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Generative Artificial Intelligence Adoption in Emerging Economies: A Technology-Organization-Environment Framework Analysis of Large Language Model Integration in Small and Medium Enterprises

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ABSTRACT

The proliferation of Generative Artificial Intelligence (GenAI), particularly Large Language Models (LLMs), has precipitated substantial transformations in organizational practices across developed economies. However, a conspicuous lacuna persists in scholarly understanding concerning the adoption dynamics within emerging market contexts where resource constraints and infrastructural limitations present distinctive challenges. This study investigates the determinants and outcomes of GenAI adoption among Small and Medium Enterprises (SMEs) across BRICS+ nations, employing the Technology-Organization-Environment (TOE) framework as theoretical foundation. Through a mixed-methods sequential explanatory design, we collected quantitative data from 487 manufacturing and service sector SMEs during March-August 2025 and supplemented findings with 32 semi-structured interviews with senior managers. Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis reveals that technological readiness ($\beta = 0.412$, $p < .001$), leadership support ($\beta = 0.378$, $p < .001$) and competitive pressure ($\beta = 0.289$, $p < .01$) significantly influence GenAI adoption. Furthermore, findings indicate that GenAI adoption mediates the relationship between organizational factors and firm performance, with AI-driven marketing strategies moderating this relationship. The study contributes to digital transformation literature by extending TOE framework applicability to GenAI contexts in resource-constrained settings and offers practical implications for policymakers seeking to foster inclusive AI ecosystems.

Keywords: Generative AI, Large Language Models, Emerging Economies, TOE Framework, SME Digital Transformation

INTRODUCTION

The contemporary landscape of technological advancement has witnessed unprecedented acceleration in artificial intelligence capabilities, with generative AI systems emerging as transformative forces across industrial and commercial domains (McKinsey Global Institute, 2023). The release of ChatGPT in November 2022 marked a pivotal inflection point, demonstrating to global audiences the practical utility of Large Language Models in tasks spanning content generation, analytical reasoning and process automation (OpenAI, 2023). Within merely two years of this release, enterprise adoption rates of generative AI surged dramatically, signifying a rapid transition from experimental curiosity to operational necessity (McKinsey, 2024). This technological revolution carries profound implications for competitive dynamics, workforce composition and economic development trajectories.

However, the diffusion of GenAI technologies exhibits marked heterogeneity across geographic and economic boundaries. While organizations in developed economies benefit from robust digital infrastructure, abundant technical talent pools and substantial financial resources for technology investments, their counterparts in emerging markets confront distinctive adoption challenges (David, 2025; Nekmahmud & Rahman, 2023). Small and medium enterprises, which constitute approximately 90% of businesses globally and contribute over 50%

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of employment worldwide, face particularly acute barriers including skill shortages, financial constraints and infrastructural gaps (Badghish & Soomro, 2024).

The BRICS+ nations - comprising Brazil, Russia, India, China, South Africa and newer members - represent a compelling context for examining GenAI adoption dynamics, given their collective potential to generate substantial economic value from generative AI technologies by 2030 (Yakov Partners, 2024). Despite burgeoning scholarly interest in AI adoption phenomena, significant theoretical and empirical gaps persist. Extant literature has predominantly focused on developed economy contexts, with limited attention to the unique institutional, cultural and economic factors shaping technology adoption decisions in emerging markets (Almashawreh et al., 2024; Soomro et al., 2025).

Moreover, while the Technology-Organization-Environment (TOE) framework has demonstrated utility in explaining various information technology adoption patterns, its application to generative AI - particularly in SME contexts - remains underexplored (Tornatzky & Fleischer, 1990; Oliveira & Martins, 2011). The present investigation addresses these lacunae by examining: (a) the technological, organizational and environmental factors influencing GenAI adoption among SMEs in BRICS+ economies; (b) the mediating role of GenAI adoption in the relationship between organizational factors and firm performance; and (c) the moderating effect of AI-driven marketing strategies on adoption outcomes.

This research makes several contributions to both theoretical understanding and managerial practice. First, it extends the TOE framework by incorporating constructs specific to generative AI adoption, including LLM accessibility, prompt engineering capabilities and algorithmic bias concerns. Second, it provides empirically validated insights into adoption determinants across multiple emerging economy contexts, enabling comparative analysis of institutional influences. Third, it offers actionable recommendations for enterprise leaders and policymakers seeking to foster responsible and effective GenAI integration within resource-constrained organizational settings.

LITERATURE REVIEW

Generative AI and Large Language Models

Generative Artificial Intelligence represents a paradigm shift in computational capabilities, encompassing systems capable of producing novel content - text, images, audio, code and video - based on patterns learned from training data. Modern GenAI systems leverage transformer architectures enabling parallel processing and attention mechanisms (Vaswani et al., 2017; Devlin et al., 2019), with contemporary models such as GPT-4, Claude and PaLM demonstrating performance approaching human-level competency on various benchmarks (OpenAI, 2023; Anthropic, 2024).

McKinsey Global Institute (2023) estimates that generative AI could contribute between USD 2.6 trillion and USD 4.4 trillion annually to the global economy, with productivity gains spanning customer operations, marketing, software engineering and research and development functions. The cost of generating outputs from large language models has declined substantially over recent years, rendering real-time AI applications increasingly viable for routine business operations (Maslej et al., 2025). This cost trajectory, combined with improvements in model reliability and reasoning capabilities, has accelerated enterprise experimentation and deployment initiatives.

Yet the rapid proliferation of GenAI technologies has also surfaced substantial concerns regarding fairness, accuracy and societal impact. Algorithmic bias stemming from training data composition can perpetuate or amplify existing inequities, particularly in high-stakes domains such as healthcare, legal services and financial decision-making (Buolamwini & Gebru, 2018). Hallucination - the generation of plausible but factually incorrect outputs - remains a persistent challenge, necessitating human oversight and verification mechanisms (Peláez-Sánchez et al., 2024). Organizations must navigate these technical limitations while simultaneously addressing workforce displacement anxieties and regulatory uncertainties.

Digital Transformation in Emerging Economies

Emerging economies occupy a distinctive position within the global digital transformation landscape, characterized by both leapfrogging opportunities and persistent structural barriers (Omol, 2023). Digital infrastructure development programs - including Digital India, Made in China 2025 and Bangladesh Vision 2041 - have substantially expanded connectivity and data availability, creating foundation conditions for AI adoption (Ateeq, 2024).

The competitive landscape in AI development shifted meaningfully during 2024, with Chinese models achieving near-parity with leading Western models on major performance benchmarks. Specifically, Alibaba's Qwen 2.5 demonstrated competitive performance against GPT-4o by September 2024, followed by DeepSeek's V3 model matching Claude 3.5 Sonnet capabilities in December 2024 (Ding, 2025; Maslej et al., 2025). This rapid convergence has altered the strategic calculus for emerging economy enterprises considering GenAI adoption.

Notwithstanding these advances, significant challenges constrain AI adoption in emerging market contexts. Infrastructure limitations - including unreliable electricity supply, limited broadband penetration in rural areas and insufficient cloud computing resources - impede the technical prerequisites for GenAI deployment (Gaglio et al., 2022). Human capital constraints manifest as shortages of professionals with AI literacy, machine learning expertise and data science competencies, necessitating substantial investments in education and training programs (UNCTAD, 2025). Financial barriers prove particularly acute for SMEs, which typically lack the capital resources to acquire expensive AI solutions or develop proprietary models.

The institutional environment in emerging economies presents both enabling and constraining factors. Government support through incentive programs, regulatory sandboxes and public-private partnerships can catalyze AI adoption by reducing perceived risks and costs (Al-Somali et al., 2024). Conversely, regulatory uncertainty, intellectual property concerns and data localization requirements may inhibit cross-border technology transfers and collaborative development initiatives. The formation of the BRICS+ AI Alliance in December 2024 - announced at the AI Journey conference in Moscow with participation from technology companies across Russia, China, India, Brazil, Iran and the UAE - reflects growing recognition among policymakers of the strategic importance of coordinated AI development approaches (Yakov Partners, 2024).

Technology-Organization-Environment Framework

The Technology-Organization-Environment (TOE) framework, initially proposed by Tornatzky and Fleischer (1990), provides a comprehensive theoretical lens for understanding technology adoption at the organizational level. The framework posits that adoption decisions are influenced by three contextual dimensions: technological factors encompassing the characteristics and availability of relevant technologies; organizational factors including structural attributes, resources and managerial processes; and environmental factors comprising external pressures, opportunities and constraints emanating from the industry, market and regulatory contexts.

Within the technological dimension, perceived relative advantage - the degree to which a technology is viewed as superior to existing alternatives - consistently emerges as a significant adoption predictor (Rogers, 2003). Compatibility with existing systems, processes and organizational values similarly influences adoption propensity, as does perceived complexity or ease of use (Ghobakhloo & Tang, 2013). For GenAI specifically, additional technological considerations include model accuracy, hallucination rates, integration capabilities with enterprise systems and availability of domain-specific fine-tuning options (Arroyabe et al., 2024).

Organizational factors encompass a wide range of structural and processual characteristics. Top management support has been consistently identified as a critical enabler, shaping resource allocation, strategic prioritization and organizational culture toward innovation (Eze et al., 2019). Organizational readiness - comprising both technological infrastructure and human capabilities - determines the capacity to effectively absorb and utilize new technologies (Lokuge et al., 2019). Firm size, while potentially moderating adoption relationships, does not uniformly predict adoption outcomes, with some evidence suggesting that SMEs may derive proportionately greater benefits from AI integration due to their operational flexibility (Kopka & Fornahl, 2024).

Environmental factors exert substantial influence on organizational technology adoption decisions. Competitive pressure - the intensity of rivalry and the perceived technology adoption by industry peers - often serves as a primary motivator for investment in new capabilities (Badghish & Soomro, 2024). Government support through financial incentives, regulatory guidance and public infrastructure investments can substantially reduce adoption barriers (Abubakar et al., 2019). Market demand, particularly from technology-savvy customers expecting enhanced service experiences, similarly drives organizational adoption initiatives.

Hypotheses Development

Building upon the theoretical foundations outlined above, we advance the following hypotheses regarding GenAI adoption determinants and outcomes in emerging economy SME contexts. First, we posit that technological readiness - encompassing IT infrastructure, data management capabilities and prior technology adoption experience - positively influences GenAI adoption propensity (H1). Organizations with established digital foundations possess the absorptive capacity to integrate novel AI technologies more effectively than those lacking such prerequisites (Cohen & Levinthal, 1990).

Second, we hypothesize that leadership vision and support positively influence GenAI adoption (H2). Senior managers who articulate compelling visions for AI-enabled transformation and commit organizational resources accordingly signal strategic priority and reduce resistance to change among organizational members (Liang et al., 2007). Third, we anticipate that competitive pressure positively influences GenAI adoption (H3), as organizations observing peer adoption of productivity-enhancing technologies face incentives to maintain competitive parity.

Fourth, we propose that GenAI adoption mediates the relationship between organizational factors (technological readiness, leadership support) and firm performance (H4). Rather than directly influencing performance outcomes, organizational characteristics create conditions conducive to technology adoption, which in turn enables performance improvements through operational efficiency gains, enhanced customer experiences and innovation capabilities (Noy & Zhang, 2023). Fifth, we hypothesize that AI-driven marketing strategies moderate the relationship between GenAI adoption and firm performance (H5), such that organizations leveraging AI for customer targeting, content personalization and marketing automation derive greater performance benefits from their adoption investments.

RESEARCH METHODOLOGY

Research Design

This study employs a sequential explanatory mixed-methods research design, comprising an initial quantitative phase followed by qualitative inquiry to elaborate and contextualize statistical findings (Creswell & Plano Clark, 2018). The mixed-methods approach is particularly appropriate for investigating GenAI adoption phenomena, which involve both measurable behavioral patterns and nuanced organizational decision-making processes that resist purely quantitative characterization. The design enables triangulation of findings across methodological traditions, enhancing the credibility and transferability of research conclusions.

Sampling and Data Collection

The target population comprised manufacturing and service sector SMEs operating within BRICS+ nations - specifically Brazil, India, China, South Africa and the United Arab Emirates - selected to represent geographic and developmental diversity within the broader emerging economy category. Purposive sampling was employed to identify organizations meeting defined eligibility criteria: (a) classification as SME per national definitions (generally 10-499 employees); (b) operation within manufacturing, professional services, or technology-enabled service sectors; (c) minimum five years of operational history; and (d) some level of digital technology utilization.

Scope boundary: This study focuses on formal, registered SMEs with established digital presence. Informal enterprises and micro-businesses (fewer than 10 employees) - while constituting a substantial portion of emerging economy business activity - were excluded due to the technological infrastructure prerequisites inherent to GenAI deployment. This boundary condition is revisited in the limitations section.

Quantitative data collection proceeded via structured online questionnaires administered through industry association networks and business chamber databases across target countries during March-August 2025. Survey instruments underwent translation and back-translation procedures for Portuguese, Hindi, Mandarin and Arabic versions, with cultural adaptation to ensure conceptual equivalence (Brislin, 1970). A total of 1,247 invitation emails yielded 523 responses, of which 487 met completeness criteria for inclusion in final analyses, representing an effective response rate of 39.1%. Non-response bias assessment via comparison of early and late respondents revealed no significant differences on key demographic or study variables.

Following quantitative data analysis, qualitative data were collected through semi-structured interviews with 32 senior managers (CEO, CTO, or operations director level) across participating organizations during September-October 2025. Interviewees were selected through purposive maximum variation sampling to represent diversity in GenAI adoption stages, industry sectors and national contexts. Interviews lasted 45-75 minutes, were conducted via video conferencing platforms and explored adoption motivations, implementation challenges, perceived outcomes and future AI integration plans. All interviews were audio-recorded with participant consent and transcribed verbatim for analysis.

Measurement Instruments

All quantitative constructs were operationalized using validated multi-item scales adapted from prior technology adoption research, with modifications to reflect GenAI-specific characteristics. Technological readiness (5 items) assessed IT infrastructure quality, data management capabilities and prior AI/ML experience, adapted from Lokuge et al. (2019). Leadership vision (4 items) measured senior management commitment to AI initiatives and strategic communication regarding technology adoption, adapted from Liang et al. (2007). Competitive pressure (4 items) evaluated perceived intensity of industry AI adoption and competitive dynamics, adapted from Badghish and Soomro (2024).

GenAI adoption (6 items) captured the breadth and depth of generative AI technology utilization across organizational functions, including content generation, customer service automation, code development and decision support applications. AI-driven marketing (4 items) assessed the application of AI technologies specifically for marketing strategy, customer targeting and content personalization. Firm performance (8 items) employed a balanced scorecard approach encompassing operational efficiency, financial performance, customer satisfaction and innovation outcomes, measured via perceptual scales anchored to industry benchmarks. All items utilized 7-point Likert scales ranging from 1 (strongly disagree) to 7 (strongly agree).

Analytical Procedures

Quantitative data analysis proceeded through Partial Least Squares Structural Equation Modeling (PLS-SEM), implemented via SmartPLS 4.0 software. PLS-SEM was selected over covariance-based SEM due to its suitability for complex models with multiple mediating and moderating relationships, its robustness to non-normal data distributions and its effectiveness with relatively smaller sample sizes per latent variable (Hair et al., 2019). The analytical sequence encompassed: (a) measurement model assessment including indicator reliability, internal consistency, convergent validity and discriminant validity; (b) structural model evaluation including path coefficient significance, effect sizes and predictive relevance; and (c) multi-group analysis to examine moderating effects and cross-national differences.

Qualitative data underwent thematic analysis following Braun and Clarke (2006) six-phase protocol: familiarization, initial coding, theme searching, theme reviewing, theme defining and report production. NVivo 14 software facilitated systematic coding and theme development. Analyst triangulation was achieved through independent coding by two researchers with subsequent reconciliation of discrepancies through discussion. Findings from qualitative analysis were integrated with quantitative results during the interpretation phase to provide richer understanding of adoption dynamics and outcomes.

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DATA ANALYSIS AND FINDINGS

Sample Characteristics

The final sample of 487 SMEs exhibited diverse characteristics across geographic, industry and organizational dimensions. Geographic distribution reflected deliberate sampling quotas: India (n = 127, 26.1%), China (n = 112, 23.0%), Brazil (n = 98, 20.1%), South Africa (n = 84, 17.2%) and UAE (n = 66, 13.6%). Industry representation included manufacturing (42.3%), professional services (28.5%), information technology (17.7%) and other technology-enabled services (11.5%). Firm size ranged from 10 to 486 employees, with mean employment of 89.4 (SD = 67.2). Regarding GenAI adoption status, 34.7% of respondents reported active utilization of generative AI tools in business operations, 41.5% were in experimentation or pilot stages and 23.8% had not yet initiated adoption activities.

Table 1 presents sample characteristics and descriptive statistics for all study variables, including reliability coefficients and average variance extracted values.

Table 1 Sample Characteristics and Descriptive Statistics (N = 487)

Variable	n / Mean	% / SD	α	AVE
Country - India	127	26.1%	-	-
Country - China	112	23.0%	-	-
Country - Brazil	98	20.1%	-	-
Country - South Africa	84	17.2%	-	-
Country - UAE	66	13.6%	-	-
Technological Readiness	4.82	1.34	0.89	0.68
Leadership Vision	5.21	1.18	0.91	0.72
Competitive Pressure	5.47	1.26	0.87	0.65
GenAI Adoption	4.18	1.52	0.93	0.71
AI-Driven Marketing	3.94	1.41	0.88	0.67
Firm Performance	4.76	1.23	0.92	0.69

Note. α = Cronbach's alpha; AVE = Average Variance Extracted.

Measurement Model Assessment

Prior to structural model estimation, rigorous assessment of measurement properties was conducted. Indicator reliability, evaluated through outer loadings, exceeded the 0.70 threshold for all items, ranging from 0.72 to 0.91. Internal consistency reliability, assessed via Cronbach's alpha and composite reliability coefficients, surpassed recommended benchmarks ($\alpha > 0.87$, $CR > 0.90$) across all constructs (see Table 1). Convergent validity, evaluated through average variance extracted (AVE), exceeded 0.50 for all latent variables, indicating that constructs captured more than half the variance attributable to their indicators (Fornell & Larcker, 1981).

Discriminant validity assessment employed multiple criteria. The Fornell-Larcker criterion was satisfied, with the square root of each construct's AVE exceeding its correlations with other constructs. The Heterotrait-Monotrait (HTMT) ratio remained below 0.85 for all construct pairs and confidence intervals did not include unity, providing further evidence of distinctiveness among theoretical constructs (Henseler et al., 2015). Common method variance was assessed through Harman's single-factor test, with the first factor accounting for 32.7% of total variance - well below the 50% threshold indicating problematic common method bias.

Structural Model Results

The structural model demonstrated adequate explanatory power, with R^2 values of 0.487 for GenAI adoption and 0.412 for firm performance, indicating that the model explained approximately 48.7% and 41.2% of variance in these endogenous constructs respectively. Stone-Geisser Q^2 values exceeded zero for all endogenous variables (Q^2 GenAI adoption = 0.31; Q^2 firm performance = 0.27), confirming predictive relevance of the structural model.

Hypothesis testing proceeded through bootstrapping with 5,000 resamples to assess path coefficient significance. Results supported all five hypotheses at conventional significance levels. Technological readiness exhibited the strongest direct effect on GenAI adoption ($\beta = 0.412$, $t = 8.74$, $p < .001$), supporting H1 and indicating that organizations with robust IT infrastructure and data management capabilities demonstrate substantially higher adoption propensity. Leadership vision similarly exerted a significant positive influence on adoption ($\beta = 0.378$, $t = 7.21$, $p < .001$), supporting H2. Competitive pressure demonstrated a somewhat weaker but nonetheless significant effect ($\beta = 0.289$, $t = 4.86$, $p < .01$), lending support to H3.

Mediation analysis confirmed that GenAI adoption mediates the relationship between organizational antecedents and firm performance (H4). The indirect effect of technological readiness on performance through adoption was significant ($\beta = 0.167$, 95% CI [0.098, 0.241]), as was the indirect effect of leadership vision ($\beta = 0.153$, 95% CI [0.089, 0.224]). Variance accounted for (VAF) values of 62.3% and 58.7% respectively indicated partial mediation, suggesting that while adoption serves as an important transmission mechanism, direct effects of organizational factors on performance also remain operative.

Moderation analysis revealed that AI-driven marketing strategies positively moderate the relationship between GenAI adoption and firm performance ($\beta = 0.184$, $t = 3.92$, $p < .001$), supporting H5. Simple slopes analysis indicated that the relationship between adoption and performance was significantly positive for organizations with high AI-driven marketing engagement ($\beta = 0.523$, $p < .001$), moderately positive for those with medium engagement ($\beta = 0.339$, $p < .001$) and weakest for those with low engagement ($\beta = 0.155$, $p < .05$). This pattern suggests that AI-driven marketing strategies amplify the performance benefits derived from GenAI adoption.

Figure 1 displays the structural model results including standardized path coefficients and significance levels for all hypothesized relationships.

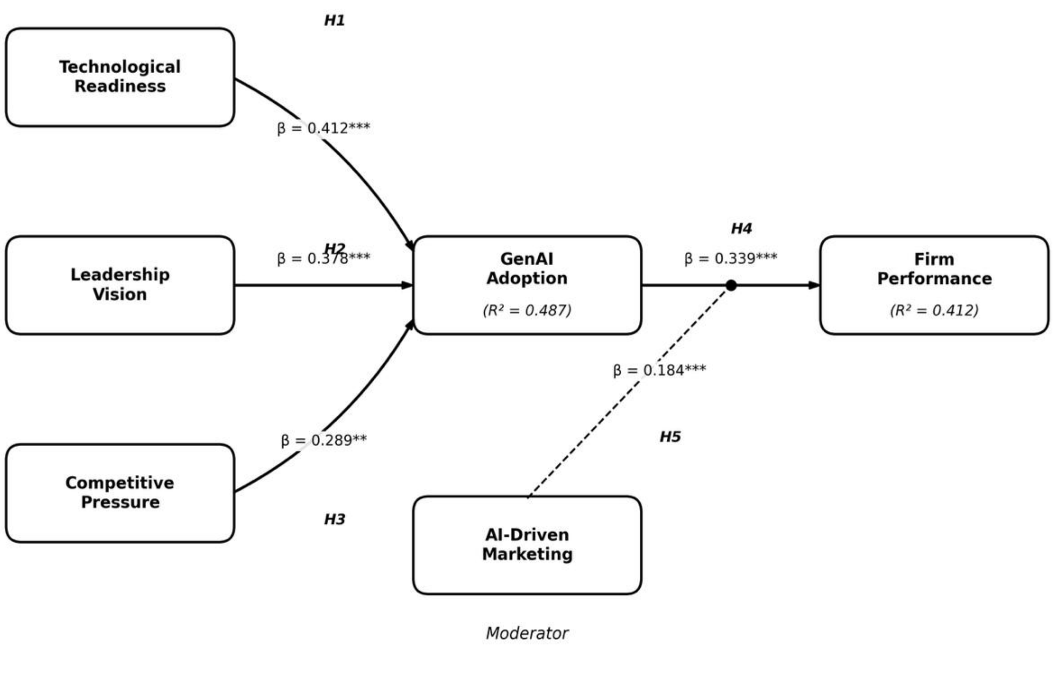

Figure 1: Structural Model Results with Path Coefficients and Significance Levels

Multi-Group Analysis

Multi-group analysis (MGA) examined whether structural relationships differed significantly across national contexts. Results revealed significant differences between China-based and other BRICS+ SMEs on the competitive pressure to adoption path ($\Delta\beta = 0.187$, $p < .05$), suggesting that competitive dynamics exert stronger influence on Chinese organizations' GenAI adoption decisions.

Conversely, the leadership vision to adoption relationship was significantly stronger among Indian and Brazilian organizations compared to Chinese counterparts ($\Delta\beta = 0.142$, $p < .05$), potentially reflecting different governance and decision-making cultures. No significant differences emerged in the technological readiness to adoption path across national subgroups, suggesting universal importance of digital infrastructure foundations for GenAI integration.

Qualitative Findings

Thematic analysis of 32 semi-structured interviews elaborated and contextualized quantitative findings. Three overarching themes emerged: (a) adoption enablers and barriers, (b) implementation challenges and (c) perceived outcomes and future intentions.

Regarding adoption enablers, interviewees consistently emphasized the importance of leadership championing. As one Indian manufacturing CEO noted: "Unless the top management believes in AI and allocates resources accordingly, nothing will happen. Our adoption started when I personally began using ChatGPT for drafting proposals and saw the productivity benefits." Competitive observation similarly emerged as a catalyst, with a Brazilian service sector manager explaining: "When we saw our competitors automating customer queries with AI, we realized we had to move quickly or risk being left behind."

Implementation challenges centered on technical and human dimensions. Data quality and accessibility presented persistent obstacles, with a South African IT director stating: "Our biggest challenge was that our data was scattered across multiple systems, often incomplete or inconsistent. The AI models we tried gave poor results until we invested in data cleaning and integration." Workforce resistance and skill gaps also constrained implementation, particularly in more traditional manufacturing contexts. A Chinese operations manager observed: "Many of our senior workers were suspicious of AI, worried about job losses. We had to invest significant time in training and reassurance before people would engage with the tools."

Perceived outcomes varied substantially by adoption stage and use case. Organizations that had progressed beyond initial experimentation reported tangible efficiency gains: "We reduced our content creation time by about 60% and improved quality through AI-assisted editing," reported a UAE marketing director. However, several interviewees cautioned against unrealistic expectations: "There is much hype about GenAI, but practical implementation requires patience and continuous refinement. The magic solution that works out of the box does not exist yet," noted an Indian CTO. Future intentions overwhelmingly favored expansion of GenAI applications, with particular interest in customer service automation, predictive analytics and internal knowledge management systems.

DISCUSSION

The findings of this investigation advance theoretical understanding of GenAI adoption in emerging economy contexts while offering actionable insights for practitioners and policymakers. The strong positive relationship between technological readiness and GenAI adoption aligns with extant literature on digital transformation prerequisites (Lokuge et al., 2019; Oliveira & Martins, 2011) and underscores the foundational importance of digital infrastructure investments. Organizations lacking robust IT systems, data management capabilities and prior technology adoption experience face substantial barriers to effective GenAI integration, regardless of their strategic intentions or external pressures.

The significant influence of leadership vision on adoption outcomes reinforces scholarship highlighting the critical role of top management support in technology innovation (Liang et al., 2007). Interestingly, qualitative findings revealed that personal experimentation by senior leaders with generative AI tools often preceded broader organizational adoption initiatives, suggesting a demonstration effect whereby executive engagement signals strategic priority and reduces employee uncertainty. This pattern aligns with evidence that informal AI tool usage - employees using personal AI tools for work tasks - often precedes and catalyzes formal organizational adoption (Brynjolfsson et al., 2025).

The competitive pressure finding merits nuanced interpretation. While mimetic pressures clearly influence adoption decisions, the multi-group analysis revealing stronger effects among Chinese organizations suggests institutional context moderation. China's highly competitive business environment, combined with rapid advancement by domestic AI developers during 2024, may amplify the salience of competitive dynamics relative to other BRICS+ contexts. Conversely, the relatively stronger leadership effect in India and Brazil may reflect organizational cultures placing greater emphasis on hierarchical decision-making authority.

The mediation of GenAI adoption between organizational factors and performance provides empirical validation for theorized value creation pathways. Rather than directly enhancing performance outcomes, organizational characteristics enable technology adoption, which in turn generates performance improvements through multiple mechanisms including operational efficiency, customer experience enhancement and innovation capabilities. The partial mediation finding suggests that organizational factors also exert direct effects on performance through channels independent of GenAI adoption, consistent with the multifaceted nature of organizational performance determinants.

The moderating role of AI-driven marketing strategies offers novel insights into conditions amplifying adoption benefits. Organizations strategically deploying AI for marketing purposes - including customer segmentation, content personalization and campaign optimization - derive substantially greater performance returns from their GenAI investments. This pattern suggests complementarities between general GenAI capabilities and domain-specific AI applications, with integrated AI strategies yielding synergistic benefits exceeding the sum of individual component effects.

IMPLICATIONS

Theoretical Implications

This study extends the TOE framework to the generative AI adoption context, demonstrating its continued relevance for explaining emerging technology adoption dynamics. The framework's tripartite structure proves well-suited for capturing the multidimensional influences shaping organizational AI integration decisions. However, our findings also suggest potential refinements: the relative importance of technological versus environmental factors may vary across institutional contexts and the emergence of personal AI tool usage as a precursor to organizational adoption points to the need for incorporating individual-level constructs within organizational adoption frameworks.

The mediation and moderation findings contribute to performance implications literature by elucidating the conditional nature of technology-performance relationships. The adoption paradox - whereby technology investments do not automatically translate to performance gains - can be partially explained through contingency factors such as complementary capabilities and strategic alignment. Organizations achieving performance benefits from GenAI adoption tend to possess not merely the technology itself but also supporting capabilities in data management, human capital and strategic implementation.

Practical Implications

For SME leaders in emerging economies, findings suggest a sequenced approach to GenAI adoption. First, organizations should assess and strengthen technological foundations - including IT infrastructure, data quality and integration capabilities - before embarking on ambitious AI initiatives. Premature adoption without adequate technological readiness risks disappointment and resource waste. Second, leadership engagement proves essential: senior executives should personally experiment with GenAI tools and communicate strategic vision for AI-enabled transformation to foster organizational receptivity.

The significant role of AI-driven marketing in amplifying adoption benefits suggests that organizations should consider customer-facing AI applications as early use cases. Marketing automation, chatbot deployment and content generation tools offer relatively accessible entry points with tangible return on investment, potentially building organizational confidence and capabilities for subsequent adoption of more complex AI applications. The integration of AI across multiple business functions - rather than isolated deployment in single domains - appears to yield multiplicative benefits.

For policymakers in BRICS+ and other emerging economies, findings underscore the importance of digital infrastructure investments as prerequisites for AI adoption. Government programs supporting broadband

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expansion, cloud computing accessibility and data center development create foundational conditions enabling private sector AI adoption. Additionally, AI literacy and skill development initiatives addressing workforce capability gaps can reduce organizational resistance and enhance implementation effectiveness. The BRICS+ AI Alliance framework provides venues for collaborative standard-setting and knowledge exchange that may accelerate adoption across member nations.

LIMITATIONS AND FUTURE RESEARCH

Several limitations warrant acknowledgment when interpreting study findings. First, the cross-sectional research design precludes definitive causal inferences regarding adoption antecedents and outcomes. While structural equation modeling provides evidence consistent with hypothesized causal pathways and temporal precedence is theoretically grounded in adoption process logic, the simultaneous measurement of independent and dependent variables cannot establish causation with certainty. Longitudinal data collection tracking organizations across multiple time points would be required to capture adoption trajectories and lagged performance effects. Future research should employ panel designs with repeated measurements to strengthen causal claims and examine how adoption effects evolve over time.

Second, reliance on perceptual measures for both independent and dependent variables raises potential common method bias concerns. Although statistical tests suggested acceptable variance attributable to method factors, future investigations would benefit from incorporating objective performance indicators such as financial statements, customer data and operational metrics.

Third, the sampling frame encompassed formal, digitally connected SMEs meeting minimum technological prerequisites for GenAI engagement. Informal enterprises, micro-businesses and firms lacking basic digital infrastructure - categories comprising significant proportions of emerging economy business ecosystems - fall outside this study's scope. While this boundary reflects pragmatic requirements of the research phenomenon (GenAI adoption presupposes digital connectivity), findings may not generalize to the broader SME population in BRICS+ contexts. The International Labour Organization estimates that informal enterprises account for over 60% of total employment in emerging economies, representing a substantial segment excluded from this analysis. Future research employing stratified sampling approaches that deliberately include firms at varying digitalization stages could illuminate adoption barriers and enablers across the full enterprise formality spectrum.

Fourth, the focus on BRICS+ nations - while capturing substantial emerging economy variation - may limit generalizability to other developmental contexts such as least developed countries, small island developing states, or post-conflict economies with distinctive adoption barriers.

Promising avenues for future research include examination of industry-specific adoption patterns, given evidence that AI impacts differ substantially across manufacturing, services and technology sectors. Investigation of responsible AI adoption practices - including algorithmic fairness, transparency and accountability mechanisms - in emerging economy contexts would address growing concerns regarding ethical AI deployment. Additionally, comparative analysis of domestic versus foreign-origin AI solutions could illuminate strategic implications of sovereign AI initiatives and technological dependency considerations.

CONCLUSION

The rapid evolution of generative AI technologies presents both transformative opportunities and formidable challenges for organizations in emerging economies. This investigation has demonstrated that GenAI adoption among BRICS+ SMEs is shaped by technological, organizational and environmental factors operating in complex interaction. Technological readiness emerges as the most influential adoption determinant, underscoring the foundational importance of digital infrastructure investments. Leadership vision and competitive pressure provide additional impetus, while AI-driven marketing strategies amplify the performance benefits derived from adoption investments.

As global AI adoption continues its exponential trajectory, emerging economy firms face imperatives to engage with these technologies or risk competitive disadvantage. Yet adoption must be approached with realistic expectations and appropriate sequencing: organizations rushing to implement AI without adequate technological foundations, leadership commitment, or complementary capabilities risk disappointment and resource misallocation.

The BRICS+ context offers unique opportunities for collaborative AI development outside traditional Western-dominated technology ecosystems. The BRICS+ AI Alliance, announced in December 2024 with participation from major technology companies across member nations, signals emerging economy recognition of the strategic importance of indigenous AI capabilities and cooperative standard-setting. By building technological readiness, fostering leadership engagement and developing complementary AI strategies, SMEs in emerging markets can position themselves to capture substantial value from the generative AI revolution while contributing to inclusive and responsible AI ecosystems benefiting diverse global stakeholders.

DECLARATIONS

Conflicts of Interest: The authors declare no known competing financial or personal interests that could have influenced the work reported in this paper.

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Data Access: Data supporting this study are available from the corresponding author upon reasonable request, compliant with institutional sharing policies.

Ethical Declarations: This study involved human participants.

Use of AI: AI tools were strictly limited to grammar checking, spelling correction and language refinement of the final manuscript.

REFERENCES

1. Abubakar, A. M., Elrehail, H., Alatailat, M. A., & Elçi, A. (2019). Knowledge management, decision-making style and organizational performance. Journal of Innovation & Knowledge, 4(2), 104-114.
2. Almashawreh, R., Talukder, M., Charath, S. K., & Khan, M. I. (2024). AI adoption in Jordanian SMEs: The influence of technological and organizational orientations. SAGE Open, 14(2), 1-15.
3. Al-Somali, S. A., Gholami, R., & Clegg, B. (2024). Cybersecurity adoption in SMEs: Technology-organization-environment framework. Information Systems Frontiers, 26(3), 1124-1141.
4. Anthropic. (2024). Claude model card and evaluations. https://www.anthropic.com
5. Arroyabe, M. F., Arranz, C. F. A., Arroyabe, J. C. F., & Arroyabe, I. F. (2024). Artificial intelligence adoption in the European Union: An empirical analysis of 12,108 SMEs. Technological Forecasting and Social Change, 198, 122953.
6. Ateeq, A. (2024). Digital transformation and organizational performance in emerging economies. Sustainability, 16(3), 1035.
7. Badghish, S., & Soomro, Y. A. (2024). Artificial intelligence adoption by SMEs to achieve sustainable business performance: Application of technology-organization-environment framework. Sustainability, 16(5), 1864.
8. Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative Research in Psychology, 3(2), 77-101.
9. Brislin, R. W. (1970). Back-translation for cross-cultural research. Journal of Cross-Cultural Psychology, 1(3), 185-216.
10. Brynjolfsson, E., Li, D., & Raymond, L. (2025). Generative AI at work. Quarterly Journal of Economics, 140(1), 71-122.
11. Buolamwini, J., & Gebru, T. (2018). Gender shades: Intersectional accuracy disparities in commercial gender classification. Proceedings of Machine Learning Research, 81, 77-91.

12. Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. Administrative Science Quarterly, 35(1), 128-152.
13. Creswell, J. W., & Plano Clark, V. L. (2018). Designing and conducting mixed methods research (3rd ed.). Sage Publications.
14. David, L. K. (2025). Digital transformation and socio-economic development in emerging economies: A multinational analysis. Technology in Society, 82, 102547.
15. Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. Proceedings of NAACL-HLT 2019, 4171-4186.
16. Ding, J. (2025). DeepSeek, Huawei, export controls and the future of the U.S.-China AI race. CSIS Analysis. Center for Strategic and International Studies.
17. Eze, S. C., Chinedu-Eze, V. C., Okike, C. K., & Bello, A. O. (2019). Factors influencing the use of e-learning facilities by students in a private higher education institution. Humanities and Social Sciences Communications, 7, 133.
18. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39-50.
19. Gaglio, C., Ferraris, A., Battisti, E., & Bresciani, S. (2022). Digital transformation and innovation in emerging economies. Journal of Product Innovation Management, 39(6), 734-754.
20. Ghobakhloo, M., & Tang, S. H. (2013). The role of owner/manager in adoption of electronic commerce in small businesses. Journal of Small Business and Enterprise Development, 20(4), 754-787.
21. Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2-24.
22. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115-135.
23. Kopka, A., & Fornahl, D. (2024). Artificial intelligence and firm performance: Evidence from European SMEs. Research Policy, 53(2), 104912.
24. Liang, H., Saraf, N., Hu, Q., & Xue, Y. (2007). Assimilation of enterprise systems: The effect of institutional pressures and the mediating role of top management. MIS Quarterly, 31(1), 59-87.
25. Lokuge, S., Sedera, D., Grover, V., & Dongming, X. (2019). Organizational readiness for digital innovation: Development and empirical calibration of a construct. Information & Management, 56(3), 445-461.
26. Maslej, N., Fattorini, L., Perrault, R., Parli, V., Reuel, A., Brynjolfsson, E., ... & Clark, J. (2025). The AI Index 2025 annual report. Stanford University Human-Centered AI Institute.
27. McKinsey Global Institute. (2023). The economic potential of generative AI: The next productivity frontier. McKinsey & Company.
28. McKinsey & Company. (2024). The state of AI in early 2024: Gen AI adoption spikes and starts to generate value. McKinsey & Company.
29. Nekmahmud, M., & Rahman, S. (2023). Digital technology adoption in SMEs: What technological, environmental and organizational factors influence in emerging countries? SAGE Open, 13(1), 1-18.
30. Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. Science, 381(6654), 187-192.
31. Oliveira, T., & Martins, M. F. (2011). Literature review of information technology adoption models at firm level. Electronic Journal of Information Systems Evaluation, 14(1), 110-121.
32. Omol, E. J. (2023). Organizational readiness for digital transformation: A conceptual framework. International Journal of Information Management Data Insights, 3(2), 100189.
33. OpenAI. (2023). GPT-4 technical report. arXiv:2303.08774.
34. Peláez-Sánchez, I. C., Velarde-Camaqui, D., & Glasserman-Morales, L. D. (2024). The impact of large language models on higher education: Exploring the connection between AI and Education 4.0. Frontiers in Education, 9, 1392091.
35. Rogers, E. M. (2003). Diffusion of innovations (5th ed.). Free Press.
36. Soomro, Y. A., Badghish, S., & Khan, M. A. (2025). Exploring AI adoption and SME performance in resource-constrained environments: A TOE-RBV perspective. Journal of Innovation & Knowledge, 10(3), 100438.
37. Tornatzky, L. G., & Fleischer, M. (1990). The processes of technological innovation. Lexington Books.

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38. UNCTAD. (2025). Technology and innovation report 2025: Frontier technologies readiness index. United Nations Conference on Trade and Development.
39. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. Advances in Neural Information Processing Systems, 30, 5998-6008.
40. Yakov Partners. (2024). Generative AI in BRICS+ countries: Trends and outlook. Yakov and Partners.