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Toward open innovation: An integrated model of artificial intelligence adoption in export-oriented textile small and medium-sized enterprises

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Abstract

Export-oriented manufacturing small and medium-sized enterprises (SMEs) in emerging economies are experiencing escalating cost volatility, regulatory unpredictability, and sustainability compliance pressures, all of which are reshaping their digital transformation decisions. Despite the extensive marketing of artificial intelligence (AI) as an innovation driver and source of competitiveness, little evidence exists on the relationship between AI adoption and post-adoption innovation outcomes under crisis situations. This study designs and empirically tests the combined Technology Acceptance Model–Technology–Organization–Environment model to explain AI adoption and its effects on open innovation performance. Green knowledge management (GKM) is examined as the moderating boundary condition. The survey data of 400 export-oriented textile SMEs from Pakistan were analyzed using partial least squares structural equation modeling. The findings indicate that perceived usefulness and perceived ease of use are core predictors of AI adoption, with top management support, resource availability, competitive pressure, and the regulatory environment playing a major role in shaping perceptions. AI adoption is a post-adoption capability that significantly drives open innovation performance, indicating that it can help overcome cost and compliance pressures for collaboration and knowledge sharing. However, GKM does not significantly mediate this relationship, suggesting that resource-poor SMEs still lack strong institutionalization of sustainability knowledge. The research adds to AI adoption theory by introducing and extending perceptual and contextual explanations and shifting the focus to innovation outcomes after adoption. In practice, the findings indicate that while AI can increase innovation resilience in crisis-affected SMEs, sustainable innovation

gains require investments in digital and sustainability expertise, along with data management, that go beyond digitalization for compliance purposes.

Keywords: Artificial intelligence; Artificial intelligence adoption; Open innovation; Technology adoption model; Technology–organization–environment framework; Manufacturing small and medium-sized enterprises

1. Introduction

Textile small and medium-sized enterprises (SMEs) in Pakistan operate amid increasing economic and institutional pressure, where rising production costs coincide with stringent global sustainability and digital compliance demands. The textile industry is the key sector of the national economy; it accounts for almost 60% of exports and approximately 40% of industry jobs (Haq, Suki, *et al.*, 2025). However, the recent increase in exports is more indicative of weakness than of enduring competitiveness, and it is mostly driven by price-sensitive value-added products, followed by a new cycle of volatility (Nasir *et al.*, 2025; Pakistan Bureau of Statistics, 2025; Pakistan Textile Council, 2025). This trend indicates that export resilience remains fragile due to structural weaknesses rather than cyclical shocks.

One key constraint is cost pressures. Average electricity tariffs of 13.2 cents per kilowatt-hour, along with instability in power supply, high interest rates, liquidity shortages, and late refunds, have significantly limited SMEs' operational and investment flexibility (All Pakistan Textile Mills Association [APTMA], 2026; State Bank of Pakistan, 2025). These pressures, which have become major clusters like Faisalabad, have led to production halts and mill closures, forcing firms to focus on short-term survival instead of strategic capacity building (Business Recorder, 2025). In this case, investments in high-tech digital technologies compete directly with basic working capital needs.

At the same time, entry into global markets is becoming more contingent on digital and sustainability compliance. Pakistan, which sells the most products to the European market, the largest export destination, has escalated the implementation of the Green Deal with policies like the Ecodesign for Sustainable Products Regulation and Digital Product Passports, which turns compliance into a data-heavy and technology-intensive issue (APTMA, 2026; Ministry of Commerce, 2025). The future introduction of the Carbon Border Adjustment Mechanism for textiles also threatens Pakistan's price-based competitiveness, strengthening the link between digital capability, sustainability performance, and export survival (EcoTextile

News, 2026). For textile SMEs, compliance is no longer optional; it is part of doing business.

Additionally, less than 1/5 of all textile SMEs have formal digital training or formal technology plans, and the use of artificial intelligence (AI) is concentrated in a small number of early adopters (Small and Medium Enterprises Development Authority [SMEDA], 2025). Where implemented, AI applications such as automated inspection and energy monitoring have delivered modest improvements in operational efficiency and waste reduction (Haq, Asim, *et al.*, 2025). Nonetheless, scaling these technologies remains challenging because of high capital investment requirements, limited technical expertise, fragmented infrastructure, and inadequate data management (Nasir *et al.*, 2025; Zahra *et al.*, 2025). The strategic value of AI is becoming more evident, but the organizational and institutional capacity to capitalize on it is limited.

Financial constraints, limited knowledge, inadequate infrastructure, policy uncertainty, and competitive pressure have consistently been cited as restrictions to research in developing nations, while policy conditions and competition have been cited as drivers of research adoption (Akpan *et al.*, 2022; Hiremath *et al.*, 2025; Sánchez *et al.*, 2025). But much of this literature presumes comparatively stable regimes and smooth investment paths, and provides little information on adoption decisions in the context of cost volatility and compliance shocks.

Moreover, theories such as the Technology Acceptance Model (TAM) focus on usefulness and ease of use as the two primary factors of adoption and show high predictive value in AI settings (Faiz *et al.*, 2024; Özel, 2025). However, TAM implicitly presupposes that positive perceptions may be converted into long-term usage, which is not a very strong assumption in resource-starved SMEs. Technology–Organization–Environment (TOE) studies, on the other hand, specify foreground managerial support, resource availability, competitive pressure, and regulatory conditions but tend to under-specify the manner in which such contextual forces are interpreted and responded to in a crisis (Badghish & Soomro, 2024; Polisetty *et al.*, 2024).

Consequently, perceptual and contextual explanations become analytically separated.

More importantly, the implementation of AI is often viewed as a destination rather than a means to innovation and competitiveness. This adoption bias is especially troublesome in export production, where survival depends on whether AI adoption creates innovation potential, not symbolic adherence. Although there is growing evidence that AI may positively affect decision-making, process efficiency, and product innovation, there is a scarcity of empirical data on whether AI can contribute to open innovation performance within crisis-exposed SMEs (Liu *et al.*, 2025; Yuan *et al.*, 2025).

The sustainability dimension further sharpens this gap. Although AI has been connected to green innovation and environmental performance, sustainability compliance of sustainability in textile SMEs is knowledge-based by nature and necessitates the ongoing generation, dissemination, and utilization of environmental knowledge at both organizational and supply-chain levels (Haq & Suki, 2025). Green knowledge management (GKM) is a key boundary condition that determines how AI-based insights contribute to innovation and compliance outcomes. Yet, its moderating role in the AI adoption innovation relationship remains underexplored, particularly in SME-dominated, resource-constrained manufacturing contexts (Haq, Suki, *et al.*, 2025; Tariq *et al.*, 2024).

Consequently, textile SMEs in Pakistan offer a high-pressure empirical context in which established theories of AI adoption challenge their traditional premises (Haq, Suki, *et al.*, 2025). Intention- and readiness-centric models fail to consider post-adoption innovation outcomes (Mahmood *et al.*, 2025). For this reason, this study integrates TAM and TOE to examine the antecedents of AI adoption and develops an integrated framework, empirically tested to assess how these factors influence the post-adoption outcome of open innovation performance (Shah *et al.*, 2022). It also introduces “green knowledge management” as a mediating variable that shapes how AI use leads to innovation under sustainability and institutional pressures. This study aims to advance understanding of AI-driven innovation in manufacturing SMEs by grounding theoretical insights in a crisis context within an emerging-market environment, offering a more realistic and outcome-oriented perspective on the phenomenon (S. Hussain *et al.*, 2026).

This study makes several distinct contributions that differentiate it from prior research. First, unlike prior studies that apply TAM or TOE in isolation (e.g., Badghish & Soomro, 2024; Faiz *et al.*, 2024), this research develops

and empirically tests an integrated TAM–TOE model in which organizational and environmental factors (top management support, resource availability, competitive pressure, regulatory environment) operate through perceptual mechanisms (perceived usefulness [PU] and perceived ease of use [PEOU]), providing a multi-level explanation of AI adoption that captures both structural constraints and cognitive processes simultaneously. Second, while most AI adoption studies focus on adoption intention or readiness as the endpoint (Polisetty *et al.*, 2024; Thomas *et al.*, 2025), this study extends the analytical scope to post-adoption innovation outcomes by examining the direct effect of AI adoption on open innovation performance, thereby shifting the focus from whether SMEs adopt AI to what occurs after AI adoption. Third, by testing GKM as a moderating boundary condition, this study introduces an underexplored sustainability-oriented mechanism into the AI adoption–innovation relationship. The non-significant moderation effect itself constitutes a novel empirical contribution by suggesting that sustainability knowledge practices in resource-constrained SMEs may not yet be sufficiently institutionalized to condition innovation outcomes. Fourth, the empirical context of crisis-affected, export-oriented textile SMEs in Pakistan provides a high-pressure setting that challenges the assumptions of stable institutional environments typically underlying technology adoption research, offering findings that are more transferable to other emerging economies facing similar volatility and compliance pressures.

2. Literature review

2.1. Artificial intelligence adoption in manufacturing small and medium-sized enterprises in emerging economies

The implementation of AI in manufacturing SMEs has become an ongoing issue in emerging economies. Firms have structural constraints that essentially determine technology-related decision-making (Soomro *et al.*, 2026). In contrast to large businesses, SMEs are generally run on a thin margin, with little technological buffer and limited absorptive capacity, and the adoption of AI is a strategic, but not an incremental, decision (Varma *et al.*, 2023). Financial constraints are consistently listed among the major obstacles in previous research, since AI implementation involves an initial investment in hardware, software, data systems, and ongoing training, which has proven prohibitive for small-scale manufacturers (Haq & Suki, 2025; Musa *et al.*, 2025). These limitations are especially acute in export-oriented manufacturing SMEs, where technology investment competes with working capital requirements and short-term survival.

In addition to financial constraints, skills shortages are one of the most important barriers to using AI. SMEs in emerging-economy manufacturing often lack employees with data analytics, systems integration, and machine learning skills, which impairs their capacity to implement and scale AI applications effectively (Boonmee *et al.*, 2025; Hiremath *et al.*, 2025). Empirical evidence from South Asia, Latin America, and Southeast Asia indicates that, despite SMEs' awareness of the potential advantages of AI, a lack of technical competence limits meaningful usage and results in fragmented or superficial adoption (Rahman, 2025; Sánchez-Rodríguez *et al.*, 2025). These results emphasize that the use of AI is not only a technological problem but a human resource and organizational learning challenge (Shahzadi *et al.*, 2024).

Adoption dynamics are also complicated by infrastructure gaps. Reliable power, data connectivity, and internet access are prerequisites for AI-based manufacturing, but these conditions remain uneven across emerging economies (Ortega-Del-Rosario *et al.*, 2025; Sánchez *et al.*, 2025). Low-quality data and a poor digital infrastructure adversely affect how SMEs can convert AI systems into actionable insights, perceived returns on investment, and establish adoption hesitation (Varma *et al.*, 2023).

Consequently, the use of AI in manufacturing SMEs tends to be in isolated instances instead of integrated manufacturing or decision-support systems. These adoption patterns are shaped by cost pressures as well as institutional settings. The high cost of implementation and maintenance is a disincentive for SMEs to invest in AI if the benefits are not clear and imminent (Haq & Suki, 2025; Musa *et al.*, 2025). At the same time, regulatory frameworks, government incentives, and institutional support can determine how viable adoption is and can impact access to finance, training, and infrastructure (Ionaşcu, 2025; Sánchez *et al.*, 2025). Some evidence suggests that positive policy associations can reduce adoption costs while weak and unstable institutional arrangements raise risk attitudes of SME decision-makers. There is an added complexity of competitive conditions. Competitive stress is frequently mentioned as a driver for SMEs to embrace AI technology for increased efficiency and innovation, as well as to stay competitive in the market (Boonmee *et al.*, 2025; Haq & Suki, 2024).

However, competition is not true of all firms. SMEs with leadership, organizational preparedness, and external linkages are better positioned to adopt AI, while others are unable to transform competitive pressure into the development of actionable capabilities (Hiremath *et al.*, 2025; Sánchez-Rodríguez *et al.*, 2025). This leads to

unbalanced adoption processes, with a few firms moving toward AI-based manufacturing and most stagnating in technology use.

Theoretically, these trends highlight the shortcomings of the linear approach and the adoption of AI as an intention-driven process in manufacturing SMEs. The complexity of adoption in emerging economies has led scholars to rely on models like the TOE model and the Resource-Based View to describe the interplay of technological preparedness, organizational capabilities, and environmental pressures (Haq & Suki, 2025). Nevertheless, the continued asymmetry in adoption rates and post-adoption value creation suggests that more remains to be said about existing explanations, especially in settings where cost volatility is high and institutional uncertainty is present (Ullah *et al.*, 2025).

In general, the literature suggests that AI usage in manufacturing SMEs of emerging economies is influenced by interdependent structural constraints, such as inadequate resources, skills deficiencies, infrastructural gaps, and cost pressures, institutional settings, and competitive forces (Varma *et al.*, 2023). These factors render AI adoption theoretically and empirically problematic because it is impossible to make adoption decisions without reflecting on the combined effect of the organizational perceptions, contextual pressures, and ability constraints on SME behavior (Usman *et al.*, 2023). This complexity offers a solid basis for incorporating perception-based and context-based frameworks in later sections to elucidate AI adoption more holistically.

2.2. Technology Acceptance Model and artificial intelligence adoption

One of the most proven theoretical frameworks for explaining the adoption of digital technologies, including AI, in organizations is the TAM. TAM assumes that two cognitive considerations, which include PU and PEOU, are the primary factors influencing adoption decisions (Haq & Suki, 2025). In AI settings, these perceptions indicate whether AI systems will improve decision quality, productivity, and innovation outcomes, and whether they can be implemented without undue complexity or disruption to current work processes (Song *et al.*, 2025).

Empirical studies have consistently found PU to be a significant predictor of AI adoption across organizational settings. Research on manufacturing SMEs, service firms, and export-oriented organizations demonstrates that intentions to adopt AI grow significantly when managers believe that AI can enhance operational effectiveness, decision accuracy, or competitiveness (Haq & Suki, 2025; Thomas *et al.*, 2025; Tiago & Almeida, 2026). The latter

effect is especially strong in emerging markets, where companies are forced to operate at a cost and must prove the need to invest in technologies by demonstrating observable performance improvement.

Perceived ease of use is also vital, especially in the initial stages of AI adoption. When AI systems are perceived as easy to grasp, compatible with existing processes, and requiring minimal technical expertise, managers and employees are more inclined to accept them (Almeida *et al.*, 2025; Song *et al.*, 2025). Existing TAM-based research also shows that PEOU positively influences PU, meaning that technologies perceived as easier to use are more likely to be viewed as useful (Pinto *et al.*, 2025; Song *et al.*, 2025). This is particularly applicable to SMEs, where a lack of digital skills and time constraints can make system complexity more sensitive.

Based on the argument in Section 2.1, the perception-based explanations might not be adequate in resource-constrained contexts. Preliminary experiences in emerging economies suggest that financial resources and infrastructure may limit the use of AI in these contexts, even when PU and PEOU are high. This is why recent research suggests integrating organizational and environmental perspectives into the TAM to account for AI adoption in SMEs (Huynh & Khoa, 2025; Tiago & Almeida, 2026). However, TAM has continued to be a key framework for understanding the cognitive processes that influence managerial assessments of AI before the effects of wider constraints.

Based on TAM and prior empirical findings, this study proposes the following hypotheses (H):

- (i) H1: PEOU positively influences PU.
- (ii) H2: PEOU positively influences AI adoption.
- (iii) H3: PU positively influences AI adoption.

2.3. Technology–Organization–Environment framework and artificial intelligence adoption

In the TOE model, organizational factors represent the strongest predictors of AI adoption among manufacturing SMEs with structural limitations common to emerging economies. The previous literature demonstrates that despite the PU and PEOU of AI technologies, its implementation is hardly possible without a solid internal organizational endorsement and preparedness (Haq & Suki, 2025; Thomas *et al.*, 2025).

It is crucial for top management to support this, which serves as a strategic indicator, validates the investment in AI, reduces perceived risk, and mobilizes organizational commitment. Empirical findings from SMEs in emerging

markets highlight the importance of leadership vision and managerial engagement in influencing SMEs' intentions to adopt AI by aligning technology initiatives with innovation goals and the company's strategy (Thomas *et al.*, 2025; Wiese *et al.*, 2025). This issue is particularly pronounced in export-oriented industries, such as textiles, where SMEs face increasing pressure to reduce costs, meet compliance standards, and leverage AI as a tool for competitiveness and survival (Haq & Suki, 2024; Roux *et al.*, 2025).

Resource availability also significantly influences AI adoption. Access to digital resources, financial capacity, infrastructure, and internal IT resources defines SMEs' ability to move beyond pilot testing toward lifelong AI application. Research indicates that, in all cases, AI is not adopted because of inadequate financial slack and poor technological infrastructure, despite managers' favorable intent (Kalleparambil & Akoum, 2025; Lai *et al.*, 2025). On the other hand, more resourceful companies have higher adoption readiness and a faster speed of AI introduction into operations (Haq & Suki, 2025).

Digital readiness is closely related and refers to the firm's preparedness in terms of data quality, digital systems, and the skills of the people working in the firm. Models of organizational readiness also highlight that the process of adopting AI should not be limited to hardware and software, but should also include employees' digital skills and the ability to manage change (Kalleparambil & Akoum, 2025; Omar & Weilbach, 2025). Internal learning mechanisms and workforce upskilling are thus crucial in helping SMEs convert AI investments to functional outputs (Xingli *et al.*, 2026).

Drawing on TOE theory and prior empirical evidence, this study proposes the following hypotheses:

- (i) H4: Top management support has a positive effect on PU of AI.
- (ii) H5: Top management support has a positive effect on PEOU of AI.
- (iii) H6: Resource availability has a positive effect on PU of AI.
- (iv) H7: Resource availability has a positive effect on PEOU of AI.

Within the TOE framework, environmental factors exert decisive influence on AI adoption in manufacturing SMEs, particularly in emerging economies where firms operate under intense external pressure. One of the most frequently cited drivers of AI adoption is competitive pressure, which compels SMEs to become more efficient, innovative, and responsive to market demands. This pressure is particularly evident in export-oriented markets,

where intensifying global competition requires SMEs to increasingly leverage AI capabilities (Haq & Suki, 2024; Thomas *et al.*, 2025). In export-driven economies, such as Pakistan's textile industry, competition from technologically superior regional competitors increases pressure to adopt AI-based cost control and quality assurance.

Regulations also influence decisions on the adoption of AI. Supportive policy frameworks, digitalization strategies, and compliance expectations signal legitimacy and reduce uncertainty surrounding AI investments (Hiremath *et al.*, 2025; Thomas *et al.*, 2025). Conversely, weak or disjointed regulations may hinder adoption even where organizational intent is favorable.

The requirement for sustainability has become an essential environmental movement. Global buyers increasingly require compliance with international standards related to traceability, energy efficiency, and emissions reduction, promoting the adoption of Green AI solutions among SMEs to optimize resource use and minimize waste (Farmanesh *et al.*, 2025; Haq, Suki, *et al.*, 2025). Empirical evidence in Pakistan indicates that sustainability-related external pressure enhances AI adoption when companies view AI as a means of regulatory compliance and export survival (Haq, Suki, *et al.*, 2025).

Lastly, a key enabling factor is government support. Monetary rewards, education, and investment in digital infrastructure alleviate resource limitations that affect SMEs and transfer environmental pressure into feasible adoption choices (Hiremath *et al.*, 2025; Thomas *et al.*, 2025). Thus, the study proposes the following hypotheses:

- (i) H8: Competitive pressure positively influences the PU of AI in manufacturing SMEs.
- (ii) H9: Regulatory environment positively influences the PU of AI in manufacturing SMEs.
- (iii) H10: Competitive pressure positively influences the PEOU of AI in manufacturing SMEs.
- (iv) H11: Regulatory environment positively influences the PEOU of AI in manufacturing SMEs.

2.4. The integration of the Technology Acceptance Model and the Technology–Organization–Environment framework: Toward a multi-level explanation of artificial intelligence adoption

Emerging literature confirms that neither the TAM nor the TOE framework is effective. The TOE framework itself cannot be relied on as an adequate description of the adoption of AI in SMEs of emerging economies in crises. TAM focuses on personal and managerial perceptions, particularly those of PU and PEOU as intermediate measures of technology adoption. However, perception-based models are based on relatively fixed organizational

resources and institutional environments, which is typically not the case in resource-constrained SME environments (Gangwar *et al.*, 2014; Song *et al.*, 2025).

The TOE framework, on the other hand, summarizes the broader organizational and environmental context in which adoption decisions are made, such as leadership support, resource availability, competitive pressure, and regulatory forces. Although TOE describes structural preparedness and external demands, decision makers' cognitive interpretation of these conditions when exploring AI technologies is not fully considered (Awa *et al.*, 2015; Omrani *et al.*, 2024). It has been empirically demonstrated that organizational and environmental drivers tend to have an indirect impact through managerial perceptions of usefulness and usability (Thomas *et al.*, 2025; Tiago & Almeida, 2026).

Recent studies thus recommend a combined TAM–TOE model, claiming that AI adoption results from the interaction between evaluation based on perception and context-based constraints. Within this category of models, TAM constructs mediate the influence of TOE factors, converting leadership-based signals, resource endowment, and environmental pressures into adoption intentions and behaviors (Lai *et al.*, 2025; Xingli *et al.*, 2026). This assimilation is especially essential in crisis-based emerging economies, which are characterized by financial volatility, infrastructure shortage, and regulatory uncertainty that exacerbate the disparity between perceived technological worth and the real adoption potential (Haque & Suki, 2025).

Based on this, the proposed study will use an integrated TAM–TOE framework to describe AI adoption in Pakistan's textile SMEs. The combination of perceptual mechanisms (PU and PEOU) and the model provides a multi-level and context-sensitive account of organizational and environmental drivers.

2.5. Artificial intelligence adoption and open innovation performance

The use of AI does not limit itself to internal efficiency improvements but transforms the way SMEs approach open innovation. AI enhances firms' capability to recognize external knowledge opportunities, organize collaborative processes, and rearrange internal and external assets to innovate by facilitating sophisticated data analytics, predictive intelligence, and real-time decision support. Emerging economies have empirically demonstrated that AI-enhanced decision-making not only strengthens sensing, seizing, and reconfiguring capabilities central to open innovation performance within firms but also improves them (Sánchez-Rodríguez *et al.*, 2025).

In manufacturing and export-based SMEs, adopting AI can enable both inbound and outbound open innovation by enhancing knowledge absorptive capacity and inter-organizational coordination. Research on Chinese apparel and Pakistani manufacturing SMEs shows that AI-based systems can increase the capacity of firms to absorb external knowledge and convert it into product and process innovation outputs (Haq & Suki, 2025; Qu & Kim, 2025). Similarly, AI-supported self-assessment and analytics tools provide actionable insights that guide collaboration choices and innovation portfolio decisions (Proença, 2024).

For export-oriented SMEs, AI-based capabilities also enable them to engage in global innovation networks, contributing to supply chain learning, exploratory and exploitative innovation, and compliance-driven innovation requirements. The experiences of cross-border and internationalized SMEs show that AI implementation enhances the performance of the innovation process by aligning internal decision-making with the needs of external partners and regulatory frameworks (Wang & Zhang, 2025). Collectively, these findings position AI adoption as a key enabler that converts organizational openness into measurable innovation performance in resource-constrained contexts. Thus, the following hypothesis is proposed:

- (i) H12: AI adoption has a positive and significant effect on open innovation performance in SMEs.

2.6. Green knowledge management as a moderator

As sustainability regulations intensify, SMEs face compliance demands that are more knowledge-intensive and extend beyond technology adoption. GKM is the ability of a firm to acquire, integrate, transmit, and utilize environmental knowledge in its organizational processes (Fadillah *et al.*, 2025; Khan *et al.*, 2024). Evidence indicates that GKM strengthens green intellectual capital and enables green innovation by embedding sustainability knowledge into routines and operational decision-making (Abdelwahed *et al.*, 2025; Abdulmuhsin *et al.*, 2025).

In AI-driven environments, the role of GKM is particularly crucial. Although AI enhances sensing, observation, and optimization, AI-driven insights do not necessarily lead to innovation unless companies can internalize, institutionalize, and disseminate sustainability-related knowledge (Cai *et al.*, 2025; Khan *et al.*, 2024). Empirical evidence shows that AI could have a greater impact on sustainability outcomes when used alongside meaningful knowledge practices that foster learning, coordination, and capacity building (Alzaghal *et al.*, 2024; Haq, Suki, *et al.*, 2025).

Green knowledge management also improves absorptive capacity by helping SMEs adapt their internal knowledge systems to external institutional pressures, including buyers' audits, environmental standards, and compliance reporting (Fadillah *et al.*, 2025; Riikkinen *et al.*, 2017). However, the tendency of AI to become an innovation-driven solution can be mitigated by poor GKM, which can increase the chances of superficial or compliance-based digitalization in export-oriented and resource-constrained environments (Arroyabe & Arranz, 2026; Khan *et al.*, 2024). As a result, it is most appropriate to enhance the boundary condition to facilitate the shift of AI adoption to open innovation performance (Abdulmuhsin *et al.*, 2025; Zhang *et al.*, 2025). Thus, the following hypothesis is proposed:

- (i) H13: GKM positively moderates the relationship between AI adoption and open innovation performance, such that the relationship is stronger when GKM is high.

2.7. Research gaps and hypotheses development

Although SMEs are increasingly adopting AI, crucial theoretical and empirical gaps remain, especially regarding crisis-related elements in emerging economies. Current research is mostly based on either perception-based theories like the TAM or context-based theories like the TOE framework (Davis, 1989; Tornatzky & Fleischer, 1990). Analyzing these points of view separately provides a partial account of AI adoption in resource-limited and well-controlled conditions (Badghish & Soomro, 2024; Haq & Suki, 2025).

Technology Acceptance Model-based studies emphasize PU and PEOU as the two main drivers of adoption and are not very concerned with the organizational capabilities and external pressures that influence managerial decisions made when there is uncertainty (Davis, 1989; Or, 2025). TOE-based research, by contrast, considers top management support, resource availability, competition, and regulatory environments, but it tends to overlook how these conditions are interpreted cognitively and how that interpretation shapes adoption behavior (Badghish & Soomro, 2024; Polisetty *et al.*, 2024). This conceptual discontinuity highlights the necessity of a multi-level explanation.

Empirically, little evidence shows how AI adoption translates into open innovation performance in manufacturing and export-oriented SMEs, particularly under sustainability compliance pressures (Qu & Kim, 2025; Sánchez-Rodríguez *et al.*, 2025). Furthermore, the boundary conditions that enable AI-based insights to

translate into innovation outcomes remain underexplored. Specifically, the moderating role of GKM as a mechanism that helps companies turn AI-enabled insights into collaborative and open innovation performance is seldom theorized (Haq, Suki, *et al.*, 2025; Khan *et al.*, 2024).

To address these gaps, this research proposes a combined TAM–TOE model that links subjective perceptions, organizational preparedness, and environmental forces to AI adoption and innovation success. The effects of organizational and environmental drivers on AI adoption are mediated by PU and PEOU, increasing open innovation performance, as shown in Figure 1. Moreover, GKM is a boundary condition that enhances the AI–innovation relationship by improving firms’ capacity to absorb, interpret, and apply sustainability-related knowledge.

3. Methodology

3.1. Research design and philosophical orientation

This research used a positivist research paradigm and a deductive line of reasoning to empirically test the theoretically constructed relationship between AI adoption, open innovation performance, and sustainability-oriented knowledge practices in textile SMEs (Hair *et al.*, 2022; Saunders *et al.*, 2019). Positivism is appropriate given the study’s emphasis on objective measurement, hypothesis testing, and theory validation using observable firm-level data.

A quantitative study design is explanatory and cross-sectional, which was used to investigate the causal relationships between perception-based, organizational, and environmental drivers and post-adoption innovation consequences. This type of design is generally suggested when testing known theoretical models and approximating structural relationships under stable measurements (Hair *et al.*, 2022; Sekaran & Bougie, 2020).

The research design is especially suitable for testing the theory under crisis and compliance pressure, whereby adoption decisions are influenced by volatility costs, regulatory requirements, and sustainability needs, rather than incremental technological decisions. The study was based on a multi-level explanatory model that incorporates the TAM (Davis, 1989) and the TOE paradigm (Tornatzky & Fleischer, 1990) to examine the interaction of managerial perceptions with organizational constraints and environmental pressures in high-risk emerging market environments.

3.2. Research context and unit of analysis

This research focused on the textile manufacturing SME industry in Pakistan, a high-pressure empirical context defined by cost volatility, reliance on exports, and increasing sustainability compliance requirements. Pakistan is a country of textile SMEs manufacturing exports and is increasingly exposed to external regulatory shocks, energy price instability, and global buyer-based

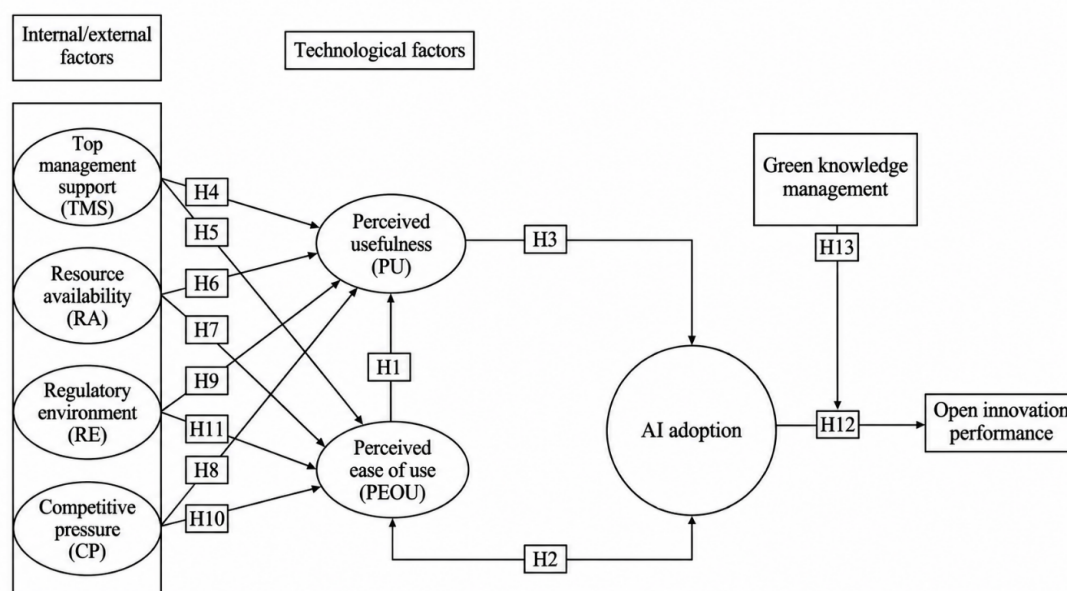


Figure 1. Integrated Technology Acceptance Model–Technology–Organization–Environment framework linking artificial intelligence (AI) adoption to open innovation performance with the moderating role of green knowledge management

sustainability requirements. Such circumstances make the industry especially relevant to the study of AI adoption decisions in times of crisis and compliance, rather than stable growth conditions.

The empirical focus was on export-based textile SMEs, which are directly involved in international markets and are subject to environmental, traceability, and digital reporting demands of major trading partners. These companies are more motivated to implement AI-based solutions to improve efficiency, manage compliance, and develop innovation capacities, but at the same time have to address intense resource and capability limitations. These two exposures offer a theoretically pertinent context for experimenting with integrated technology adoption frameworks.

The unit of analysis was the firm, and the data were gathered at the firm level, including owners, chief executive officers, operations managers, information technology managers, and sustainability/compliance leads. Respondents were selected as key informants because they are directly involved in strategic technology choices, resource allocation, and innovation projects. The use of senior managers as key informants is well supported in prior SME technology adoption research, as they possess comprehensive knowledge of their organizations' technological capabilities, operational strengths and weaknesses, external environmental pressures, and post-adoption outcomes. Furthermore, this study acknowledges its focus on a single industry within a single country as a limitation but justifies this design as a deliberate trade-off that enhances contextual depth and strengthens theory testing in a rapidly evolving empirical setting.

3.3. Sampling strategy and data collection procedure

The population targeted was the export-oriented textile manufacturing SMEs based in Pakistan. The sampling frame was developed based on firm listings from SMEDA, provincial textile associations, exporter directories, and industry networks to ensure that firms exposed to international market competition and sustainability compliance requirements are represented. The firm was the unit of analysis, and responses were gathered from knowledgeable decision-makers engaged in AI adoption, digitalization, or innovation-related activities.

A purposive sampling method was used to ensure that respondents had adequate managerial, technical, or operational knowledge relevant to the study constructs. This method was appropriate for learning more about technology use and strategy in SMEs. As per the

requirements of partial least squares structural equation modeling (PLS-SEM), to check whether the sample size was adequate for estimating the model with many predictor variables and interaction effects, both the ten-times rule and statistical power were applied, and both showed that the obtained sample size was adequate.

The sample size determination followed multiple complementary criteria consistent with PLS-SEM best practices. First, the ten-times rule was applied, which requires that the minimum sample size be at least 10 times the maximum number of structural paths directed at any endogenous construct in the model (Hair *et al.*, 2022). In this study, the endogenous construct with the most incoming paths was PU, with four predictors (top management support, resource availability, competitive pressure, regulatory environment), yielding a minimum requirement of 40 responses. Second, the inverse square root method proposed by Kock and Hadaya (2018) was applied, which provides a more precise minimum sample size estimate based on desired statistical power. Using this method with a significance level of 0.05, a minimum path coefficient of 0.10, and a desired statistical power of 80%, the minimum required sample size was estimated at approximately 155 respondents. Third, G*Power 3.1 software was used to conduct an a priori power analysis for a medium effect size ($f^2 = 0.15$), significance level of 0.05, and power of 0.95 with nine predictors, resulting in a minimum required sample of 166 respondents (Cohen, 1992; Faul *et al.*, 2009). The final usable sample of 400 responses substantially exceeds all three thresholds, ensuring adequate statistical power for detecting both direct and moderation effects. Furthermore, the sample represents the target population of export-oriented textile SMEs in Pakistan by drawing respondents from major textile clusters including Punjab (62%), Sindh (26%), Khyber Pakhtunkhwa (7%), and other regions (5%), which mirrors the geographic distribution of textile manufacturing activity in Pakistan (SMEDA, 2025). The purposive sampling ensured that respondents held decision-making roles relevant to AI adoption and innovation, enhancing the representativeness of the sample for the constructs under investigation.

The data were gathered over three months using a structured questionnaire administered through online survey websites and a select field-centric distribution. A total of 520 questionnaires were distributed. Of these, 436 were returned, yielding a response rate of 83.8%. Following screening for incomplete responses, missing values, straight-lining, and inconsistencies, 36 questionnaires were eliminated. A total of 400 usable responses were selected as the final sample for further analysis. Figure 2 illustrates the sampling framework of data collection.

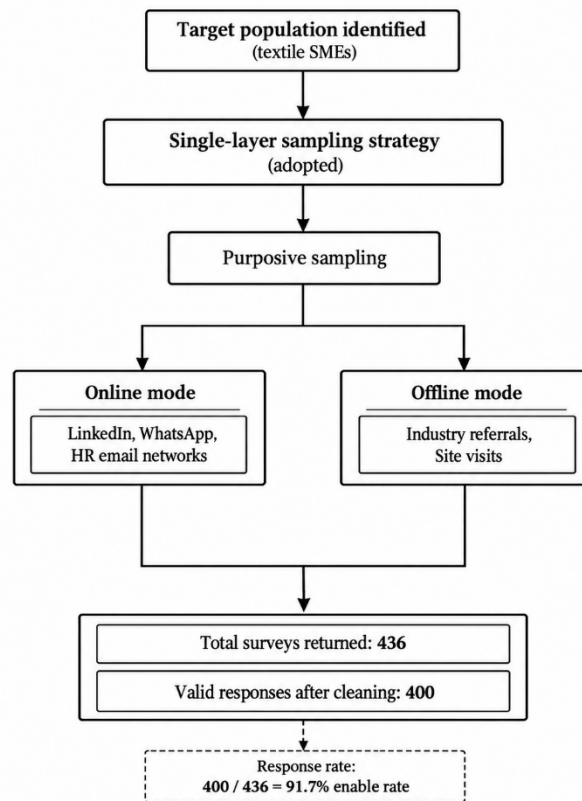


Figure 2. Sampling framework for data collection

All retained questionnaires were complete, with no systematic missing data. Preliminary data screening ensured that there were not too many missing values, outliers, or common response biases. Procedural solutions, such as respondent anonymity and item randomization, were used to reduce common method bias.

3.4. Measurement instrument development

The measurement tool was designed to be conceptually sound, contextually relevant, and empirically reliable in capturing AI adoption and innovation dynamics within the Pakistani textile industry. SME manufacturing is susceptible to cost volatility and to sustainability compliance pressure. Multi-item reflective scales based on previous successful studies of AI adoption, innovation, and green management literature were used to operationalize all constructs; wording was tailored to the manufacturing and export-oriented SME setting.

The PU and PEOU were measured using five items each, including managers' views on AI's potential to enhance performance and usability in both operational and compliance-related decision-making (Davis, 1989;

Song *et al.*, 2025). Validated scales based on leadership commitment, financial and digital readiness, market rivalry, and regulatory stringency were used to measure TOE constructs such as top management support, resource availability, competitive pressure, and regulatory environment (Badghish & Soomro, 2024; Haq & Suki, 2025).

The study operationalized AI as the degree of actual use in production, monitoring, and decision-support processes rather than adoption intention, a major limitation in previous SME research. Open innovation performance was measured by firms' ability to collaborate inbound and outbound on knowledge, solve problems together, and commercialize innovations (Carrasco-Carvajal *et al.*, 2023; Crema *et al.*, 2014). GKM became a subject of capture in terms of acquiring, sharing, and applying sustainability-related knowledge, which is a prerequisite for transforming AI capabilities into innovation outcomes (Haq, Suki, *et al.*, 2025; Khan *et al.*, 2024).

All items were measured on a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5). Control variables including firm size, firm age, and

export orientation were included to account for structural heterogeneity among SMEs. All questions were also slightly rephrased to match the context of textile manufacturing SMEs in Pakistan while maintaining their original conceptual meaning. Table 1 provides the list of constructs, measurement items, and sources in their entirety.

3.5. Questionnaire design and pretesting

The questionnaire was designed to ensure content validity, clarity, and contextual relevance for decision-makers in the textile manufacturing SMEs in Pakistan that work under cost volatility and sustainability compliance pressures. The measurement items were systematized into construct-specific sections, using neutral words and similar response formats to minimize cognitive load and common method bias. The questionnaire was administered in English, the managerial language of communication in Pakistan's export-oriented textile industry.

Expert review was used to determine content

validity with three domain specialists experienced in AI integration, SME operations, and sustainability standards. Reviewers evaluated item relevance, clarity, and contextual appropriateness, resulting in slight modifications without changing construct meaning.

A pilot test was then conducted with 30 SME managers not included in the final sample. Feedback focused on item clarity, survey length, and interpretability. According to pilot feedback, ambiguous wording was narrowed down and unnecessary wording eliminated, leading to a final instrument that could be used for large-scale data collection.

3.6. Data preparation and screening

The dataset was filtered before hypothesis testing to ensure it was accurate and appropriate for multivariate analysis. Missing values, straight-lining and response patterns were analyzed for inconsistencies. Questionnaires with large amounts of missing data or patterned answers

Table 1. Construct measurement, indicator specification, and scale sources

Construct	Theoretical basis	Indicator code	No. of items	Measurement model specification	Source/Scale adaptation
Perceived usefulness (PU)	Technology acceptance model (TAM)	PU1–PU5	5	Reflective	Adapted from Davis (1989); extended to artificial intelligence (AI) contexts following Song <i>et al.</i> (2025); Thomas <i>et al.</i> (2025)
Perceived ease of use (PEOU)	Technology acceptance model (TAM)	PEOU1–PEOU5	5	Reflective	Adapted from Davis (1989); AI adoption refinements from Faiz <i>et al.</i> (2024); Özel (2025)
Top management support (TMS)	Technology–Organization–Environment (TOE) organizational context	TMS1–TMS5	5	Reflective	Adapted from Tornatzky & Fleischer (1990); Haq & Suki (2025); Badghish & Soomro (2024)
Resource availability (RA)	TOE organizational context	RA1–RA5	5	Reflective	Adapted from TOE-based SME studies (Sánchez <i>et al.</i> , 2025; Tiago & Almeida, 2026)
Competitive pressure (CP)	TOE environmental context	CP1–CP5	5	Reflective	Adapted from Polisetty <i>et al.</i> (2024); Thomas <i>et al.</i> (2025); Roux <i>et al.</i> (2025)
Regulatory environment (RE)	TOE environmental context	RE1–RE4	4	Reflective	Adapted from Badghish & Soomro (2024); Sánchez <i>et al.</i> (2025); sustainability compliance literature
AI adoption (AIAD)	Post-acceptance technology use	AIAD1–AIAD5	5	Reflective	Adapted from Haq & Suki (2025); Song <i>et al.</i> (2025); reflects extent and intensity of AI use
Open innovation performance (OIP)	Open innovation theory	OIP1–OIP5	5	Reflective	Adapted from Crema <i>et al.</i> (2014); Carrasco-Carvajal <i>et al.</i> (2023); Qu & Kim (2025)
Green knowledge management (GKM)	Knowledge-based view/sustainability	GKM1–GKM5	5	Reflective	Adapted from Khan <i>et al.</i> (2024); Abdulmuhsin <i>et al.</i> (2025); Haq, Suki, <i>et al.</i> (2025)

Note: All constructs were specified as reflective measurement models, consistent with prior TAM–TOE and innovation studies and the assumption that observed indicators reflect underlying latent constructs (Hair *et al.*, 2022).

were eliminated. Missing values that were not zero were insignificant and were addressed using mean replacement, in line with PLS-SEM guidelines regarding small proportions of missing data (Hair *et al.*, 2022).

Outliers were assessed using standardized residuals and leverage diagnostics. No extreme multivariate outliers greater than the recommended levels were identified. Skewness and kurtosis statistics were used to determine normality. Since some of the indicators were not normally distributed, the variance-based method of analysis was considered suitable. Descriptive statistics were calculated to describe respondent and firm characteristics and to provide a rough picture of construct distributions.

To elaborate on the data screening and validation process, all 436 returned questionnaires were subjected to a systematic multi-step screening protocol before analysis. First, responses were examined for completeness; questionnaires with more than 10% missing values on any single construct were excluded, consistent with Hair *et al.* (2022) recommendations for PLS-SEM. Second, straight-lining detection was performed by identifying respondents who selected the same response option across all items within a construct or across multiple constructs, indicating inattentive responding. Third, response time analysis was conducted on online submissions to flag questionnaires completed in unrealistically short durations. Fourth, Mahalanobis distance was computed to identify multivariate outliers at a significance level of $p < 0.001$, and no cases exceeded the critical chi-square threshold. Through these procedures, 36 questionnaires were eliminated, yielding 400 usable responses. The remaining data were assessed for univariate normality using skewness (± 2) and kurtosis (± 7) thresholds (Byrne, 2016), and while some indicators exhibited mild non-normality, this further validated the use of PLS-SEM, which does not require strict distributional assumptions. Additionally, common method bias was assessed statistically using Harman's (1976) single-factor test, which confirmed that no single factor explained the majority of variance, and full collinearity variance inflation factor (VIF) values at the construct level remained below 3.3, ruling out common method variance as a substantive concern (Kock, 2015). The reliability and suitability of responses were further confirmed through the measurement model assessment reported in Section 4.2, where all constructs demonstrated satisfactory indicator reliability, internal consistency, convergent validity, and discriminant validity.

3.7. Common method bias and endogeneity concerns

The data were cross-sectional and self-reported; hence,

procedural and statistical solutions were applied to reduce common method bias. To minimize evaluation apprehension (Podsakoff *et al.*, 2003), respondents were assured of anonymity, questions were kept non-evaluative, and the predictor and criterion variables were conceptually separated within the questionnaire.

Harman's single-factor test was conducted statistically, and the results showed that no single factor accounted for most of the variance (Harman, 1976). Additionally, VIF values were tested at the construct level and remained below conservative thresholds, indicating that common method variance could not have influenced the results (Kock, 2015). The theoretical specification of the models and the addition of relevant control variables helped address potential endogeneity issues.

3.8. Analytical strategy

SmartPLS (version 4) was used to implement PLS-SEM due to its suitability for prediction-oriented research, complex models, and moderation analysis. PLS-SEM has been used in research with several latent constructs, non-normal data, and theory extension rather than strict theory confirmation (Hair *et al.*, 2022).

The methodology is consistent with the aim of the study, which is to describe AI adoption and post-adoption innovation results in crisis conditions and compliance. PLS-SEM also allows simultaneous evaluation of the measurement and structural models, enables interaction effects such as the moderating function of GKM, and focuses on predictive significance, which is key to understanding the competitiveness of SMEs in unstable environments.

The selection of PLS-SEM over covariance-based structural equation modeling (CB-SEM) and other alternatives such as regression-based approaches is justified on several methodological and theoretical grounds. First, PLS-SEM is a variance-based technique that maximizes the explained variance of endogenous constructs, making it particularly suited for prediction-oriented research where the primary objective is to explain and predict target constructs rather than to confirm a pre-established theory (Hair *et al.*, 2022; Sarstedt *et al.*, 2022). Unlike CB-SEM, which requires multivariate normal data distributions and large sample sizes to achieve stable parameter estimates, PLS-SEM performs robustly with non-normal data distributions, as confirmed by the skewness and kurtosis diagnostics in this study (Hair *et al.*, 2019). Second, the integrated TAM-TOE model tested in this study involves a complex structural configuration with nine latent constructs, multiple mediation pathways, and a moderation interaction term (AI adoption $\times$ GKM).

PLS-SEM is recommended for complex models with interaction effects, where CB-SEM may face identification or convergence issues (Hair *et al.*, 2022; Rigdon, 2016). Third, this study extends existing theory by integrating TAM and TOE frameworks and examining post-adoption outcomes, positioning it as exploratory-confirmatory rather than strictly confirmatory. PLS-SEM is better suited to theory development and extension, whereas CB-SEM is optimal for theory confirmation with well-established structural relationships (Henseler *et al.*, 2016). Fourth, the sample size of 400 respondents, while adequate for PLS-SEM based on the inverse square root method and the ten-times rule, may not meet the more stringent requirements of CB-SEM for a model of this complexity (Kock & Hadaya, 2018). Finally, PLS-SEM has been widely adopted in recent TAM-TOE and AI adoption research in SME contexts, ensuring methodological comparability with the relevant literature (Badghish & Soomro, 2024; Haq & Suki, 2025; Qu & Kim, 2025).

3.9. Ethical considerations

The research followed strict ethical standards. All respondents provided voluntary and informed consent before completing the surveys. Participants were fully briefed on the study purpose, their right to withdraw at any time, and the scholarly use of the data.

The study ensured confidentiality and anonymity because it did not collect personally identifiable information and reported results only in aggregate. Data were safely stored and accessed only for research purposes, in accordance with accepted ethical principles in social science research involving human subjects.

All survey instruments, consent forms, and data collection procedures were reviewed and approved by the ethics committee prior to data collection. Informed consent was obtained from all participants, and no vulnerable populations were involved. Participants were informed of their right to withdraw at any stage without penalty, and all data were anonymized and stored securely on password-protected systems accessible only to the research team.

4. Results

4.1. Respondent profile and descriptive statistics

The respondent profile and descriptive statistics are presented in Table 2. The sample consisted of respondents selected from export-oriented textile manufacturing SMEs in Pakistan, with a balanced mix of managerial and operational decision-makers. Most respondents were men (78.0%), reflecting the sector's workforce composition, and most were between the ages of 31 and 50 years,

indicating a high level of managerial maturity and industry experience. The educational level was high, with close to 60% possessing a master's or professional degree, which enhances the validity of the answers regarding technology and strategic decision-making.

Regarding organizational roles, more than 70% of the respondents held top or middle management positions, enabling them to provide informed perspectives on AI adoption, resource allocation, and organizational innovation practices. The sample consisted of firms of different sizes and ages; however, the majority of the sample was made up of medium-sized and older firms, which aligns with the structure of the textile export sector in Pakistan. Descriptive statistics showed sufficient variability in all constructs, which is appropriate for conducting the multivariate analysis.

4.2. Measurement model assessment

The reflective measurement model was evaluated by a rigorous multi-criteria approach, including indicator reliability, internal consistency, convergent validity, and discriminant validity, in line with best practices in PLS-SEM.

As shown in Table 3, most indicator loadings exceeded the recommended threshold of 0.70, indicating satisfactory indicator reliability. Although one indicator of GKM1 had a slightly lower loading (0.678), it was retained because of its theoretical relevance. Moreover, the construct demonstrated strong internal consistency and convergent validity, with a composite reliability (CR) of 0.887 and an average variance extracted (AVE) of 0.612, both of which exceed the recommended thresholds. Retaining GKM1 is consistent with methodological recommendations that theoretically important indicators may be preserved when overall construct reliability and validity are not compromised. The alpha and CR values for all constructs ranged from 0.867 to 0.953, indicating a high level of internal consistency but not exceeding the thresholds that would indicate item redundancy.

The VIF values of each indicator were less than 3.5, which suggests that multicollinearity does not pose a risk to the stability or interpretability of the estimated parameters. This is especially significant considering the conceptual closeness of TAM constructs and AI adoption. The validity (convergent) of all constructs was determined since AVE scores were above the 0.50 threshold. Interestingly, AI adoption and PU had the highest AVE values, indicating strong construct coherence and implying that respondents shared a similar perception of the operational and strategic value of AI in times of crisis and compliance constraints.

Table 2. Sample profile of respondents (*n* = 400)

Variables	Frequency (<i>n</i>)	Percentage (%)
Gender		
Male	312	78
Female	88	22
Age (Years)		
Below 30	72	18
31–40	156	39
41–50	118	29.5
Above 50	54	13.5
Education level		
Bachelor's degree	162	40.5
Master's degree	198	49.5
PhD/Professional qualification	40	10
Position in firm		
Top management	82	20.5
Middle management	204	51
Operational/technical staff	114	28.5
Work experience		
Less than 5 years	68	17
5–10 years	142	35.5
11–15 years	114	28.5
More than 15 years	76	19
Firm size		
Small (≤ 100 employees)	96	24
Medium (101–500 employees)	184	46
Large (> 500 employees)	120	30
Firm age		
Less than 10 years	88	22
10–20 years	176	44
More than 20 years	136	34
Location		
Punjab	248	62
Sindh	104	26
Khyber Pakhtunkhwa	28	7
Other regions	20	5

The heterotrait–monotrait (HTMT) criterion was used to measure discriminant validity. Table 4 reports all HTMT ratios below the conservative threshold of 0.90, which ensures sufficient construct distinctiveness. Although comparatively greater HTMT values were noted between PU, PEOU, and AI adoption, this follows a theoretically expected pattern, as these concepts are conceptually related. Notably, these values do not cross the acceptable boundaries, meaning that it is conceptually related and not empirically redundant.

Taken together, the measurement model exhibited good psychometric qualities, indicating the theoretically based interdependences of technology perceptions, organizational context, and use of AI. This provides a sound foundation for estimation and hypothesis testing using a structural model.

4.3. Structural model evaluation

The structural model was evaluated to test the hypothesized relationships, analyze the explanatory and predictive power, and assess the strength of the integrated TAM–TOE framework under crisis-driven and sustainability compliance conditions. A bootstrapping procedure was used to evaluate hypotheses with 5,000 resamples. Confidence intervals (CIs), standardized path coefficients, effect sizes (f^2), explained variance (R^2), and predictive relevance (Q^2) were analyzed.

The outcome of both the direct and indirect hypothesis testing is reported in Table 5. The results support the perception-based mechanisms postulated by the TAM. PEOU had a significant positive effect on PU, consistent with the TAM, which posits that technologies perceived as easier to use are more likely to be perceived as useful.

The TOE framework's organizational and environmental antecedents were important in shaping managerial perceptions. They positively impacted top management support and resource availability. PU and PEOU proved that leadership and financial–digital preparedness are key antecedents of positive technology perceptions. Competitive pressure was relatively intense, reflecting the urgency created by competitiveness and sustainability requirements in the Pakistani textile industry. The regulatory environment also exerted considerable influence, highlighting compliance-based necessity as a motivator of AI adoption.

Artificial intelligence adoption exhibited a strong and positive effect on open innovation performance, confirming its role as a post-adoption capability that enhances collaborative innovation and external knowledge integration. However, the moderating role of GKM on the AI adoption–open innovation relationship

Table 3. Measurement model reliability, indicator loadings, and convergent validity

Construct	Indicator	LF	VIF	Alpha	CR	AVE
Reliability and validity results						
AI adoption	AIAD1	0.911	3.350	0.939	0.953	0.803
	AIAD2	0.901		0.939		
	AIAD3	0.900		0.939		
	AIAD4	0.886		0.939		
	AIAD5	0.882		0.939		
Competitive pressure	CP1	0.814	2.018	0.876	0.910	0.669
	CP2	0.835		0.876		
	CP3	0.829		0.876		
	CP4	0.795		0.876		
	CP5	0.817		0.876		
Green knowledge management	GKM1	0.678	1.961	0.872	0.887	0.612
	GKM2	0.889		0.872		
	GKM3	0.713		0.872		
	GKM4	0.759		0.872		
	GKM5	0.853		0.872		
Open innovation performance	OIP1	0.846	2.379	0.904	0.929	0.723
	OIP2	0.841		0.904		
	OIP3	0.857		0.904		
	OIP4	0.857		0.904		
	OIP5	0.850		0.904		
Perceived ease of use	PEOU1	0.868	2.779	0.923	0.942	0.764
	PEOU2	0.878		0.923		
	PEOU3	0.864		0.923		
	PEOU4	0.877		0.923		
	PEOU5	0.881		0.923		
Perceived usefulness	PU1	0.880	2.822	0.925	0.943	0.768
	PU2	0.877		0.925		
	PU3	0.881		0.925		
	PU4	0.870		0.925		
	PU5	0.874		0.925		
Resource availability	RA1	0.832	2.249	0.894	0.922	0.702
	RA2	0.853		0.894		
	RA3	0.855		0.894		
	RA4	0.819		0.894		
	RA5	0.830		0.894		
Regulatory environment	RE1	0.847	2.082	0.867	0.910	0.715
	RE2	0.827		0.867		
	RE3	0.856		0.867		
	RE4	0.853		0.867		

(Cont'd...)

Table 3. (Continued)

Construct	Indicator	LF	VIF	Alpha	CR	AVE
Reliability and validity results						
Top management support	TMS1	0.824		0.885		
	TMS2	0.856		0.885		
	TMS3	0.824	2.113	0.885	0.916	0.685
	TMS4	0.821		0.885		
	TMS5	0.812		0.885		

Note: Indicator loadings above 0.70 indicate satisfactory indicator reliability, while CR values above 0.70 and AVE values above 0.50 confirm internal consistency and convergent validity. One indicator (GKM1) with a loading marginally below 0.70 was retained due to its theoretical relevance and acceptable construct-level CR and AVE, following recommended PLS-SEM guidelines (Hair et al., 2022).

Abbreviations: AVE: Average variance extracted; CR: Composite reliability; LF: Standardized outer loading; VIF: Variance inflation factor.

Table 4. Discriminant validity assessment using the heterotrait–monotrait criterion

Constructs	AIAD	CP	GKM	OIP	PEOU	PU	RA	RE	TMS
AIAD	1	–	–	–	–	–	–	–	–
CP	0.601	1	–	–	–	–	–	–	–
GKM	0.064	0.03	1	–	–	–	–	–	–
OIP	0.722	0.452	0.238	1	–	–	–	–	–
PEOU	0.815	0.672	0.062	0.598	1	–	–	–	–
PU	0.85	0.551	0.073	0.593	0.775	1	–	–	–
RA	0.604	0.634	0.049	0.402	0.612	0.627	1	–	–
RE	0.581	0.573	0.05	0.421	0.654	0.59	0.596	1	–
TMS	0.667	0.549	0.063	0.459	0.687	0.661	0.566	0.602	1

Notes: Diagonal elements represent unity. All heterotrait–monotrait values are below the conservative threshold of 0.90, indicating satisfactory discriminant validity among constructs. Relatively higher heterotrait–monotrait values between perceived usefulness, perceived ease of use, and AI adoption reflect theoretically expected proximity within the Technology Acceptance Model rather than empirical redundancy (Davis, 1989; Hair et al., 2022).

Abbreviations: AIA: Artificial intelligence adoption; CP: Competitive pressure; GKM: Green knowledge management; OIP: Open innovation performance; PEOU: Perceived ease of use; PU: Perceived usefulness; RA: Resource availability; RE: Regulatory environment; TMS: Top management support.

was not supported, suggesting that sustainability-oriented knowledge practices may not yet be sufficiently institutionalized to condition innovation outcomes in crisis-pressured SMEs. The results narrative in Section 4.3 has been enhanced with explicit analytical interpretation of each significant path, referencing comparable prior findings (e.g., Qu & Kim, 2025; Thomas *et al.*, 2025). It includes a detailed paragraph interpreting R^2 values (PU = 0.56; PEOU = 0.56; AI adoption = 0.49; open innovation performance = 0.44) against Hair *et al.* (2022) benchmarks, explaining the proportion of variance explained in each construct and the corresponding predictor variables.

The structural model demonstrates strong explanatory and predictive capability. The R^2 values for PU, PEOU, and AI adoption are all above the recommended values for behavioral and organizational research (Table 6), which suggests that a significant proportion of variance was explained by the model. The R^2 value in the model of open innovation performance provides additional support that AI adoption is a meaningful factor in understanding the outcomes of open innovation.

Stone-Geisser Q^2 , based on blindfolding values, was used to determine predictive relevance. The positive Q^2

Table 5. Relationships of variables

Hypothesis	Relationship	Std. β	t -value	p -value	Decision	95% CI (LL, UL)
H1	PEOU $\rightarrow$ PU	0.111	2.469	0.014	Supported	0.02, 0.21
H2	PEOU $\rightarrow$ AIA	0.391	5.45	<0.001	Supported	0.24, 0.55
H3	PU $\rightarrow$ AIA	0.513	7.772	<0.001	Supported	0.36, 0.66
H4	TMS $\rightarrow$ PU	0.328	7.772	0.003	Supported	0.21, 0.45
H5	TMS $\rightarrow$ PEOU	0.138	6.963	<0.001	Supported	0.05, 0.24
H6	RA $\rightarrow$ PU	0.257	6.147	0.001	Supported	0.15, 0.38
H7	RA $\rightarrow$ PEOU	0.252	4.986	0.003	Supported	0.11, 0.34
H8	CP $\rightarrow$ PU	0.111	2.469	0.014	Supported	0.01, 0.22
H9	RE $\rightarrow$ PU	0.165	3.573	<0.001	Supported	0.04, 0.29
H10	CP $\rightarrow$ PEOU	0.271	6.147	0.013	Supported	0.16, 0.39
H11	RE $\rightarrow$ PEOU	0.201	4.986	<0.001	Supported	0.12, 0.29
H12	AIA $\rightarrow$ OIP	0.666	22.549	<0.001	Supported	0.53, 0.79
H13	AIA $\times$ GKM $\rightarrow$ OIP	0.054	0.613	0.541	Not supported	-0.18, 0.26

Note. Bootstrapping based on 5,000 resamples. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. AIA $\times$ GKM = Interaction term representing the moderating effect of green knowledge management on the relationship between AI adoption and open innovation performance.

Abbreviations: AIA: Artificial intelligence adoption; CI: Confidence interval; CP: Competitive pressure; GKM: Green knowledge management; LL: Lower limit; OIP: Open innovation performance; PEOU: Perceived ease of use; PU: Perceived usefulness; RA: Resource availability; RE: Regulatory environment; TMS: Top management support; UL: Upper limit.

Table 6. Explanatory power, predictive relevance, and effect sizes

Endogenous construct	R^2	Q^2	Key predictors	f^2 Interpretation
Perceived usefulness	0.56	0.31	TMS, RA, CP, RE	Small–moderate
Perceived ease of use	0.56	0.31	PU, TMS, RA, CP, RE	Moderate
AI adoption	0.49	0.28	PU, PEOU	Large
Open Innovation performance	0.44	0.29	AI adoption	Large

Note. R^2 values of 0.25, 0.50, and 0.75 indicate weak, moderate, and substantial explanatory power, respectively. f^2 values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects (Hair et al., 2022).

Abbreviations: AI: Artificial intelligence; CP: Competitive pressure; GKM: Green knowledge management; OIP: Open innovation performance; PEOU: Perceived ease of use; PU: Perceived usefulness; RA: Resource availability; RE: Regulatory environment; TMS: Top management support.

values of all endogenous constructs were far above zero, indicating that the model has in-sample explanatory but out-of-sample predictive relevance.

The mediation structure implied by the integrated TAM–TOE framework was formally tested by examining the indirect effects of TOE-based organizational and environmental antecedents on AI adoption through the mediating roles of PU and PEOU. All indirect effects

were estimated using a bootstrapping procedure with 5,000 resamples and 95% bias-corrected CIs (Hair *et al.*, 2022). The indirect effects are presented in Table 7. The results indicate that all TOE antecedents exerted significant indirect effects on AI adoption through PU and PEOU, thereby supporting the mediation structure of the integrated model. Specifically, top management support exerted an indirect effect on AI adoption through PU ($\beta = 0.168$, 95% CI: 0.089–0.251) and through PEOU

($\beta = 0.054$, 95% CI: 0.019–0.097). Resource availability exerted indirect effects through PU ($\beta = 0.132$, 95% CI: 0.066–0.203) and PEOU ($\beta = 0.099$, 95% CI: 0.040–0.163). Competitive pressure exerted indirect effects through PU ($\beta = 0.057$, 95% CI: 0.011–0.108) and PEOU ($\beta = 0.106$, 95% CI: 0.050–0.170). The regulatory environment exerted indirect effects through PU ($\beta = 0.085$, 95% CI: 0.022–0.152) and through PEOU ($\beta = 0.079$, 95% CI: 0.026–0.136). The variance accounted for values, calculated as the ratio of the indirect effect to the total effect, ranged from 28% to 67%, indicating partial mediation across the significant indirect pathways. These findings support the central proposition of the integrated TAM–TOE framework that organizational and environmental factors influence AI adoption indirectly through managers' perceptions of usefulness and ease of use, rather than solely through direct effects on adoption behavior.

Analysis of effect size (f -values) indicates that the effects of PU and AI adoption are large. Their own endogenous constructs and TOE-based organizational and environmental factors indicate small to moderate effects, which are theoretically significant. The integrated framework uses multi-level logic; contextual pressures affect perceptions of managers; perceptions result in adoption; and adoption results in innovation.

All structural paths were evaluated for multicollinearity using VIFs. All VIF values were below the conservative threshold of 3.5, indicating no collinearity issues. This supports the robustness of the structural model estimates

by confirming that the estimated path coefficients are not distorted by the overlapping predictors. The validated structural model is presented in Figure 3.

4.4. Moderation and post-adoption outcome discussion

This section interprets the moderating role of GKM and explores the adoption of AI as a post-adoption capability that influences open innovation performance in Pakistani textile manufacturing SMEs under crisis and compliance pressures.

However, as expected, no significant moderation effects of GKM were observed in the relationships between AI adoption and open innovation performance. This finding provides insights into the role of sustainability-oriented practices in shaping AI-driven innovation outcomes. Knowledge processes in Pakistani textile SMEs are still in their infancy and not yet a strategic skill for multiplying the returns of AI. Although previous literature identifies GKM as an enabling factor in converting digital innovation into sustainable innovation, these effects seem to be conditional upon institutionalized knowledge routines, formal learning processes, and cross-functional integration, which are limited in resource-poor SMEs.

In particular, if the moderation is not significant, this does not imply that it is not relevant for GKM. Rather, it indicates a misfit between externally imposed sustainability rules and the internal organizational capability. Today, compliance is more of a ticking-the-box, audit-related

Table 7. Indirect effects and mediation results

Indirect Path (TOE → Mediator → AIA)	Indirect β	SE	95% CI (LL, UL)	VAF (%)
TMS → PU → AIA	0.168	0.042	0.089, 0.251	51.20%
TMS → PEOU → AIA	0.054	0.021	0.019, 0.097	16.50%
RA → PU → AIA	0.132	0.034	0.066, 0.203	67.30%
RA → PEOU → AIA	0.099	0.029	0.040, 0.163	50.00%
CP → PU → AIA	0.057	0.025	0.011, 0.108	28.40%
CP → PEOU → AIA	0.106	0.03	0.050, 0.170	39.10%
RE → PU → AIA	0.085	0.034	0.022, 0.152	51.50%
RE → PEOU → AIA	0.079	0.028	0.026, 0.136	39.20%

Note: All significant indirect effects based on 95% bias-corrected bootstrapped confidence intervals excluding zero; n.s. = not significant (CI includes zero).

Abbreviations: AIAD: AI adoption; CI: Confidence interval; CP: Competitive pressure; LL: Lower limit; PEOU: Perceived ease of use; PU: Perceived usefulness; RA: Resource availability; RE: Regulatory environment; TOE: Technology–organization–environment; TMS: Top management support; UL: Upper limit; VAF: Variance accounted for (indirect effect / total effect $\times$ 100).

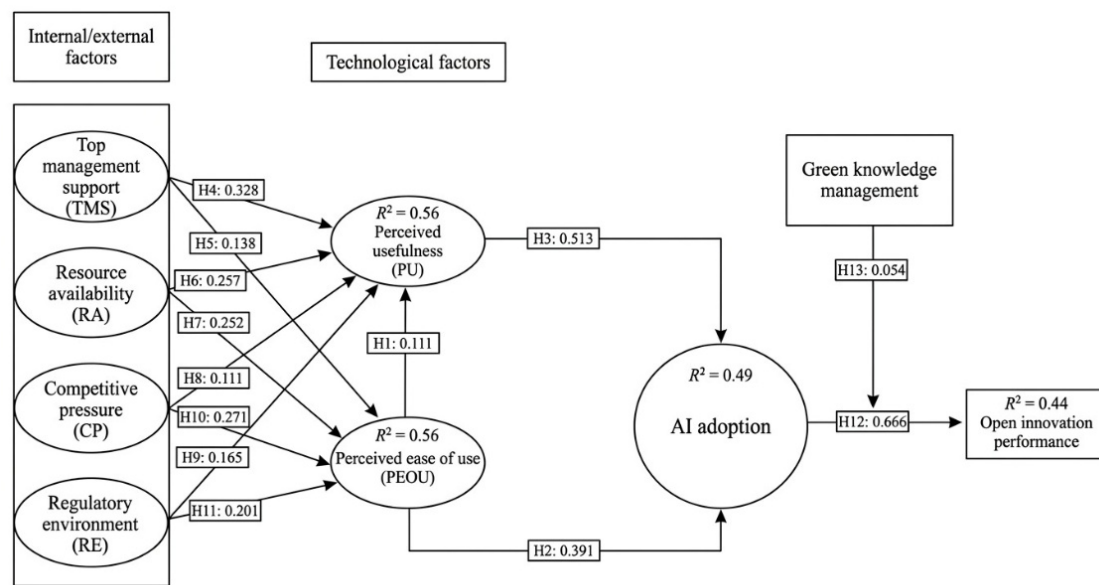


Figure 3. Partial least squares structural equation modeling validated structural model

Note. Model shows significant paths, R^2 values for endogenous constructs, and moderation effects.

exercise, with green knowledge treated as disjointed documentation rather than a shared strategic asset. Therefore, the implementation of AI contributes to better operational efficiency and decision-making, but the lack of integration of green knowledge restricts the potential of AI to support sustainable open innovation.

Conversely, the impact of AI adoption on open innovation is positive and robust. The results show that integrating AI into core processes increases SMEs' capacity to engage in teamwork, knowledge sharing, and innovation networks by translating AI adoption from intention into practice through usage intensity. This is particularly salient for export-oriented textile SMEs facing energy cost shocks and stringent buyer compliance requirements, where AI-enabled analytics support data standardization, transparency, and external collaboration

Together, the results suggest an imbalance in capability development. SMEs may be able to leverage AI to enhance open innovation and organizational resilience; however, they may not yet possess the capacity to embed sustainability knowledge deeply enough to influence these outcomes. This implies a gradual capability process where AI presents short-term innovation gains, and the long-term sustainability of these gains is determined by the maturity of GKM practices.

This section sharpens the integrated TAM–TOE framework by clarifying these boundary conditions and contributing to a more context-sensitive conceptualization

of AI-enabled innovation in crisis contexts in manufacturing SMEs in emerging markets.

5. Discussion

This study examined how AI adoption unfolds and generates innovation outcomes in Pakistan's textile manufacturing SMEs operating under acute cost volatility, regulatory pressure, and sustainability compliance mandates. The findings demonstrate that AI adoption in this context is neither a discretionary technological upgrade nor a linear innovation strategy. Instead, it emerges as a crisis-driven, compliance-oriented organizational capability whose innovation value is shaped by interactions among managerial perceptions, organizational constraints, and institutional pressures, as proposed in the integrated TAM–TOE framework (Davis, 1989; Haq & Suki, 2025; Tornatzky & Fleischer, 1990).

Consistent with the problem articulated in Section 1, the results indicate that textile SMEs adopt AI primarily as a response to survival threats, including rising energy costs, export uncertainty, and tightening sustainability regulations, rather than as an exploratory innovation investment (Sánchez-Rodríguez *et al.*, 2025). In this setting, PU reflects AI's ability to stabilize operations, improve decision accuracy, and support compliance under resource scarcity, rather than its potential to generate radical innovation. This finding aligns with crisis-driven digitalization research, which shows that SMEs prioritize

resilience and short-term viability when adopting advanced technologies under uncertainty.

The strong effects of top management support, resource availability, competitive pressure, and regulatory environment on PU and PEOU confirm that managerial cognition is embedded within structural and institutional realities (Badghish & Soomro, 2024; Tiago & Almeida, 2026). Leadership commitment and minimum resource thresholds legitimize AI initiatives internally, while competitive and regulatory pressures shape how managers interpret the risks and benefits of adoption. This directly addresses a key limitation of perception-centric TAM studies, which often assume that favorable beliefs translate seamlessly into adoption, overlooking the constraints faced by SMEs in emerging economies (Faiz *et al.*, 2024; Özel, 2025).

Importantly, the findings extend prior research by demonstrating that AI adoption significantly enhances open innovation performance, validating the study's focus on post-adoption outcomes rather than adoption intention alone. AI adoption improves SMEs' capacity to engage in inbound and outbound knowledge exchange, collaborate with buyers and partners, and participate in innovation networks. This result is particularly salient in export-oriented manufacturing, where innovation increasingly depends on data credibility, traceability, and responsiveness to global buyers (Carrasco-Carvajal *et al.*, 2023; Crema *et al.*, 2014; Qu & Kim, 2025). AI-enabled analytics allow firms to standardize information flows and reduce coordination frictions, enabling openness even under severe cost and liquidity constraints (Sánchez-Rodríguez *et al.*, 2025).

The analysis also makes it clear that capability development is asymmetric with respect to structure. Surprisingly, the relationship between AI adoption and open innovation performance is not significantly affected by GKM. The results contradict the dominant green innovation and knowledge-based literature, which suggests that sustainability-oriented knowledge more generally increases digital innovation outcomes. Sustainability knowledge is not fully institutionalized in textile SMEs to serve as a strategic boundary condition in Pakistan.

This non-significant moderation effect reflects a contextual misalignment between external sustainability pressure and internal learning capability. Sustainability compliance in export textiles is largely externally imposed through audits, buyer codes of conduct, and regulatory deadlines, leading firms to treat green knowledge as fragmented documentation rather than as an innovation-enabling resource. While AI adoption improves operational efficiency and decision-making, the absence of integrated

green knowledge routines limits its capacity to catalyze sustainability-oriented open innovation. Similar contextual constraints have been observed in other emerging-market manufacturing settings, where resource scarcity and weak institutional support inhibit the strategic deployment of green capabilities.

Taken together, these findings suggest a staged capability development pathway. In the short term, AI adoption driven by cost shocks and regulatory pressure enhances innovation openness and operational resilience, even without mature sustainability knowledge systems (Haq & Suki, 2025; Hiremath *et al.*, 2025). In the longer term, however, the sustainability and scalability of these innovation gains depend on whether SMEs can institutionalize GKM and integrate it with digital systems. Without this transition, AI-enabled innovation is likely to remain efficiency-oriented rather than sustainability-driven.

By grounding AI adoption within a high-pressure emerging-market context, this study demonstrates that adoption behavior, innovation outcomes, and sustainability mechanisms cannot be adequately explained through static or universal models. The integrated TAM–TOE framework proves valuable precisely because it captures the interaction between perception, organization, and environment, while the post-adoption findings clarify where theoretical expectations diverge from empirical reality. These insights provide a coherent foundation for the subsequent sections, which elaborate the study's theoretical contributions and managerial and policy implications.

The findings of this study also contribute to the growing discourse on the relationship between organizational resilience and AI adoption in SMEs, particularly in contexts characterized by crises, disasters, and disruptions such as the COVID-19 pandemic. The pandemic exposed the extreme vulnerability of manufacturing SMEs in emerging economies, where supply chain disruptions, demand volatility, and workforce restrictions forced firms to accelerate digital transformation efforts as a survival mechanism (Akpan *et al.*, 2022; Shah *et al.*, 2022). The present findings parallel these observations by demonstrating that AI adoption in Pakistani textile SMEs is fundamentally crisis-driven, motivated by cost shocks and regulatory pressures rather than discretionary innovation investment. Research on post-COVID-19 SME recovery consistently shows that AI-enabled capabilities such as predictive analytics, automated quality inspection, and real-time supply chain monitoring enhance organizational adaptability and business continuity by enabling faster response to disruptions and reducing dependence on manual processes (Roux *et al.*, 2025; Soomro *et al.*, 2026).

In the context of this study, the strong direct effect of AI adoption on open innovation performance ($\beta = 0.666$, $p < 0.001$) suggests that AI functions as a resilience mechanism that enables SMEs to maintain and expand collaborative innovation networks even under adverse conditions. This aligns with dynamic capabilities theory, which posits that firms capable of sensing, seizing, and reconfiguring resources through digital technologies are better positioned to adapt to environmental turbulence (Sanchez-Rodriguez *et al.*, 2025). Furthermore, the experience of COVID-19 has underscored the importance of digital readiness as a precondition for resilience. The significant effects of top management support and resource availability on AI adoption perceptions in this study reinforce the argument that organizational preparedness is essential for converting crisis-induced pressures into adaptive capabilities rather than reactive coping behaviors. However, the non-significant moderation of GKM also reveals a critical limitation of crisis-driven AI adoption: while AI enhances short-term operational resilience and innovation openness, its capacity to support long-term sustainability-oriented resilience requires the development of institutionalized knowledge management practices that go beyond compliance-based responses. Future research should therefore examine how AI adoption trajectories evolve across pre-crisis, crisis, and post-crisis phases, and whether the resilience gains observed in this study are sustained over time or diminish in the absence of continued organizational learning and investment.

5.1. Theoretical implications

The study contributes to the body of AI adoption literature in several ways, including innovation and sustainability in SMEs, especially in crisis-prone environments in emerging markets.

First, the results extend the TAM by demonstrating that PU and PEOU are not merely cognitive constructs but are also shaped by organizational and environmental forces. Although TAM traditionally conceptualizes these constructs as individual perceptions influencing technology acceptance, the findings suggest that their formation is also contingent upon broader contextual factors. This study demonstrates that managerial perceptions as individual-level assessments of performance provide adequate evidence that different varieties of performance management can yield diverse results (Umer *et al.*, 2024). Top management support, resource availability, regulatory pressure, and competitive intensity are key determinants of such perceptions in resource-constrained SMEs. By empirically validating these pathways, this study reinforces calls to embed TAM within broader institutional and organizational frameworks rather than treating it as

a standalone explanation of technology acceptance (Badghish & Soomro, 2024; Haq & Suki, 2025).

Second, integrating TAM and TOE advances AI adoption theory by resolving a long-standing fragmentation between perception-based and context-based explanations. TOE-based research focuses on readiness and pressure but tends to be less specific on the cognitive aspects of how decision-makers process these limitations (Tiago & Almeida, 2026; Tornatzky & Fleischer, 1990). The findings show that the organization and the environment do not directly cause AI adoption, but rather work through PU and PEOU, which supports the mediating role of managerial sense-making in crisis circumstances. This multi-level description is especially useful for SMEs that can encounter volatile costs and regulatory shocks, and whose adoption choices are restricted and risk-sensitive in nature (Ahmad *et al.*, 2023).

Third, the research adds to innovation theory by shifting the analytical focus from AI adoption as a final destination to AI adoption as a post-adoption capability. The high impact of AI implementation on performance in open innovation justifies the perspective of AI as a general-purpose technology, whose value is determined by recombining with external knowledge streams and joint practices (Carrasco-Carvajal *et al.*, 2023; Crema *et al.*, 2014). This result challenges adoption-centric models that treat uptake as equivalent to value creation and highlights the significance of studying how AI is redefining learning, coordination, and openness in export-oriented SMEs (Sanchez-Rodriguez *et al.*, 2025).

Fourth, the insignificant moderating effect of GKM provides a critical boundary condition to green innovation theory. Much of the sustainability literature assumes that green knowledge can enhance digital-to-innovation connections everywhere. This research confirms that assumption by showing that the effectiveness of GKM depends on context. In manufacturing SMEs in emerging markets, where sustainability practices are often adopted in response to external pressures rather than fully embedded within organizational routines, green knowledge remains fragmented and under-institutionalized, limiting its ability to enhance AI-powered innovation. This observation narrows down the knowledge-based perspective by demonstrating that knowledge resources actually generate strategic moderation effects only when they are backed by consistent routines, learning processes and institutional fit (Usman *et al.*, 2023).

Together, these contributions position the combined TAM-TOE model as a more plausible theory of AI adoption and innovation when faced with crisis and compliance pressure, as well as where sustainability-oriented extensions need further capability maturity.

Fifth, this study makes a substantive contribution to the Knowledge-Based View (KBV) of the firm (Grant, 1996; Kogut & Zander, 1992). The KBV posits that firms generate and sustain competitive advantage through the integration, transfer, and application of knowledge resources. In the context of AI-driven innovation, this study extends the KBV in three important ways. First, it demonstrates that knowledge-related organizational factors—specifically resource availability and top management support—function as antecedents that shape how decision-makers cognitively appraise AI technologies, thereby mediating the translation of organizational knowledge endowments into adoption behavior. This is consistent with the KBV argument that managerial cognition and sense-making are central to the knowledge creation and deployment process (Spender, 1996). Second, the positive effect of AI adoption on open innovation performance reflects a KBV logic: firms that successfully deploy AI as a knowledge-processing technology become better positioned to integrate external knowledge from buyers, supply-chain partners, and regulatory bodies, thereby enhancing their dynamic knowledge absorptive capacity (Cohen & Levinthal, 1990; Zahra & George, 2002). Third, and most importantly, the non-significant moderating effect of GKM constitutes a novel KBV boundary condition. From a KBV perspective, knowledge resources generate strategic value only when they are tacit, non-imitable, and deeply embedded in organizational routines and structures (Barney, 1991; Grant, 1996). In Pakistani textile SMEs, sustainability knowledge remains largely explicit, externally imposed through audits and buyer codes, and insufficiently codified into organizational processes to function as a strategic resource. This finding advances the KBV by specifying the conditions under which knowledge fails to act as a strategic moderator: when knowledge is compliance-reactive rather than proactively institutionalized, it cannot condition the relationship between digital capabilities and innovation outcomes. These insights collectively strengthen the KBV-grounded understanding of how knowledge resources mediate and moderate the AI-innovation relationship under institutional and resource constraints.

5.2. Managerial and policy implications

The results provide a number of practical implications for SME managers, industry stakeholders, and policymakers in export-oriented manufacturing industries. The findings underscore that the benefits of innovation from the introduction of AI can be realized only if the following conditions for introduction are met: as part of the fundamental way of doing things, not as a symbolic and/or experimental investment. The more companies can leverage AI to drive production control, decision-making

and process optimization, the more they can be part of an open innovation network, partner with customers, and respond to compliance needs. Managers should thus prioritize use intensity and integration depth over initial adoption or pilot projects.

Nonetheless, the lack of a moderating role of GKM indicates a serious gap in management. If sustainability knowledge is treated as audit evidence or as compliance information for buyers, then it is limited in its strategic value. Managers should institutionalize green knowledge by disseminating it across functions, via common data practices and by linking it to digital systems to fully leverage the innovation potential of AI for sustainability. In the absence of these efforts, AI-based innovation will continue to be efficiency-oriented and short-term, rather than sustainability-oriented and scalable.

From a policy perspective, these results caution against the assumption that regulatory pressure alone will drive sustainable digital transformation. Although compliance requirements may stimulate AI adoption, they do not necessarily foster the organizational learning processes required to translate AI adoption into green innovation. Regulation should therefore be complemented by implementation measures, such as capacity-building (government-sponsored online courses), data governance support, and incentives for knowledge-sharing platforms in industrial clusters.

The results suggest that industry associations and export organizations need collaborative solutions. Adopting AI and green knowledge in individual SMEs can be less costly and more straightforward with the help of common digital infrastructures, consistent sustainability data models, and learning programs. These ecosystem-level interventions are particularly important in contexts where firm resource constraints remain high, such as the textile industry in Pakistan. In the long run, these results indicate that AI can be a resilience tool during a crisis, but it needs to be sustainable and open innovation, which requires integrated managerial and policy action to institutionalize knowledge and learning capabilities.

Based on the empirical findings, this study proposes a staged AI-innovation-sustainability framework that reflects the practical implications and provides a structured pathway for policymakers, industry associations, and SME managers. The framework identifies three sequential capability stages.

Stage 1 (foundation building) involves establishing the organizational prerequisites for AI adoption, including top management commitment, minimum resource thresholds (digital infrastructure, financial slack, workforce skills),

and awareness of competitive and regulatory pressures. Policy interventions at this stage should include subsidized digital literacy programs, tax incentives for AI-related capital investment, and cluster-level digital infrastructure development.

Stage 2 (operational integration) focuses on embedding AI into core production, monitoring, and decision-support processes to realize innovation gains. At this stage, SMEs transition from pilot AI projects to integrated deployment, which the findings show significantly enhances open innovation performance. Policy support should include industry-wide data standardization protocols, shared AI service platforms for SME clusters, and buyer-supplier innovation partnerships facilitated through export promotion agencies.

Stage 3 (sustainability institutionalization) addresses the capability gap identified by the non-significant moderation of GKM. This stage requires SMEs to develop formal routines for green knowledge acquisition, sharing, and application that are integrated with AI-enabled decision systems. Policy interventions should include mandatory sustainability knowledge training tied to export certification, green innovation grants conditional on knowledge management capacity, and cross-firm sustainability learning networks supported by industry associations and government agencies. The framework recognizes that sustainable and scalable AI-driven innovation cannot be achieved through technology adoption alone, but requires a progressive development of complementary organizational and institutional capabilities. This staged approach offers a realistic pathway for emerging-market manufacturing SMEs where resources are scarce, institutions are evolving, and the pressure for both competitiveness and sustainability compliance is intensifying simultaneously.

5.3. Limitations

In addition to its contributions, this study is subject to a number of limitations, which must be considered. First, the study used a cross-sectional design, which makes it difficult to investigate and follow learning processes and capability over time. Longitudinal data would be useful for understanding the causal and sequencing effects of innovation, as the adoption of AI, GKM, and innovation outcomes are fundamentally evolutionary (Qazi *et al.*, 2022).

Second, the research is based on the perceptual measures of single key informants in firms. Despite the use of procedural and statistical solutions to reduce common method bias, the research can be further enhanced with robustness in future studies through the use of multi-

respondent designs or objective performance indicators, especially with respect to innovation and sustainability outcomes (Haq *et al.*, 2026).

Third, the empirical specialization of the textile manufacturing SMEs in Pakistan, theoretically and rationally motivated, prevents the extrapolation of results to other industries or organizational environments. There is a unique exposure of export manufacturing to energy costs and sustainability mandates, and AI adoption dynamics can vary among service-oriented or domestically-oriented SMEs (Haq, Asim, *et al.*, 2025).

Lastly, the GKM was operationalized as a reflective firm-level construct. Although they are suitable to the goals of this study, other conceptualizations, including formative or configurational, may be able to better represent the richness of sustainability knowledge practices (Masood *et al.*, 2024).

5.4. Future research directions

Based on these constraints, several promising directions for future research emerge. Longitudinal and process studies should examine how AI adoption evolves from early adoption to sustained use, particularly in crisis contexts where sustainability is an essential concern (Alzboon *et al.*, 2025). This type of study could contribute to the understanding of the influence of GKM in the transition of companies from reactive sustainability practices to proactive ones (A. Hussain & Khan, 2025).

Second, future studies could explore configurational and nonlinear relationships among AI adoption, organizational capabilities, and innovation outcomes using mixed-methods designs. This would assist in revealing other avenues that SMEs can build innovation resilience with constraints (Li *et al.*, 2025).

Third, extending the integrated TAM-TOE model to ecosystem analysis would provide valuable insights. Analyzing the position of buyers, regulators, industry associations, and digital platforms would show how the external actors influence the post-adoption innovation paths, particularly within global value chains (Zhang *et al.*, 2025).

Fourth, cross-country comparisons of emerging economies or emerging and developed markets would enable researchers to evaluate the boundary conditions identified in this study. This kind of work may reveal the weak moderating effect of GKM as being setting-specific, or as being indicative of a general trend in manufacturing sectors dominated by SMEs (Al-Dhanhani & Yassin, 2025).

Lastly, future research should investigate the relationship between AI and other Industry 4.0

technologies. Technologies such as the Internet of Things and blockchain may complement AI by enhancing traceability, transparency, and collaborative innovation across supply chains (Zahra *et al.*, 2025).

6. Conclusion

This study investigated the effects of AI adoption on open innovation performance of export-oriented SMEs under crisis and compliance pressure, using the textile industry in Pakistan as a high-stakes empirical setting. By incorporating the TAM and the TOE framework, this study extends this integration to post-adoption innovation outcomes, providing a direct response to the limitations of the adoption-centric and context-insensitive explanations found in existing studies (S. Hussain *et al.*, 2026).

The results indicate that managers' perceptions collaboratively determine the adoption of AI in SMEs, along with organizational and environmental constraints. PU and PEOU are key factors in adoption decisions, but they are systematically conditioned by the support of top management, availability of resources, regulatory environment, and competition pressure (Alzboon *et al.*, 2025). This substantiates that the use of AI in emergency-prone emerging economies is not an entirely rational process, but is instead a structural one, which is the result of limited managerial sense-making in the face of cost volatility and institutional pressures (Raza *et al.*, 2025).

More importantly, the study shows that AI adoption meaningfully enhances open innovation performance when it is incorporated in the fundamental operational and decision-making processes (Ullah *et al.*, 2025). This emphasizes the strategic importance of going beyond adoption intention to post-adoption deployment intensity. Meanwhile, the insignificant mediating effect of GKM demonstrates that sustainability knowledge is still not a mature strategic resource that can help to increase AI-enabled innovation in most textile SMEs. This finding, instead of discrediting the model, narrows down the existing theory by showing that the sustainability-oriented capabilities are dependent on the depth of organizational learning and institutional alignment (Li *et al.*, 2025).

Collectively, the study progresses toward a more realistic and result-oriented perspective of AI-enabled innovation in emerging-market manufacturing SMEs (Masood *et al.*, 2024). It demonstrates that AI can be used to strengthen and open up technology in times of crisis, but that its long-term sustainability depends on whether firms and institutions shift from being reactive in their compliance to being proactive in building capability (Haq, Suki, *et al.*, 2025).

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Conflict of interest

The authors declare no competing interests.

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Ethics approval and consent to participate

This study was conducted in accordance with the ethical principles of research involving human participants. Ethical approval was obtained from the relevant research ethics committee of Universiti Utara Malaysia (UUM/OYAGSB/T-13-3) dated April 1, 2026, prior to data collection. Participation in the study was entirely voluntary, and all respondents were informed about the purpose of the research, the confidentiality of their responses, and their right to withdraw from the study at any time without any consequences. Informed consent was obtained from all participants before they completed the survey questionnaire. No personally identifiable information was collected, and all data were analyzed and reported in aggregate form to ensure participant anonymity and confidentiality.

Consent for publication

All participants provided informed consent prior to participating in this study. No personally identifiable information was collected, and all data were anonymized before analysis. Therefore, publication of individual participant data or images was not applicable. The authors obtained the necessary consent from participants for the use of their responses for academic research and publication purposes.

Availability of data

The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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