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Mediating role of AI adoption between the relationship of leadership vision, change management capability, competitive pressure, trading partnerships, and SME performance

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Abstract

This study investigates the critical drivers of artificial intelligence (AI) adoption in SMEs. The mediating role of AI adoption on the relationship between leadership vision, change management capability, competitive pressure, trading partnerships, and SME performance is also investigated. This research employs a quantitative methodology, collecting data through structured questionnaires from senior and middle-level managers of manufacturing SMEs in Pakistan. Data were analyzed using the software SmartPLS for partial least squares structural equation modeling (PLS-SEM). The results reveal that trading partnerships are the most critical drivers of AI adoption in SMEs within an emerging economy, followed by change management capabilities and leadership vision. These factors contribute to improving SME performance in competitive and resource-constrained markets, aligning with Sustainable Development Goal 9 (industry, innovation, and infrastructure). Additionally, AI adoption mediates the relationship between trading partnerships, competitive pressure, and SME performance. This research uncovers unique insights by integrating the technology-organization-environment (TOE) framework, Resource-based view theory, and diffusion of innovations theory simultaneously in a

proposed research framework that tests the critical drivers of AI adoption in SMEs within an emerging economy.

Keywords: AI adoption, SME performance, industry 4.0, competitive pressure, trading partnerships, technology-organization-environment (TOE) framework, leadership vision.

1. Introduction

Small and medium-sized enterprises (SMEs) are crucial to job creation and economic growth, representing nearly 90% of all businesses and significantly contributing to gross domestic product (GDP) and innovation (International Council for Small Business, 2019; Cudilla, 2020). Their role is vital in emerging and developed economies, projected to generate around 600 million jobs by 2030, sustaining economic dynamism and competitiveness (European Commission, 2023; Haris et al., 2023). In Pakistan, SMEs are key to the non-agricultural workforce, industrial resilience, and exports. However, challenges like infrastructural deficits, resource limitations, and economic instability hinder technological progress (State Bank of Pakistan, 2023). The Global Innovation Index highlights a significant need for innovation within Pakistani SMEs to boost global competitiveness (World Intellectual Property Organization, 2022).

In this context, Industry 4.0, also known as the fourth industrial revolution, represents a pivotal shift towards integrating advanced digital technologies with traditional manufacturing and operations processes. This revolution leverages technologies such as the internet of things (IoT), artificial intelligence (AI), big data, cloud computing, and cyber-physical systems (CPS) to create inter-connected, autonomous systems capable of intelligent decision-making (Nosalska et al., 2019; Zhang et al., 2024). For SMEs, the transition towards Industry 4.0 offers potential for increased efficiency, flexibility, and improved decision-making through the use of data-driven insights, but it also presents significant challenges, including the need for cybersecurity, addressing skill gaps, and managing high investment costs.

Artificial Intelligence (AI), a cornerstone of Industry 4.0, is recognized as a transformative force that redefines traditional operations through automation and augmentation (Jarrahi, 2018; Wamba-Taguimdje et al., 2020). AI’s ability to process large volumes of data, learn from it, and make informed decisions can revolutionize operations within SMEs, leading to enhanced efficiency and competitiveness. However, artificial intelligence (AI) adoption presents unique challenges for SMEs in developing economies like Pakistan due to limited technological readiness, skill deficits, and infrastructural gaps (Anwar et al., 2018; Ullah et al., 2023). The incorporation of AI into business processes within this Industry 4.0 framework requires careful leadership and strategic planning, particularly in environments constrained by economic and technological limitations.

Key components of Industry 4.0, such as big data analytics, cloud computing, and advanced robotics, offer SMEs the potential to improve operational efficiency, enhance product quality, and adapt quickly to changing market demands (Sharabov & Tsochev, 2020). Yet, SMEs in emerging markets face significant barriers, such as the high cost of investment in these technologies and the need for interoperability across systems. Leadership vision and change management play crucial roles in overcoming these barriers and fostering a culture of innovation that supports AI adoption (Heredia-Calzado & Duréndez, 2019). Additionally, external pressures, such as competitive forces and trading partnerships, further drive the urgency for AI adoption in SMEs, aligning with global trends in digital transformation (Rabby et al., 2021).

Studies on artificial intelligence (AI) adoption by large enterprises and developed economies are plentiful; however, research into how small- and medium-sized enterprises (SMEs) in emerging markets like Pakistan utilize AI is scarce. This study seeks to fill this gap by integrating the technology-organization-environment (TOE) framework, diffusion of innovations (DOI), and resource-based view (RBV) theories to explore the unique dynamics of AI adoption in SMEs. It examines how leadership vision, change management capability, competitive pressure, and trading partnerships influence the deployment and success of AI technologies in improving SME performance, thus emphasizing AI's role in improving firm outcomes even under resource-constrained environments. Despite the potential benefits, research on how these organizational and environmental factors collectively shape AI adoption and mediate SME performance, particularly in developing markets, remains limited. Accordingly, the following research questions guide this study:

- RQ1: Do leadership vision, change management capability, competitive pressure, and trading partnerships have a positive influence on artificial intelligence adoption in SMEs?
- RQ2: Does artificial intelligence adoption mediate the relationship between leadership vision, change management capability, competitive pressure, and trading partnerships, and SME performance?

This study makes an imperative theoretical contribution by integrating the TOE framework, RBV theory, and DOI theory into a single model. The proposed framework highlights the importance of aligning organizational strategies with AI adoption and underscores how Industry 4.0 technologies can help SMEs overcome limitations and drive competitiveness. The findings provide practical insights for policymakers and business leaders, demonstrating how AI adoption, trading partnerships, and change management can collectively contribute to SME performance, particularly in developing markets like Pakistan, and align with SDG 9 (Industry, Innovation, and Infrastructure). In a rapidly evolving global economic landscape, integrating Industry 4.0 technologies into SMEs can enhance operational efficiencies, foster innovation, and maintain competitive advantages. However, as this research highlights, the success of such technological transitions depends on both internal organizational factors and external environmental conditions.

The next sections review the associated literature, research methods, findings, and implications, offering a roadmap for leveraging AI in SMEs for global economic development.

2. Literature Review

2.1 Resource-Based View (RBV)

The resource-based view (RBV) suggests that firms can achieve sustained competitive advantage through the possession and effective utilization of resources that are valuable, rare, inimitable, and non-substitutable (Barney, 1991). In the context of SMEs, particularly in emerging economies, Artificial intelligence (AI) represents a transformative resource that enables firms to optimize decision-making, drive innovation, and improve operational efficiency (Mikalef & Gupta, 2021; Badghish & Soomro, 2024). For SMEs, which often face limitations in financial and human capital, AI offers a means to maximize the utilization of existing resources and enhance performance by enabling data-driven insights and automation.

The integration of AI as a resource aligns with the RBV framework, enhancing competitive advantage through technological empowerment. The studies by Mikalef & Gupta (2021) and Badghish & Soomro (2024) specifically underscore AI's impact on operational efficiency and sustainable business performance, providing a critical assessment of its strategic value to resource-constrained SMEs.

Leadership vision is a critical driver of artificial intelligence (AI) adoption. Leaders who recognize AI’s strategic potential and align it with long-term business objectives can effectively marshal resources towards AI integration. A forward-thinking leadership approach creates the necessary organizational momentum for successful AI implementation, particularly in contexts where technological adaptation is necessary for competitiveness (Chaudhuri et al., 2022). Furthermore, the capability to manage organizational change is essential for transitioning to AI-driven processes. Effective change management helps overcome employee resistance and fosters a culture that embraces innovation and technological advancement (Jalil et al., 2024; Lada et al., 2023).

In the context of Industry 4.0, where digital technologies are reshaping industries through automation, intelligent systems, and real-time data processing, AI adoption is becoming a critical factor for maintaining competitiveness. The ability of leadership to envision AI as part of their strategic framework and the organizational capacity to manage change directly influence SMEs’ capacity to adopt and integrate AI technologies as a means of enhancing their overall performance. Accordingly, this study develops the following hypotheses:

- H1: Leadership vision positively influences AI adoption in SMEs.
- H2: Change management capability positively influences AI adoption in SMEs.

2.2. Diffusion of Innovations (DoI) Theory

The Diffusion of Innovations (DoI) theory examines how new technologies spread through organizations and social systems, emphasizing the role of communication, perceived benefits, and technological compatibility in influencing adoption (Rogers, 1995). In SMEs, especially those in emerging markets, Artificial intelligence adoption is significantly influenced by how its advantages are perceived relative to existing technologies, as well as the ease with which AI can be integrated into current operations (Oliveira et al., 2014; Jalil et al., 2024). This theory is directly applicable to the studies cited, where AI's perceived benefits drive its adoption, reflecting a critical evaluation of how technological perceptions influence SME decision-making processes.

Competitive pressure is a significant external driver that pushes SMEs towards adopting AI. In the highly digitalized environments of Industry 4.0, firms that fail to incorporate AI risk losing their competitive standing. AI technologies enable firms to automate tasks, optimize operations, and provide superior customer service, which are critical for competitiveness in fast-evolving markets (Kurup & Gupta, 2022; Arroyabe et al., 2024). The studies by Kurup & Gupta and Arroyabe et al. provide empirical evidence that underscores the necessity of AI adoption for maintaining market competitiveness, highlighting the role of competitive pressure as a catalyst for technological advancement.

Another crucial driver of artificial intelligence (AI) adoption is trading partnerships. The collaborative relationships that SMEs develop with their trading partners, such as suppliers, vendors, or business allies, provide access to the resources and knowledge necessary for AI integration. Trading partners not only supply SMEs with the necessary technological tools but also facilitate knowledge exchange, which reduces the learning curve for AI adoption and increases the likelihood of successful implementation (Dyer & Singh, 2018). Strong trading partnerships can also motivate SMEs to adopt AI in order to maintain compatibility and efficiency within interconnected business networks (Silva et al., 2023). Therefore, this study posits that:

- H3: Competitive pressure positively influences AI adoption in SMEs.
- H4: Trading partnerships positively influence AI adoption in SMEs.

2.3. The Mediating Role of Artificial Intelligence Adoption in SME Performance

Artificial intelligence (AI) plays a pivotal mediating role in the relationship between organizational and environmental factors and SME performance. Through AI adoption, SMEs can enhance their operational efficiency, improve decision-making, and foster innovation, thereby translating strategic initiatives into tangible performance outcomes (Mikalef & Gupta, 2021). In Industry 4.0, where technological integration is vital for competitiveness, AI serves as a bridge that transforms leadership vision, change management capability, and external pressures into improved business performance.

AI's mediating role is particularly evident in how it aligns leadership vision and change management efforts with firm performance. By adopting AI, SMEs can turn strategic foresight into actionable outcomes such as better resource utilization, streamlined processes, and enhanced customer engagement. Similarly, AI allows SMEs to respond to competitive pressures more effectively by automating routine tasks, gaining data-driven insights, and improving product offerings. Furthermore, AI facilitates the integration of trading partnerships by optimizing supply chain interactions and ensuring that SMEs remain competitive within their business ecosystems (Wamba-Taguimdje et al., 2020). This mediating effect is crucial for SMEs striving to compete in the increasingly digitalized environments of Industry 4.0. Artificial intelligence adoption enables SMEs to transform environmental and organizational inputs into performance gains, ultimately helping them stay relevant in a rapidly changing technological landscape. Consequently, this study introduces the following hypotheses:

- H5: AI adoption mediates the relationship between leadership vision and SME performance.
- H6: AI adoption mediates the relationship between change management capability and SME performance.
- H7: AI adoption mediates the relationship between competitive pressure and SME performance.
- H8: AI adoption mediates the relationship between trading partnerships and SME performance.

2.4. Artificial Intelligence and SME Performance in the Context of Industry 4.0

The integration of AI is critical for improving SME performance, especially in the context of Industry 4.0, which emphasizes interconnected systems, intelligent automation, and data-driven decision-making. AI enables SMEs to automate processes, enhance operational flexibility, and introduce innovations that align with the demands of the digital economy. Through AI, SMEs can reduce costs, increase productivity, and improve customer engagement by delivering personalized, data-driven solutions (Mikalef & Gupta, 2021b).

In the Industry 4.0 framework, AI acts as a key enabler for digital transformation. By integrating AI into their operations, SMEs can leverage real-time data analytics, improve supply chain co-ordination, and automate complex tasks. AI's ability to drive innovation, optimize resource use, and provide strategic insights makes it an essential asset for achieving competitiveness and sustainability in the Industry 4.0 landscape (Wamba-Taguimdje et al., 2020). The adoption of artificial intelligence thus directly contributes to enhanced firm performance by improving operational efficiencies and enabling SMEs to adapt to market shifts and customer demands. Therefore, this study put forth that:

- H9: AI adoption positively influences SME performance

This literature review underscores the importance of AI adoption in driving SME performance, particularly within the framework of Industry 4.0. By integrating the resource-based view (RBV), diffusion of Innovations (DoI) theory, and the Technology-Organization-Environment (TOE) framework, the review highlights how leadership vision, change management capability, competitive pressure, and trading partnerships influence AI adoption. Furthermore, AI's mediating role in transforming these factors into performance outcomes emphasizes its significance as a strategic tool for competitiveness and growth, particularly for SMEs in emerging economies like Pakistan. Artificial intelligence adoption is not only essential for improving SME performance but also a critical enabler of digital transformation in the Industry 4.0 era. SMEs that embrace AI are better positioned to innovate, reduce costs, and improve customer satisfaction, ultimately achieving sustainable growth in an increasingly competitive global marketplace.

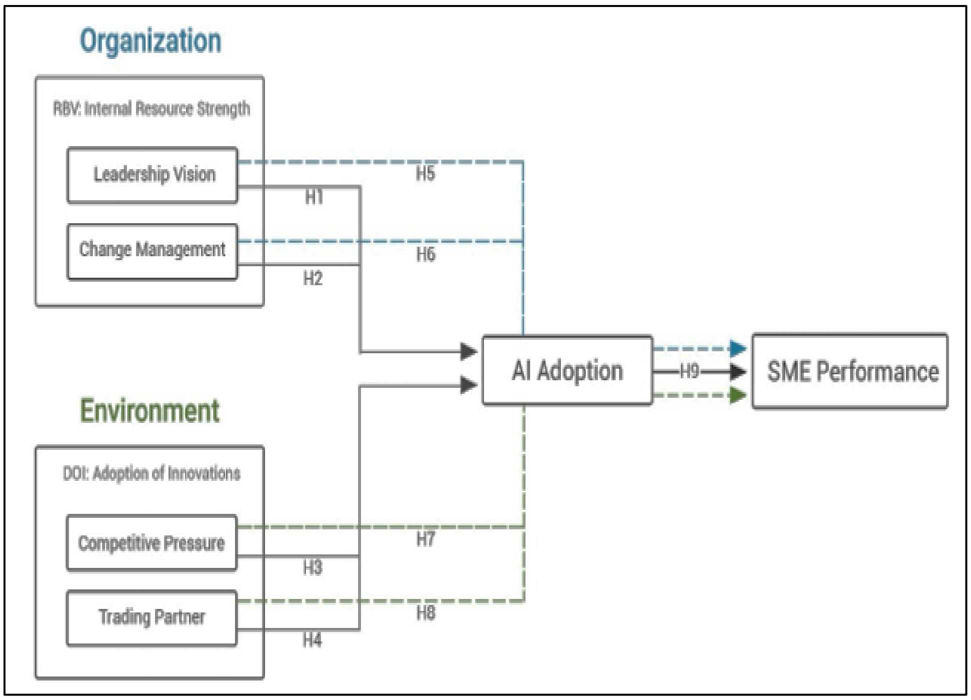

Figure 1. Proposed Theoretical Framework

3 Research Methodology

3.1. Population and Sampling Technique

This study adopts a quantitative method, grounded in the positivist paradigm, to evaluate the theoretical model discussed in the literature. To ensure a comprehensive analysis, five hundred questionnaires were distributed via Google Forms, targeting upper and middle management of manufacturing SMEs in Pakistan. This method facilitated easy access and completion, enhancing the response rate. The sampling strategy employed was stratified random sampling, ensuring proportional representation of various strata within the manufacturing sector, which aligns with the study's objectives (Sekaran & Bougie, 2016).

The focus was on SMEs in the manufacturing sector involved in the export market, which includes 6,561 entities contributing significantly to the nation's GDP and employment (Exportsinfo, 2020). Contact details were sourced from the Chamber of Commerce database, and the survey was further disseminated through WhatsApp groups popular among SME managers, thus broadening the study's reach. This sample size exceeds the minimum of 384 respondents recommended by Krejcie and Morgan (1970) for statistical generalization to a larger population. Data collection extended over three and a half months, beginning on November 18, 2023. From the initial samples, 151 were identified as outliers and excluded, leaving 349 samples for analysis.

The final sample comprised a slight majority of male participants (56.7%) compared to females (43.3%). Most respondents (77%) were between the ages of 21 and 40 years, reflecting a youthful demographic within management in this sector. Only 23% were between 41 and 60 years old. In terms of familiarity with AI applications, over three-quarters of the respondents (77%) had less than two years of experience, indicating a relatively novice level of engagement with AI technologies in the manufacturing sector, while the remainder had more than two years of experience.

3.2. Measurement of Instruments

The questionnaire is structured into two parts. Section A details the demographic characteristics of the participants, while Section B gathers data on artificial intelligence (AI) adoption, as well as organizational and environmental factors and SME performance, drawing on various sources. SME performance is assessed through four items that include financial, operational, and market indicators, based on frameworks from Bu et al. (2020) and Chen et al. (2016). The questionnaire includes constructs like leadership vision (4 items), competitive pressure (3 items), trading partnerships (3 items), and AI adoption (7 items), with the items modified from Kurup and Gupta (2022) to reflect strategic support from senior management. The section on change management capability consists of three items, derived from Kurup and Gupta (2022) and Leyer and Schneider (2021), which evaluate an organization's ability to manage technological changes. All items use a 7-point Likert scale, ranging from 'strongly disagree' (1) to 'strongly agree' (7).

4. Results

4.1 Partial Least Squares-Structural Equation Modelling (PLS-SEM)

The PLS-SEM approach was utilized due to its suitability for exploratory studies where the primary aim is prediction and theory building, especially in complex models involving multiple constructs and indirect relationships. Unlike CB-SEM, which assumes that data are multivariate normal and requires a large sample size for stable and reliable estimates, PLS-SEM can handle smaller sample sizes and non-normal data, making it more appropriate for this study's data set, which includes a wide range of variables with varying scales of measurement. Moreover, PLS-SEM allows for the assessment of both the measurement model and the structural model simultaneously, providing robustness in handling complex models (Henseler & Schuberth, 2020; Sarstedt et al., 2019).

Before conducting further analysis, the research involved an initial evaluation of multivariate skewness and kurtosis, utilizing web power software as recommended by Sarstedt and Ringle (2017) and Cain et al. (2017). The results from this evaluation demonstrated that the data collected from the survey did not adhere to multivariate normality, displaying considerable skewness and kurtosis. Consequently, PLS-SEM was chosen due to its robustness in handling non-normality, which circumvents the potential biases that could arise with CB-SEM in such conditions. As a result, the study employed SmartPLS software for PLS-SEM analysis, ensuring that the findings remained reliable despite the lack of normal data distribution (Cain et al., 2017).

4.2 Assessment of Measurement Model

The measurement model was evaluated using several tests, including internal consistency reliability, convergent validity, and discriminant validity. The outer loadings of the indicators were examined to assess construct item reliability, with a threshold of 0.70 required for reliability (Hair et al., 2019). Convergent validity was determined based on three criteria:

1. Factor loadings should exceed 0.700;
2. Composite reliability should be greater than 0.700;
3. Average Variance Extracted (AVE) should be above 0.500 (Hair et al., 2019).

Table 1 specifics that these criteria were met, confirming that the model demonstrates adequate internal consistency reliability and convergent validity. To assess discriminant validity, the uniqueness of each construct was evaluated (Hair et al., 2019). The Heterotrait-Monotrait ratio of correlations (HTMT) with a threshold of 0.85 was used to determine discriminant validity, with values below 0.85 indicating satisfactory discriminant validity (Henseler & Schuberth, 2020). As shown in Table 2, this criterion was also satisfied.

Table 1: Reliability and Validity Results

Construct	Items	Loadings	Cronbach's Alpha	CR	AVE
Leadership Vision	L1	0.810	0.735	0.882	0.585
	L2	0.843			
	L3	0.821			
	L4	0.736			
Change Management Capability	CMC1	0.829	0.898	0.945	0.577
	CMC2	0.788			
	CMC3	0.878			
Firm Performance	FP1	0.858	0.796	0.939	0.514
	FP2	0.806			
	FP3	0.814			
	FP4	0.642			
Competitive Pressure	CP1	0.717	0.832	0.917	0.674
	CP2	0.704			
	CP3	0.867			
Trading Partnerships	TP1	0.896	0.756	0.917	0.524
	TP2	0.860			
	TP3	0.792			
AI Adoption	AIA1	0.828	0.848	0.878	0.583
	AIA2	0.729			
	AIA3	0.889			
	AIA4	0.820			
	AIA5	0.810			
	AIA6	0.800			
	AIA7	0.760			

Discriminant validity was also evaluated using the Heterotrait-Monotrait ratio (HTMT) as a measure. HTMT values should be below 0.85 or 0.90. Table 2 shows that the values are well within these threshold limits.

Table 2: HTMT Ratio of Correlation Matrix

Variable	1	2	3	4	5	6
(1) Leadership Vision (L)						
(2) Change Management Capability (CMC)	0.512					
(3) Firm Performance (FP)	0.636	0.552				
(4) Competitive Pressure (CP)	0.509	0.418	0.584			
(5) Trading Partnerships (TP)	0.428	0.769	0.823	0.388		
(6) AI Adoption (AIA)	0.694	0.497	0.526	0.794	0.153	-

The measurement model's analysis demonstrates that the constructs exhibit strong internal consistency, convergent validity, and discriminant validity, meeting established criteria for reliable measurement. Specifically, each construct shows high reliability, with Cronbach's Alpha and Composite Reliability values above 0.70, indicating a robust internal consistency across items. The AVE values, all exceeding 0.50, confirm adequate convergent validity by showing that constructs capture substantial variance among indicators, as seen in constructs like Leadership Vision (AVE = 0.585) and AI Adoption (AVE = 0.583). Additionally, discriminant validity is well-supported by the HTMT ratios, with all values below the threshold of 0.85, signifying that each construct measures distinct dimensions within the model. This multidimensional approach confirms that the constructs are both internally consistent and uniquely defined, thereby ensuring that the model is well-suited for further structural analysis and that its findings will be reliable and interpretable across varying contexts.

4.3. Assessment of Structural Model

After validating the psychometric properties of the measurement model, the structural model was examined to evaluate the hypothesized relationships by analyzing standardized beta coefficients, standard errors, t-values, and p-values. The path significance levels were assessed using the bootstrapping method with 5,000 resamples. The results of the PLS-SEM approach shown in Table 3 revealed that leadership vision had a positive effect on AI adoption in manufacturing SMEs ($\beta = 0.362$; $t = 9.55$; $p < 0.001$), thus supporting H1. This finding aligns with recent literature, which underscores the pivotal role of leadership in facilitating AI adoption by fostering a conducive environment for technology integration (Badghish & Soomro, 2024). Likewise, AI adoption in manufacturing SMEs was significantly and positively influenced by change management capability ($\beta = 0.475$; $t = 11.31$; $p < 0.001$), giving support for H2. This result echoes findings by Arroyabe et al.

(2024), who highlighted that an organization's readiness and flexibility are critical for embracing digital transformations like AI.

In contrast, competitive pressure showed no significant effect on AI adoption among manufacturing SMEs ($\beta = 0.033$; $t = 1.40$; $p = 0.160$), contrary to expectations, thus rejecting H3. This lack of significance may reflect contextual factors, suggesting that external pressures alone are insufficient to drive AI adoption without corresponding internal support structures. Similarly, in the context of Malaysia, competitive pressure was also found to have no significant impact on AI adoption. Instead, factors such as Top Management Commitment and Organization Readiness played a more critical role in influencing AI adoption (Lada et al., 2023). For H4, the results indicated that trading partnerships had a significant positive effect on AI adoption ($\beta = 0.529$; $t = 12.15$; $p < 0.001$), aligning with the TOE framework, which emphasizes the role of inter-organizational networks in resource sharing and technology adoption (Badghish & Soomro, 2024). Additionally, AI adoption significantly influenced the performance of manufacturing SMEs ($\beta = 0.759$; $t = 34.15$; $p < 0.001$), thus supporting H5. These findings reinforce the understanding that artificial intelligence adoption enhances operational efficiency and performance in SMEs, a perspective widely discussed in recent studies on AI's role in boosting SME productivity in Industry 4.0 contexts.

Table 3: Hypotheses Testing Results (Direct Effect)

Relationship	**Std. Beta**	**Std. Error**	***t*-values**	***p*-value**	**2.50%**	**97.50%**	**Decision**	**R^2**	**f^2**	**Q^2**
L → AIA	0.362	0.038	9.55	<0.001	0.287	0.437	Supported		0.15	
CMC → AIA	0.475	0.042	11.31	<0.001	0.392	0.558	Supported		0.20	
CP → AIA	0.033	0.050	1.40	0.160	-0.065	0.131	Not Supported	0.45 0.51	-	0.30 0.36 -
TP → AIA	0.529	0.045	12.15	<0.001	0.440	0.618	Supported		0.25	
AIA → FP	0.759	0.022	34.15	<0.001	0.708	0.798	Supported		0.30	

Note: L = Leadership Vision, CMC = Change Management Capability, TP = Trading Partnerships, AIA = AI Adoption, CP = Competitive Pressure, FP = Firm Performance.

The R^2 value for AI adoption is 0.45, showing that 45% of the variance in AI adoption is explained by factors such as leadership vision, change management capability, competitive pressure, and trading partnerships. Similarly, the R^2 value for SME performance stands at 0.51, indicating that 51% of the variance in SME performance is explained by AI adoption.

4.4. Mediating Effect of AI Adoption

Mediation analysis was performed using the Sobel test (Baron & Kenny, 1986) and bootstrapping techniques (Hayes, 2009) to assess the indirect effects of latent variables. A bootstrapping with 5,000 subsamples was utilized to determine the indirect effects of AI adoption. Table 5 shows that the indirect effect of leadership vision through AI adoption on firm performance was not significant (β = 0.018, t = 0.541, p = 0.588), suggesting that AI adoption does not mediate the relationship between leadership vision and firm performance, thereby rejecting H6. Similarly, the change management capability's influence through AI adoption on firm performance did not exhibit a significant mediation effect (β = -0.039, t = 0.929, p = 0.355), thereby rejecting H7.

In contrast, trading partnerships showed a significant mediating effect through AI adoption on firm performance (β = 0.272, t = 8.177, p < 0.001), as did the indirect relationship between competitive pressure and firm performance through AI adoption (β = 0.393, t = 12.955, p < 0.001), supporting H8 and H9. This implies that AI adoption acts as a crucial intermediary that translates the influence of external pressures and partnerships into tangible performance outcomes, a finding consistent with recent studies that highlight AI's role as a transformative agent in SMEs (Arroyabe et al., 2024; Lada et al., 2023). The mediating role of AI underscores its importance in converting external partnerships and competitive forces into enhanced performance, especially in emerging markets where SMEs face unique challenges and opportunities for digital transformation.

Table 4: Mediating Effect of AI Adoption

Relationship	Std. Beta	Std. Error	t-Values	p Values	2.50%	97.50%	Decision
L → AIA → FP	0.018	0.033	0.541	0.588	-0.094	0.062	Not supported
CMC → AIA → FP	-0.039	0.042	0.929	0.355	-0.095	0.074	Not supported
TP → AIA → FP	0.272	0.033	8.177	0.000	0.207	0.338	Supported
CP → AIA → FP	0.393	0.030	12.955	0.000	0.331	0.450	Supported

Note: L = Leadership Vision, CMC = Change Management Capability, TP = Trading Partnerships, AIA = AI Adoption, CP = Competitive Pressure, FP = Firm Performance.

5. Discussion

This study examines the relationships between organizational factors (leadership vision and change management capability) and environmental factors (competitive pressure and trading partnerships) in the context of artificial intelligence (AI) adoption and its impact on SME performance within an emerging nation. The research contributes to the existing literature by demonstrating the mediating role of AI adoption in linking these factors with SME performance, aligning with the transformative potential of AI in Industry 4.0.

The findings underscore the critical role of leadership vision in driving artificial intelligence (AI) adoption, a notion that has been previously highlighted in studies emphasizing strategic foresight's role in integrating advanced technologies (Mikalef & Gupta, 2021). Leadership provides a foundational influence by aligning artificial intelligence initiatives with long-term business objectives, as well as by fostering a culture of digital transformation (Dey et al., 2023). Leaders facilitate an environment conducive to digital transformation by allocating resources, promoting skill development, and cultivating adaptability within their workforce, as observed in studies across different sectors (Barton et al., 2022; Wamba-Taguimdje et al., 2020). These insights reinforce that while leadership is central to initiating AI integration, the mere presence of leadership vision may be insufficient to directly influence SME performance without the support of external factors.

Similarly, the importance of change management capability in facilitating AI integration is highlighted in this study, aligning with previous research on organizational adaptability to technological shifts (Ambati et al., 2020). Change management allows SMEs to systematically address the adjustments needed for successful AI integration, aligning with findings from Kulkov et al. (2023) on the role of strategic change management in AI implementation. However, like leadership vision, change management capability did not show a direct impact on SME performance, suggesting that a more holistic approach, incorporating external collaborations and competitive dynamics, is necessary to realize AI's full potential (Badghish & Soomro, 2024; Lada et al., 2023).

Moving to environmental factors, trading partnerships emerged as a significant driver of artificial intelligence (AI) adoption, supporting previous findings on the role of external collaborations in enabling AI-driven growth (Kurup & Gupta, 2022). Particularly in emerging markets with resource constraints, trading partnerships offer SMEs vital access to resources, knowledge, and expertise, facilitating AI adoption (Mocanu et al., 2024). This supports the view that external partnerships are essential to overcome internal limitations in technology adoption (Silva et al., 2022).

Interestingly, competitive pressure, while initially hypothesized to drive artificial intelligence (AI) adoption, showed an insignificant direct effect. This finding suggests that competition alone may not be sufficient to drive AI adoption in emerging market SMEs. Instead, SMEs may require a supportive organizational framework or partnerships to translate competitive pressures into actual AI adoption. This finding contrasts with traditional assumptions and models, like Rogers' Diffusion of Innovations Theory (1995), which emphasize competition as a primary driver for technology adoption. Here, trading partnerships appear more instrumental in driving AI adoption for SMEs aiming to respond to Industry 4.0 pressures and competitive dynamics (Kurup & Gupta, 2022; Arroyabe et al., 2024).

Additionally, this study underscores AI's role as a mediator that connects both organizational and environmental factors to SME performance. AI adoption effectively bridges internal strategic efforts with external market demands, enhancing decision-making, customer engagement, and operational efficiency (Mikalef & Gupta, 2021; Barton et al., 2022). This mediating role is particularly relevant in Industry 4.0, where AI enables smart manufacturing, supply chain automation, and personalized customer solutions (Wamba-Taguimdje et al., 2020). The findings reinforce that while internal organizational factors, such as leadership and change management, are necessary for artificial intelligence (AI) adoption, external supports like trading partnerships are crucial to fully harnessing AI's potential for performance improvements (Silva et al., 2022).

Furthermore, the study highlights the need to recognize SMEs as unique entities with diverse needs, rather than a homogeneous group. The capacity of SMEs to adopt AI and achieve performance gains relies on a unique interplay of internal readiness and external support, underscoring the importance of developing context-specific strategies for success in emerging markets (Mocanu et al., 2024). By implementing policies that encourage collaborations between SMEs and larger organizations, emerging economies can cultivate ecosystems conducive to technological advancement.

In conclusion, this study advances the discussion on AI adoption and its performance outcomes by emphasizing the essential role of environmental factors—particularly trading partnerships—in shaping how SMEs can leverage AI for sustainable growth in the digital era. This nuanced approach not only expands our understanding of AI adoption but also provides actionable insights for policymakers and SME leaders in fostering competitive advantage in resource-constrained contexts.

5.1. Implications of the Study

5.1.1 Theoretical Implications

This study delivers a significant contribution to new knowledge and existing theory by integrating the TOE framework, DOI theory, and RBV into a unified model, advancing the understanding of the critical drivers of artificial intelligence (AI) adoption in SMEs, particularly in emerging markets like Pakistan. By positioning AI as a strategic resource within the Industry 4.0 context, the research explores how SMEs leverage AI to drive competitiveness and innovation, addressing a critical gap in current literature. The study extends DOI theory by demonstrating that AI adoption in SMEs is driven by both internal and external factors, particularly leadership vision, competitive pressure, and trading partnerships. In contrast to prior studies that focused on simpler technology adoptions, this research positions AI as a complex innovation with transformative potential. SMEs in emerging markets, where resource constraints are prevalent, can achieve competitive advantages by adopting AI, with external collaborations such as trading partnerships playing a pivotal role in facilitating this process (Mocanu et al., 2024).

The study adapts the TOE framework by showing how both organizational readiness and external pressures, such as trading partnerships and competitive dynamics, influence AI adoption in SMEs. This reflects the Industry 4.0 environment, where AI integration is essential for automation and data-driven decision-making (Wamba-Taguimdje et al., 2020). By emphasizing the importance of trading partnerships, the research highlights how external support helps SMEs navigate technological complexity, especially in emerging markets where infrastructural limitations exist (Kurup & Gupta, 2022).

From an RBV perspective, the research positions AI as a critical strategic asset that enhances firm performance by enabling operational efficiency, innovation, and market competitiveness. Leadership vision and change management capability are framed as key resources that allow SMEs to effectively integrate AI into their business processes. The R^2 value of 0.45 for AI adoption and 0.51 for firm performance underscores AI's significant mediating role, supporting the view that AI is not just a tool but a source of sustained competitive advantage in the Industry 4.0 era (Barney, 1991).

The findings advance current debates by focusing on artificial intelligence (AI) adoption in resource-constrained environments like Pakistan, offering insights that are applicable to other emerging markets. The study highlights that AI adoption is influenced by specific contextual factors, such as competitive pressures and trading partnerships, which are crucial for overcoming infrastructural and financial barriers. These insights provide valuable contributions to the literature on digital transformation in developing economies, offering lessons for SMEs and policymakers aiming to foster AI adoption for economic growth and sustainability (Jalil et al., 2024).

This study not only deepens theoretical understanding by integrating the TOE, DOI, and RBV frameworks but also addresses the practical implications of AI adoption for SMEs in emerging markets. The research contributes new knowledge on how SMEs can leverage AI as a strategic resource in the Industry 4.0 landscape, emphasizing the importance of leadership, change management, and external partnerships in driving performance improvements.

5.2.2 Practical Implications

The findings of this research offer valuable implications for SMEs, technology vendors, and policymakers, particularly within the context of Industry 4.0 and artificial intelligence (AI) adoption. The study provides SMEs with a strategic roadmap for integrating AI into their operations. It highlights the importance of aligning AI initiatives with business objectives, emphasizing the role of leadership vision and change management in ensuring smooth transitions. SMEs can leverage AI to optimize processes, improve decision-making, and enhance customer engagement, especially in resource-constrained environments. By focusing on the role of trading partnerships and external collaborations, SMEs are encouraged to seek partnerships that can provide the necessary support for AI adoption, such as access to expertise, resources, and technology.

The research offers insights for technology vendors on tailoring AI tools and solutions to the specific needs of SMEs in emerging markets like Pakistan. By understanding the challenges these businesses face, such as limited resources and technological infrastructure, vendors can develop more accessible and scalable AI solutions that support

SMEs in their digital transformation. The study underscores the need for AI solutions that are not only technically robust but also adaptable to the unique operational contexts of SMEs, including their focus on cost-effectiveness and ease of implementation.

Policymakers can draw from this study to create an enabling environment for AI adoption within SMEs. The findings suggest that fostering AI integration requires supportive infrastructure, favorable regulatory frameworks, and incentives for collaboration between SMEs and technology providers. By facilitating access to AI technologies and promoting public-private partnerships, policymakers can enhance SME competitiveness and drive national economic growth. Additionally, the study advocates for targeted policies that address the barriers SMEs face in AI adoption, such as financial support, digital literacy programs, and streamlined regulations. This research offers actionable insights for key stakeholders in promoting AI adoption, driving innovation, and ensuring SMEs remain competitive in the rapidly evolving Industry 4.0 landscape.

5.3.3 Limitations and Directions for Future Research

This study's focus on a specific geographic and sectoral context does limit its generalizability. Future research could explore artificial intelligence (AI) adoption across various countries and sectors, particularly in resource-rich versus resource-constrained environments, to better understand contextual differences in adoption drivers and performance outcomes. Additionally, future studies could incorporate constructs such as digital infrastructure readiness, organizational learning, and employee digital skills, which may provide further insights into AI adoption barriers and enablers within SMEs.

Methodologically, longitudinal studies capturing changes over time could offer a more comprehensive understanding of AI adoption's evolving impacts on SME performance. Future research might also apply mixed-methods approaches, combining quantitative surveys with qualitative case studies, to gain a deeper understanding of both statistical relationships and the nuanced organizational behaviors behind them.

From a theoretical perspective, integrating the Technology-Organization-Environment (TOE) framework with dynamic capabilities theory would allow for an examination of how SMEs can strategically reconfigure their internal resources and adapt to external conditions to sustain competitive advantage through AI. This alignment with dynamic capabilities theory could be particularly useful for understanding how SMEs leverage AI-driven innovation to navigate disruptions in the Industry 4.0 era. Finally, ongoing research on AI's transformative potential is crucial, with implications for SMEs, policymakers, and technology providers who aim to foster innovation, operational efficiency, and sustainable growth.

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