strategic coherence. Without such a roadmap, SMEs can underestimate the complexity of AI integration, resulting in slow adoption, failed projects, or wasted investment.

Actionable strategies to build a methodology-driven approach include the following six steps:

1. **Conduct a Comprehensive Readiness Assessment**
   Evaluate the organizational technological infrastructure, digital maturity, workforce competencies, leadership alignment, and financial capacity to establish a realistic starting point for AI adoption.
2. **Define Strategic Objectives and Use Cases**
   Set measurable AI-related goals related to business priorities, such as improving efficiency, improving customer experience, or enabling data-driven decisions.
3. **Select Appropriate AI Solutions and Deployment Models**
   Choose between off-the-shelf, customized, or cloud-based AI tools based on internal needs, available resources, and scalability requirements.
4. **Implement in Phases with Pilot Projects** Begin with small-scale pilots to validate the feasibility and value of AI, make necessary adjustments and build internal trust and capacity before greater deployment.
5. **Integrate Training and Change Management**
   Ensure ongoing staff training and transparent communication to address resistance, clarify roles and reinforce the value of AI as an enhancement tool.
6. **Measure, Adjust, and Scale Strategically**
   Establish key performance indicators (KPI) to track progress. Use insights from early phases to iterate and scale AI solutions in broader operations.

Table 5 summarizes this methodology in six actionable phases, offering a practical guide to align technological adoption with organizational and strategic readiness. While this represents an initial framework, future research can refine it into diagnostic and maturity-assessment tools.

Table 5. AI adoption methodology for SMEs: phases and key activities.

Phase	Key Activities
1. Current State Assessment	Evaluate technological infrastructure, workforce competencies, leadership alignment, digital maturity, and financial capacity. Identify strengths, weaknesses, and readiness for AI adoption.
2. Strategic Objectives	Define clear, measurable business goals for AI adoption, ensuring alignment with overarching business priorities such as efficiency, customer experience, and data-driven decision-making.
3. AI Solution Selection	Choose appropriate AI tools and deployment models (custom vs. off-the-shelf; cloud-based vs. on-premise) based on business needs, available resources, and scalability requirements.
4. Pilot Project Implementation	Conduct small-scale pilot projects to validate AI solutions, assess feasibility, and build internal trust before full-scale implementation.
5. Training and Change Management	Provide ongoing employee training to enhance AI-related skills. Implement change management practices to address resistance, align roles, and emphasize AI's role in augmenting human capabilities.
6. Measurement and Scaling	Establish key performance indicators (KPIs) to evaluate AI impact. Use insights from pilot phases to refine strategies and scale AI solutions across broader organizational functions.

Figure 2 visually complements Table 5 by illustrating the phased AI adoption methodology tailored for SMEs. Each stage—ranging from readiness assessment to full-scale deployment—maps directly to the structured process outlined in the table. The diagram highlights the logical flow of activities, key decision points, and feedback loops, offering a coherent blueprint for aligning AI implementation with technological, organizational, and strategic priorities. This visual synthesis reinforces the structured and iterative nature of AI adoption and supports SME leaders in navigating complexity with clear, actionable steps.

Figure 2. AI Adoption primary methodology for SMEs.

In summary, developing a structured and phased methodology is fundamental for SMEs to adopt AI effectively. A systematic approach ensures organizational alignment, minimizes risk, and allows sustainable scaling, transforming AI from a conceptual ambition into an operational and strategic advantage.

It is important to emphasize that the roadmap AI adoption based methodology proposed in this section represents a primary conceptual framework derived from the synthesis of the literature rather than original empirical data (e.g., interviews or questionnaires for small businesses). As such, it serves as a structured starting point for guiding SMEs through AI adoption but requires empirical validation to test its applicability, robustness, and adaptability in real-world contexts. Future research should focus on operationalizing this roadmap through field studies, participatory design workshops, and comparative case analyzes to refine its stages, define maturity metrics, and assess its effectiveness across sectors and geographies. Although outside the scope of this article, this validation is critical to transform this initial framework into a reliable decision support and diagnostic tool tailored to the practical needs and constraints of SMEs.

7. Discussion: Lessons Learned, Limitations, and Future Research Directions

A statement that captures the core of this discussion is as follows.

> "AI adoption is no longer optional for SMEs; it has become a strategic lever for transformation and a core requirement to remain competitive in a digital and increasingly regulated marketplace."

This section consolidates the theoretical and practical insights derived from the challenge–solution framework presented throughout the study. It is organized into two parts.

First, the Section 7.1 synthesizes the key takeaways from the ten AI adoption challenges identified, providing guidance to SMEs, policymakers, and researchers through the lens of the TOE–DOI framework. These insights are intended to support SMEs in adopting AI not only as a technological upgrade, but also as a core enabler of strategic transformation.

Second, the Section 7.2 critically reflects on the methodological scope and context dependence of the findings. It highlights areas requiring further empirical validation and proposes research pathways to enhance the generalizability and operational relevance of the model, particularly in light of emerging technologies such as generative AI and evolving global AI governance frameworks.

7.1. Lessons Learned

Building on the analysis of adoption barriers and implementation strategies, this section presents ten key lessons for SMEs, policymakers, and researchers, structured around the TOE–DOI framework.

1. *AI presents transformative opportunities for SMEs.*
   AI enables automation, smarter decision-making, customer personalization, and new value creation pathways. When aligned with the lean structures and constraints of SMEs, these tools can significantly enhance competitiveness and innovation (TOE: Technological).
2. *Adoption lags due to multi-dimensional barriers.*
   Despite its potential, AI uptake in SMEs remains slow. Challenges include technological complexity, financial constraints, lack of digital culture, and limited external support. The TOE–DOI framework helps identify and address these systematically at the structural and perceptual levels.

3. *Adoption strategies must reflect SME-specific realities.*
   SMEs operate with unique restrictions, limited resources, agile decision-making, and informal structures. Effective adoption of AI requires tailored and scalable approaches sensitive to these characteristics (TOE: Organizational).
4. *AI must be embedded in strategy—not treated as a side project.*
   AI should be part of the firm's core strategic planning, not an isolated technology experiment. This requires long-term vision, structured roadmaps, and alignment of leadership. Our six-phase implementation model offers practical guidance for SMEs to embed AI into their growth strategies (TOE: Organizational + Technological).
5. *Organizational culture is a key enabler.*
   A culture that supports experimentation, learning, and inclusive change management promotes smoother adoption of AI. Overcoming fear and resistance requires leadership to create safe spaces for adaptation (TOE: Organizational).
6. *Talent development and upskilling are essential.*
   Technical and managerial knowledge of AI must be built internally. Upskilling existing staff and reducing dependence on external consultants enhances sustainability and internal capability (TOE: Organizational).
7. *Accessible, modular, and open-weight solutions can democratize adoption.*
   Cloud-based platforms, plug-and-play tools, and open-weight LLMs—such as LLaMA, DeepSeek-R1, Mistral, and Falcon—offer SMEs scalable, transparent, and cost-effective alternatives to proprietary systems. These models support self-hosted, hybrid, or cloud-based deployment, enabling greater control over data, compliance, and customization. By lowering technical and financial barriers, open-weight solutions empower SMEs to adopt AI in ways that align with their strategic goals and operational realities (TOE: Technological + Organizational).
8. *Data quality and governance underpin successful AI.*
   Reliable, accessible, and clean data is the foundation for effective AI. SMEs must invest in data infrastructure, governance protocols, and integration tools such as APIs to ensure actionable insights (TOE: Technological).
9. *Ethical and responsible AI must be integrated from the start.*
   As SMEs adopt powerful AI tools, governance mechanisms around fairness, transparency, and data protection are essential. Lightweight and actionable frameworks can help SMEs ensure trust and compliance (TOE: Organizational + Environmental).
10. *Public-private ecosystems should support SME AI adoption.*
   Collaboration with universities, governments, tech providers and AI computation centers can provide SMEs with access to expertise, infrastructure and financial support, especially in early adoption phases (TOE: Environmental).

These lessons provide a solid roadmap for SMEs to pursue AI not just as a technology trend, but as a strategic enabler for sustainable growth, inclusion, and resilience.

7.2. Limitations and Future Research

Although this study offers a comprehensive and structured framework for understanding AI adoption in SMEs through the TOE–DOI lens, several limitations must be acknowledged.

- First, the proposed challenge mapping matrix (Table 4) is constructed from secondary literature and has not yet been validated through primary data collection or empirical fieldwork.
- Second, the findings are context sensitive and may not generalize uniformly across all industries, regions, or firm sizes, particularly given the rapidly evolving nature of generative AI technologies and regulatory landscapes.

- Third, the framework assumes a relatively linear adoption trajectory, whereas real-world implementation processes are often iterative, adaptive, and path-dependent.

These limitations point to the need for an iterative multi method research agenda that can empirically test, contextualize, and refine the framework across business environments and stages of digital maturity.

Building on the challenge mapping matrix presented in this study, several future research opportunities emerge that can strengthen both theoretical understanding and practical implementation of AI adoption in SMEs.

1. The proposed model would benefit from empirical validation across sectors and geographies. Although the framework is grounded in robust literature, its operationalization should be tested through case studies, surveys, and longitudinal studies. As shown by [123], AI assimilation affects firm performance via dynamic capabilities such as absorptive capacity and customer agility. Future research could explore how these mediators vary between different levels of digital maturity and organizational size.
2. Studies such as [6,13] highlight structural disparities in AI adoption between SMEs and larger enterprises. These include differences in project management integration, support levels, and digital readiness. Comparative analyzes and longitudinal research could uncover which internal or contextual factors allow certain SMEs to overcome common adoption bottlenecks such as infrastructure gaps, talent shortages, and strategic misalignment.
3. Strategic alignment remains an underexplored area. Refs. [115,124] propose structured adoption roadmaps tailored to SMEs, yet these models require broader testing across industries and regions. Future work could examine how such phased approaches perform under varying degrees of resource constraint, leadership involvement, or policy support.
4. Generative AI (Gen-AI) tools represent a transformative opportunity, particularly for smaller firms. However, as noted in [3,119], there is limited empirical data on how SMEs integrate Gen-AI into workflows or innovation cycles. Future studies should investigate adoption pathways, productivity outcomes, and organizational learning processes associated with Gen-AI tools such as ChatGPT, Copilot, or Jasper. Furthermore, exploring how Gen-AI supports sustainability goals, as discussed by [3], could guide AI strategies oriented to climate in SMEs.
5. Implementing ethical and responsible AI remains another urgent area. Ref. [67] calls for lightweight governance models that can be embedded in SMEs with limited regulatory capacity. More research should explore how such models can be institutionalized, including stakeholder engagement practices, explainability protocols, and ethical impact audits, especially in environments with emerging or fragmented regulatory oversight.
6. Technology-wise, infrastructure readiness and integration continue to be critical barriers, as detailed in [97,112]. Future research should address modular, cloud-based, and API-driven architectures that support interoperability and scalability, especially for resource-constrained SMEs in emerging economies.
7. In addition, studies at the policy and ecosystem level could build on and [100], investigating the role of public–private partnerships, national digital strategies, and innovation funding to support the AI adoption journeys of SMEs. Exploring how government interventions affect regional disparities and inclusive innovation will help craft context-specific recommendations for digital policy frameworks.
8. Finally, as proposed by [125], the evolving taxonomy of AI applications in innovation management provides a rich avenue to study how SMEs use AI in innovation of

product, process and business model. Mapping these applications to industry verticals and innovation stages can offer valuable granularity to existing adoption models.

In summary, future research should deepen empirical insights into the strategic, technical, and ethical dimensions of AI in SMEs, aligned with real-world adoption scenarios, and build an evidence-based foundation for inclusive, scalable, and responsible AI transformation guided by the TOE–DOI framework, which offers a robust lens to analyze both structural conditions and perception-driven adoption dynamics. This research agenda should also respond directly to the interrelated challenges of evolution identified in Section 4, validate the proposed solutions, and uncover new patterns of adoption, resistance, and impact in diverse SME environments.

8. Conclusions

This study has argued that for SMEs, adopting AI is no longer optional—it is a critical driver of strategic transformation, innovation, and long-term competitiveness. Although AI offers unprecedented opportunities to automate operations, personalize customer engagement, and improve decision-making, successful implementation requires navigating a complex landscape of technological, organizational, and environmental barriers.

To address this complexity, the paper applied an integrated TOE framework enriched with selected attributes of DOI theory. This combined lens enabled a multidimensional analysis that incorporates both structural conditions and perception-driven adoption dynamics. Eleven key challenges were identified across the TOE dimensions, and each was matched with actionable context-sensitive strategies, ranging from talent development and modular infrastructure design to responsible AI governance and public–private ecosystem support.

In addition to the challenge mapping matrix, the study proposes a six-phase structured roadmap methodology for AI adoption, detailed in Section 6. This methodology addresses the need for a clear, phased approach tailored to SMEs' constraints, guiding firms through readiness assessment, solution selection, piloting, and scaling. Table 5 and Figure 2 provide a visual and practical synthesis of this process. By offering a structured methodology aligned with TOE–DOI dimensions, the paper contributes operational guidance to a domain often dominated by abstract strategy.

The proposed model and primary roadmap are particularly relevant in a fast-evolving environment shaped by the rise of generative AI and emerging regulatory norms. An emerging enabler in this landscape is the rapid development of open-weight high-performance LLMs, such as DeepSeek-R1, Mistral, and Falcon. These models democratize access to advanced AI capabilities by offering SMEs greater transparency, customizability, and control over deployment. Unlike proprietary systems, open-weight LLMs allow for local or cloud-based hosting, fine-tuning, and integration aligned with specific organizational and regulatory contexts—especially critical for SMEs navigating data sensitivity, compliance, and cost constraints.

Although the framework offers strong conceptual and practical relevance, its broader applicability depends on continued empirical validation and contextual refinement. A dedicated limitations-and-future-research agenda have been outlined to align strategic, technical, and ethical insights with real-world implementation contexts. These directions reinforce the need for adaptive, inclusive, and scalable pathways to AI adoption in SMEs.

Ultimately, this paper contributes to the growing body of research focused on enabling small firms to participate meaningfully in the era of digital transformation. It calls for policies, infrastructures, and leadership models that empower SMEs to adopt AI not merely as a tool, but as a strategic enabler of inclusive and sustainable innovation. The central message is clear: In a world defined by accelerating innovation cycles, SMEs that delay AI adoption today may risk irrelevance tomorrow.

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