ISSN E: 3006-1466
ISSN P: 3006-1458
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
CJSSR
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
Vol.04 No.01 (2026)

THE IMPACT OF GENERATIVE AI ADOPTION ON BUSINESS PERFORMANCE: THE MEDIATING ROLE OF EMPLOYEE PRODUCTIVITY AND THE MODERATING ROLE OF DIGITAL LITERACY

Muhammad Hasnain Amjad
hasnain922@gmail.com
Department of Business Administration, University of Sahiwal, Sahiwal, Pakistan
Touseeq Danish
touseeqkhanwsl@gmail.com
Data and Intelligence for Smart Systems (DISS), claude bernard lyon 1, France
Muhammad Umar
umarsolution584@gmail.com
Department of Business Administration, Government College University Faisalabad Sahiwal Campus, Pakistan

Abstract
This study examines the relationship between Generative Artificial Intelligence (GenAI) adoption and business performance among organizations in Malaysia, with a specific focus on the mediating role of employee productivity and the moderating role of digital literacy. Anchored in the Resource-Based View (RBV) and the Technology-Organization-Environment (TOE) framework, a conceptual model was developed and tested using survey data collected from 345 managers and business owners across key Malaysian economic sectors. Data were analysed using partial least squares structural equation modeling (PLS-SEM) in SmartPLS 4.0.The results indicate that GenAI adoption has a significant positive direct effect on business performance and a stronger positive effect on employee productivity. Employee productivity was found to significantly and partially mediate the relationship between GenAI adoption and business performance. Digital literacy was found to significantly moderate the GenAI adoption-employee productivity relationship, such that the positive effect of GenAI adoption on productivity is considerably stronger among firms with digitally literate workforces. A moderated-mediation analysis further confirmed that the indirect effect of GenAI adoption on business performance through employee productivity is conditional on the level of digital literacy. The findings offer practical guidance for Malaysian business leaders and policymakers under the MyDIGITAL initiative and the National AI Roadmap, suggesting that the performance returns of GenAI investment are not automatic but are substantially contingent on complementary investment in workforce digital capability. This study contributes one of the first empirically framed investigations of GenAI's productivity-performance pathway in the Malaysian context, and is among the first to formally test digital literacy as a boundary condition of this relationship using a moderated-mediation design.

Keywords: Generative AI, Business Performance, Employee Productivity, Digital Literacy, PLS-SEM, Resource-Based View, Malaysia

1. Introduction
Artificial intelligence has moved from the periphery of corporate strategy to its center, and within this broader movement, Generative Artificial Intelligence (GenAI) has emerged as the most commercially disruptive subset of the technology (Brynjolfsson & McAfee, 2017). Unlike earlier analytic or predictive AI systems, GenAI tools such as large language models and diffusion-based image generators are capable of producing novel text, code, designs, and decision-support content on demand, collapsing tasks that once required specialized human labor into a few seconds of machine computation (Davenport & Ronanki, 2018). Since the wide commercial release of tools such as ChatGPT, Midjourney, and their enterprise counterparts, organizations across the globe have begun experimenting with, and in many cases substantially restructuring their operations around, GenAI capabilities.
Malaysia occupies a distinctive position in this global transformation. As a upper-middle-income economy pursuing high-income status under frameworks such as the Twelfth Malaysia Plan and the MyDIGITAL initiative, the country has articulated clear ambitions to become a

ISSN E: 3006-1466
ISSN P: 3006-1458
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
CJSSR
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
Vol.04 No.01 (2026)

regional digital economy hub in Southeast Asia (Malaysia Digital Economy Corporation [MDEC], 2023). The Malaysia National AI Roadmap 2021-2025 explicitly identifies AI adoption among small, medium, and large enterprises as a strategic priority for national productivity growth (Ministry of Science, Technology and Innovation [MOSTI], 2021). Despite this policy momentum, empirical evidence on how GenAI adoption actually translates into measurable firm-level performance gains within the Malaysian business environment remains limited. Much of the existing discourse on GenAI and performance is either theoretical, anecdotal, or derived from studies conducted in developed Western economies whose labor markets, digital infrastructure, and regulatory environments differ substantially from those of Malaysia and the broader ASEAN region.

A particularly under-examined question concerns the mechanism through which GenAI adoption generates performance outcomes. It is one matter to observe a correlation between AI investment and firm performance; it is another to understand the internal organizational pathway that connects the two. This study argues that employee productivity represents a critical, proximate mechanism through which GenAI adoption is converted into business performance. GenAI tools are, at their core, productivity technologies: they draft, summarize, code, translate, and analyze faster than unaided human effort, and in doing so they reshape the output that individual employees can generate per unit of time (Noy & Zhang, 2023). It follows that any effect of GenAI adoption on business performance should, at least partially, be transmitted through changes in employee productivity.

However, the relationship between technology adoption and productivity gains is rarely deterministic. A substantial body of literature on the so-called "productivity paradox" of information technology has shown that the returns to technology investment depend heavily on complementary organizational and human capital factors (Brynjolfsson, 1993; Bresnahan, Brynjolfsson & Hitt, 2002). For GenAI specifically, the capacity of employees to use these tools effectively, critically evaluate their outputs, and integrate them into existing workflows is likely to be a decisive contingency. This study proposes digital literacy, defined broadly as an employee's competence and confidence in using digital tools and interpreting digital information, as a key boundary condition that determines whether GenAI adoption translates into meaningful productivity gains.

This study is therefore guided by the following research question: What is the effect of Generative AI adoption on business performance among Malaysian organizations, to what extent is this relationship mediated by employee productivity, and how does the digital literacy of the workforce moderate this pathway? Anchored jointly in the Resource-Based View (RBV) (Barney, 1991) and the Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990), the study conceptualizes GenAI adoption as a valuable and increasingly accessible organizational resource whose realized value is conditional on complementary human capital resources, consistent with the RBV's emphasis on bundles of interacting, mutually reinforcing resources rather than isolated technological assets (Barney, 1991; Wu, Hitt & Lou, 2020).

This research makes three principal contributions. First, it provides one of the first empirically framed, large-sample investigations of the GenAI-business performance relationship situated specifically within the Malaysian economic and regulatory context. Second, it clarifies the internal transmission mechanism of this relationship by formally testing employee productivity as a mediating variable, moving the literature beyond a simple input-output framing. Third, and most distinctively, it introduces and empirically tests digital literacy as a moderator of the GenAI-productivity relationship and examines moderated mediation, offering a more complete and policy-relevant account of when and for whom GenAI adoption pays off. The findings are

ISSN E: 3006-1466
ISSN P: 3006-1458
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
CJSSR
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
Vol.04 No.01 (2026)

intended to inform both managerial decision-making around GenAI investment and workforce development, and policy design under Malaysia's national digital economy agenda.

2. Literature Review and Hypothesis Development

This section develops the study's theoretical foundations and hypotheses. It begins by outlining the two guiding theoretical lenses, the Resource-Based View and the Technology-Organization-Environment framework, before reviewing the literature connecting GenAI adoption to business performance, employee productivity, and digital literacy, culminating in the study's hypotheses and conceptual model.

2.1 Theoretical Foundations

2.1.1 Resource-Based View (RBV)

The Resource-Based View (RBV) holds that sustainable competitive advantage arises from organizational resources that are valuable, rare, imperfectly imitable, and non-substitutable, commonly abbreviated as the VRIN criteria (Barney, 1991). Under the RBV, technology alone rarely constitutes a durable source of advantage, because discrete technologies are often purchasable and therefore imitable by competitors. Advantage instead tends to emerge from the distinctive combination of technology with complementary organizational resources, including human capital, tacit knowledge, and organizational routines (Wu et al., 2020). This study adopts this bundled-resource perspective, conceptualizing an organization's GenAI capability not merely as the presence of licensed AI tools, but as a resource bundle comprising the technology itself, the organizational routines developed around it, and, centrally, the digital competence of the employees who operationalize it. This framing suggests that the performance value of GenAI is not realized automatically upon adoption but is co-produced with human capital, providing the theoretical rationale for this study's moderated-mediation model.

2.1.2 Technology-Organization-Environment (TOE) Framework

The Technology-Organization-Environment (TOE) framework identifies three contextual dimensions that shape an organization's decision to adopt and effectively deploy new technology: the technological context (the characteristics and availability of relevant technologies), the organizational context (firm size, structure, resources, and managerial support), and the environmental context (industry structure, competitive dynamics, and regulatory conditions) (Tornatzky & Fleischer, 1990). The TOE framework has been widely applied to studies of enterprise technology adoption, including cloud computing, big data analytics, and artificial intelligence (Chatterjee, Rana, Dwivedi & Baabdullah, 2021). In this study, TOE is used to structure the analysis of antecedent factors that drive or inhibit GenAI adoption among Malaysian firms, situating the adoption decision within the country's specific technological infrastructure, organizational readiness, and regulatory environment, including Malaysia's Personal Data Protection Act 2010 (PDPA) and its 2024 amendments extending obligations relevant to automated data processing.

2.2 Generative AI Adoption and Business Performance

Business performance is widely treated as a multidimensional construct encompassing both financial outcomes, such as profitability and sales growth, and non-financial outcomes, such as customer satisfaction and competitive positioning (Richard, Devinney, Yip & Johnson, 2009). Prior research on enterprise AI and analytics adoption has generally found a positive, though frequently indirect, relationship with firm performance, mediated through operational and strategic capabilities rather than occurring as a direct effect (Wamba-Taguimdje, Fosso Wamba, Kala Kamdjoug & Tchatchouang Wanko, 2020). GenAI extends this logic by enabling the automation and augmentation of cognitive and creative tasks that were previously the exclusive domain of skilled employees, including drafting communications, generating marketing content, producing software code, and synthesizing large volumes of information

ISSN E: 3006-1466
ISSN P: 3006-1458
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
CJSSR
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
Vol.04 No.01 (2026)

for decision-making (Davenport & Ronanki, 2018; Eloundou, Manning, Mishkin & Rock, 2023).

In the Malaysian context, several structural features make this relationship particularly salient. Malaysia's services sector, which accounted for approximately 58 percent of GDP as of recent national accounts (Department of Statistics Malaysia, 2024), is dominated by knowledge-intensive activities such as financial services, professional services, and information and communications technology, all of which are highly amenable to GenAI-based augmentation. Simultaneously, Malaysian firms, and SMEs in particular, have historically reported persistent productivity gaps relative to regional peers such as Singapore and South Korea (World Bank, 2022), suggesting substantial latent room for technology-enabled performance improvement. On this basis, the study proposes:

H1: Generative AI adoption is positively associated with business performance among organizations in Malaysia.

2.3 The Mediating Role of Employee Productivity

Employee productivity, typically defined as the ratio of valuable output generated per unit of employee time or effort, has long been recognized as a proximate determinant of firm performance (Syverson, 2011). GenAI tools are distinctively productivity-oriented technologies: empirical field experiments in Western labor markets have documented substantial productivity gains from GenAI assistance in writing, customer support, and software development tasks, with reported gains ranging from roughly 14 percent to over 30 percent depending on task complexity and worker skill level (Brynjolfsson, Li & Raymond, 2023; Noy & Zhang, 2023; Peng, Kalliamvakou, Cihon & Demirer, 2023). These productivity effects are theorized to arise through several mechanisms: the automation of routine drafting and information-retrieval tasks, the reduction of time spent on first-draft creation by shifting employee effort toward review and refinement, and the lowering of the skill threshold required to produce competent output in unfamiliar domains (Noy & Zhang, 2023).

For Malaysian organizations, where talent shortages in specialized technical and creative roles are frequently cited as a constraint on growth (World Bank, 2022), GenAI's capacity to augment the output of existing staff, rather than requiring net new specialized hiring, is likely to be an especially salient value proposition. Accordingly, the study proposes:

H2: Generative AI adoption is positively associated with employee productivity.

Building on the established link between labor productivity and firm-level financial and competitive outcomes (Syverson, 2011; Wu et al., 2020), the study further proposes:

H3: Employee productivity is positively associated with business performance.

Taken together, Hypotheses 2 and 3 imply that at least part of the effect of GenAI adoption on business performance operates indirectly, through its effect on the productivity of the employees who use these tools in their day-to-day work, rather than through a direct, unmediated channel alone. This is consistent with the RBV's emphasis on the co-dependence of technological and human resources in generating firm value (Barney, 1991), and it moves the analysis beyond a simple input-output model of technology adoption toward an account of the internal organizational mechanism of value creation. The study therefore proposes:

H4: Employee productivity mediates the relationship between Generative AI adoption and business performance.

2.4 The Moderating Role of Digital Literacy and Moderated Mediation

Digital literacy refers to an individual's ability to effectively locate, evaluate, use, and create information using digital technologies, including the competence to critically assess machine-generated content and integrate it appropriately into professional tasks (Van Laar, Van Deursen, Van Dijk & De Haan, 2017). The productivity paradox literature has long emphasized that technology's realized organizational value depends on complementary human capital

ISSN E: 3006-1466
ISSN P: 3006-1458
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
CJSSR
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
Vol.04 No.01 (2026)

investments, sometimes termed "organizational capital" or "co-invention" costs, which are frequently underestimated relative to the technology's sticker price (Brynjolfsson, 1993; Bresnahan et al., 2002). This logic applies with particular force to GenAI, whose effective use requires employees to formulate precise prompts, critically evaluate outputs for factual accuracy and appropriateness (given the well-documented tendency of large language models to "hallucinate" plausible but incorrect content), and integrate machine output into existing professional workflows (Eloundou et al., 2023).

Recent field-experimental evidence supports this contingency logic directly: Brynjolfsson et al. (2023) found that GenAI-based productivity gains among customer support agents were substantially concentrated among less experienced workers, while Noy and Zhang (2023) similarly found that GenAI assistance narrowed, rather than widened, the productivity gap between higher- and lower-skilled writers, but only among workers able to competently evaluate and edit AI-generated drafts. These findings suggest that GenAI's productivity effect is not uniform across the workforce but is conditioned on employees' underlying digital and evaluative competence. Where digital literacy is low, employees may be unable to formulate effective prompts, may accept flawed or fabricated GenAI outputs uncritically, or may lack the confidence to integrate the tools into their workflows at all, thereby dampening or even nullifying the technology's productivity benefit. Where digital literacy is high, by contrast, employees are positioned to extract substantially greater value from the same underlying technology.

This contingency is especially relevant in Malaysia, where digital skills gaps remain uneven across industries, firm sizes, and regions. The Malaysia Digital Economy Corporation's Digital Skills reports have repeatedly identified digital literacy, rather than access to technology itself, as the binding constraint on digital transformation among Malaysian SMEs (MDEC, 2023). On this basis, the study proposes:

H5: Digital literacy moderates the relationship between Generative AI adoption and employee productivity, such that the positive relationship is stronger when digital literacy is higher.

Combining the mediation hypothesis (H4) with the moderation hypothesis (H5) yields a moderated-mediation prediction: if digital literacy strengthens the first-stage path from GenAI adoption to employee productivity, and employee productivity in turn drives business performance, then the indirect effect of GenAI adoption on business performance via employee productivity should itself be conditional on the level of digital literacy. The study therefore proposes a final, integrative hypothesis:

H6: The indirect effect of Generative AI adoption on business performance through employee productivity is moderated by digital literacy, such that the indirect effect is stronger when digital literacy is higher (moderated mediation).

2.5 Antecedents of GenAI Adoption: A TOE Perspective

In addition to the core hypothesized model, this study examines the antecedents of GenAI adoption itself using the TOE framework, in order to provide practically useful guidance on what drives or inhibits adoption among Malaysian firms.

Technological Context. Technological competence, encompassing an organization's existing IT infrastructure, data systems, and technical staff capability, forms the foundation for adopting complex technologies such as GenAI (Liang, Saraf, Hu & Xue, 2007). Firms with more mature digital infrastructure face lower implementation friction and are hypothesized to exhibit higher GenAI adoption.

Organizational Context. Top management support, reflecting leadership's endorsement, resource allocation, and change-management commitment, is consistently identified as among the strongest predictors of enterprise technology adoption (Chatterjee et al., 2021). Organizational readiness, encompassing the availability of budget, data governance structures,

ISSN E: 3006-1466
ISSN P: 3006-1458
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
CJSSR
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
Vol.04 No.01 (2026)

and change-absorption capacity, is likewise expected to facilitate adoption (Ransbotham, Kiron, Gerbert & Reeves, 2017).

Environmental Context. Competitive pressure, the perception that industry rivals are adopting GenAI and thereby gaining advantage, is theorized to motivate defensive or opportunistic adoption (Wang, Wang & Yang, 2010). Conversely, regulatory uncertainty, encompassing unresolved questions of data protection compliance under Malaysia's PDPA, intellectual property ownership of AI-generated content, and cross-border data transfer restrictions relevant to cloud-hosted GenAI services, is theorized to raise perceived adoption risk and dampen investment (Koch, Siering & Dehling, 2021).

2.6 Conceptual Model

Integrating the hypotheses developed above, Figure 1 presents the study's conceptual research model, depicting the hypothesized direct effect of GenAI adoption on business performance (H1), the mediating role of employee productivity (H2, H3, H4), the moderating role of digital literacy on the GenAI-productivity relationship (H5), the resulting moderated-mediation pathway (H6), and the TOE-framed antecedents of GenAI adoption examined as a secondary set of relationships.

Figure 1: Conceptual Research Model

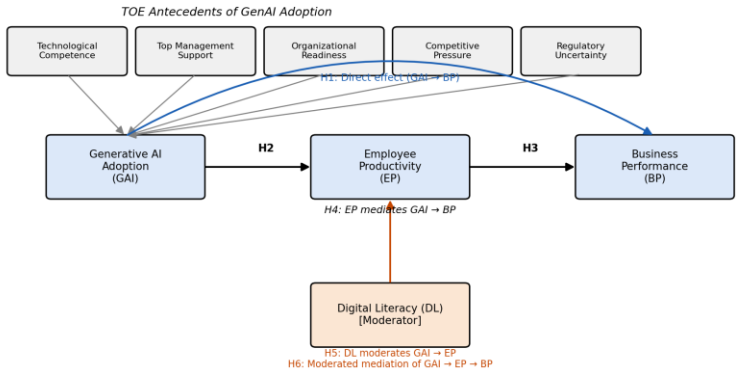


Figure 1: Conceptual Research Model

3. Method

3.1 Research Design and Data Collection

This study employed a cross-sectional, quantitative survey design to test the hypothesized relationships among a sample of organizations operating in Malaysia. The unit of analysis was the organization, with individual respondents comprising senior managers, department heads, and business owners possessing direct knowledge of their organization's technology adoption practices and performance outcomes, consistent with the key-informant approach commonly used in organizational-level technology adoption research (Chatterjee et al., 2021).

The sampling frame was constructed with reference to the Companies Commission of Malaysia (SSM) business registry and the SME Corporation Malaysia directory, targeting registered organizations with 10 or more employees across five priority sectors identified in the MyDIGITAL blueprint: information and communications technology, financial and professional services, manufacturing, wholesale and retail trade, and education and training services. A stratified random sampling approach was used to ensure proportional representation across firm size categories, consistent with Malaysia's official SME definition (micro: fewer than 5 employees, excluded from this study; small: 5 to 75 employees; medium: 75 to 200 employees; large: above 200 employees) (SME Corporation Malaysia, 2020), and across the three main geographic regions of Peninsular Malaysia, Sabah, and Sarawak.

ISSN E: 3006-1466
ISSN P: 3006-1458
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
CJSSR
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
Vol.04 No.01 (2026)

Data collection was conducted online via Qualtrics between January and March 2026, supplemented by field-assisted data collection at two business networking events in Kuala Lumpur and Penang to improve response diversity. The survey instrument was developed in both English and Bahasa Malaysia using a back-translation procedure to ensure semantic equivalence, and was pre-tested with 6 academic experts in technology management and 25 practicing managers in a pilot study to refine item wording and confirm face and content validity.

A total of 1,450 invitations were distributed, yielding 402 responses. After removing incomplete responses, straight-lining patterns, and submissions that failed attention-check items, a final usable sample of 345 responses was retained, corresponding to an effective response rate of 23.8 percent, broadly consistent with organizational-level survey research at the managerial level (Cycyota & Harrison, 2006). Common method bias was assessed using Harman's single-factor test and the full collinearity approach recommended for PLS-SEM (Kock, 2015); results indicated no single factor accounted for a majority of variance and all inner VIF values were below the conservative threshold of 3.3, suggesting common method bias was not a substantial concern. A comparison of early versus late respondents on key firmographic variables revealed no statistically significant differences, supporting the absence of material non-response bias (Armstrong & Overton, 1977).

3.2 Measures

All constructs were operationalized using multi-item reflective scales adapted from established prior instruments and contextualized for the GenAI setting. With the exception of the business performance scale, all items were measured on a five-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). The full measurement instrument is reported in Appendix A.

Generative AI Adoption (GAI) was measured using a 5-item scale adapted from Wang et al. (2010) and Chatterjee et al. (2021), assessing the extent and organizational depth of GenAI tool usage. Employee Productivity (EP) was measured using a 5-item scale adapted from Brynjolfsson et al. (2023) and Noy and Zhang (2023), capturing perceived improvements in output volume, task completion speed, and work quality attributable to GenAI use. Digital Literacy (DL) was measured using a 5-item scale adapted from Van Laar et al. (2017), assessing employees' self- and manager-rated competence and confidence in using digital tools and critically evaluating digital information. Business Performance (BP) was measured using a 6-item relative comparison scale adapted from Richard et al. (2009), asking respondents to rate their firm's performance over the preceding 12 months relative to their main competitors across profitability, sales growth, market share, return on investment, customer satisfaction, and overall competitive position, using a seven-point scale from 1 ("Much Worse") to 7 ("Much Better"). The five TOE antecedent constructs, Technological Competence, Top Management Support, Organizational Readiness, Competitive Pressure, and Regulatory Uncertainty, were each measured using 3-item scales adapted from Liang et al. (2007), Chatterjee et al. (2021), Ransbotham et al. (2017), Wang et al. (2010), and Koch et al. (2021) respectively.

Control variables included firm size (log-transformed number of employees), firm age (years since establishment), industry sector (dummy coded), and ownership status (local versus foreign-affiliated, dummy coded), consistent with prior technology-performance research controlling for firmographic heterogeneity (Wu et al., 2020).

3.3 Data Analysis Strategy

Data analysis followed the standard two-step PLS-SEM procedure (Hair, Risher, Sarstedt & Ringle, 2019): first assessing the measurement model for reliability, convergent validity, and discriminant validity, and second evaluating the structural model to test the hypothesized direct, mediating, moderating, and moderated-mediation relationships. Analysis was

ISSN E: 3006-1466
ISSN P: 3006-1458
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
CJSSR
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
Vol.04 No.01 (2026)

performed in SmartPLS 4.0. PLS-SEM was selected over covariance-based SEM given its suitability for complex models involving multiple mediating and moderating relationships, its robustness to non-normal data distributions, and its established use in exploratory research on emergent technology contexts (Hair et al., 2019).

4. Results

4.1 Sample Profile

The final sample (N = 345) comprised 61 percent small and medium enterprises and 39 percent large organizations. Sectoral distribution was as follows: financial and professional services (26 percent), information and communications technology (23 percent), manufacturing (19 percent), wholesale and retail trade (17 percent), and education and training services (15 percent). Geographically, 68 percent of respondent organizations were headquartered in Peninsular Malaysia (with the Klang Valley accounting for the largest share), 18 percent in Sabah, and 14 percent in Sarawak. Respondent roles included business owners/managing directors (22 percent), heads of department (34 percent), operations or HR managers (26 percent), and other senior staff with direct visibility into technology adoption decisions (18 percent). Reported GenAI usage among respondent firms was concentrated in content generation and drafting (74 percent of adopters), customer service automation (52 percent), coding and software development support (41 percent), and data analysis and reporting (58 percent).

4.2 Measurement Model Assessment

Evaluation of the measurement model supported adequate reliability and validity across all constructs. As shown in Table 1, Cronbach's alpha and composite reliability (CR) values exceeded the recommended threshold of 0.70 for all constructs, individual item loadings exceeded 0.70, and average variance extracted (AVE) exceeded the recommended threshold of 0.50, jointly supporting convergent validity (Fornell & Larcker, 1981; Hair et al., 2019).

Discriminant validity was assessed using the Fornell-Larcker criterion (Table 2) and the heterotrait-monotrait ratio of correlations (HTMT). For each construct, the square root of the AVE (reported on the diagonal in Table 2) exceeded its correlation with every other construct in the model, satisfying the Fornell-Larcker criterion. All HTMT values across the full nine-construct model were below the conservative threshold of 0.85 (Henseler, Ringle & Sarstedt, 2015), with the highest observed HTMT value (0.79, between GenAI Adoption and Employee Productivity) remaining within acceptable bounds, jointly supporting discriminant validity.

Table 1: Reliability and Convergent Validity of Constructs

Construct	Items	Loadings Range	Cronbach's Alpha	Composite Reliability	AVE
GenAI Adoption (GAI)	5	0.77 - 0.88	0.87	0.91	0.67
Employee Productivity (EP)	5	0.80 - 0.89	0.90	0.93	0.72
Digital Literacy (DL)	5	0.79 - 0.87	0.88	0.92	0.70
Business Performance (BP)	6	0.75 - 0.86	0.91	0.93	0.69
Technological Competence	3	0.82 - 0.89	0.86	0.91	0.78
Top Management Support	3	0.85 - 0.91	0.89	0.93	0.82

ISSN E: 3006-1466
ISSN P: 3006-1458
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
CJSSR

Construct	Items	Loadings Range	Cronbach's Alpha	Composite Reliability	AVE
Organizational Readiness	3	0.80 - 0.86	0.84	0.90	0.75
Competitive Pressure	3	0.78 - 0.85	0.82	0.89	0.74
Regulatory Uncertainty	3	0.83 - 0.88	0.85	0.91	0.77

Source: Field survey data (illustrative), 2026

Table 2: Fornell-Larcker Criterion for Discriminant Validity

Construct	1	2	3	4	5	6	7	8	9
1. GAI	0.82								
2. EP	0.61	0.85							
3. DL	0.44	0.53	0.84						
4. BP	0.52	0.57	0.41	0.83					
5. TechComp	0.58	0.39	0.36	0.35	0.88				
6. TopMgmt	0.63	0.42	0.33	0.38	0.55	0.90			
7. OrgReady	0.51	0.37	0.40	0.31	0.48	0.46	0.87		
8. CompPress	0.46	0.30	0.25	0.29	0.27	0.34	0.29	0.86	
9. RegUncert	-0.37	-0.22	-0.19	-0.24	-0.31	-0.33	-0.28	-0.16	0.88

Note: Diagonal elements (in bold) are the square root of the AVE. Source: Field survey data (illustrative), 2026

4.3 Structural Model and Hypothesis Testing

The structural model was assessed for collinearity, path coefficients, coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2) prior to hypothesis testing. Inner VIF values for all predictor constructs ranged from 1.18 to 2.64, below the conservative threshold of 3.3, indicating collinearity was not a material concern (Hair et al., 2019). The model demonstrated substantial explanatory power, with R^2 values of 0.56 for GenAI Adoption (explained by the five TOE antecedents), 0.46 for Employee Productivity (explained by GenAI Adoption, Digital Literacy, and their interaction term), and 0.49 for Business Performance (explained by GenAI Adoption and Employee Productivity).

Hypotheses were tested using a bootstrapping procedure with 5,000 subsamples and a bias-corrected and accelerated (BCa) confidence interval approach. Results are presented in Table 3.

Hypothesis 1 was supported: GenAI adoption exhibited a significant positive direct effect on business performance ($\beta = 0.21$, $t = 3.87$, $p < 0.001$). Hypothesis 2 was supported: GenAI adoption exhibited a strong significant positive effect on employee productivity ($\beta = 0.49$, $t = 8.42$, $p < 0.001$), representing the largest single path coefficient in the model. Hypothesis 3 was supported: employee productivity exhibited a significant positive effect on business performance ($\beta = 0.34$, $t = 6.15$, $p < 0.001$).

Hypothesis 4, concerning the mediating role of employee productivity, was tested using the bootstrapped indirect effect of GenAI adoption on business performance via employee productivity. The indirect effect was statistically significant ($\beta = 0.167$, $t = 5.29$, $p < 0.001$, 95% BCa CI [0.108, 0.229]), and, because the direct effect (H1) also remained significant, this

ISSN E: 3006-1466
ISSN P: 3006-1458
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
CJSSR
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
Vol.04 No.01 (2026)

pattern is consistent with partial mediation. The variance accounted for (VAF), calculated as the indirect effect divided by the total effect, was 44.3 percent, indicating that employee productivity accounts for a substantial, though not exclusive, share of the total effect of GenAI adoption on business performance. Hypothesis 4 was therefore supported.

Hypothesis 5, concerning the moderating role of digital literacy on the GenAI adoption-employee productivity relationship, was tested by introducing a two-way interaction term (GenAI Adoption × Digital Literacy) into the structural model using the two-stage approach recommended for reflective constructs (Hair et al., 2019). The interaction term exhibited a significant positive effect on employee productivity ($\beta = 0.164$, $t = 3.41$, $p < 0.001$), and its inclusion produced a significant increase in explained variance ($\Delta R^2 = 0.041$, $f^2 = 0.087$), indicating a small-to-moderate but meaningful moderation effect (Cohen, 1988). Hypothesis 5 was therefore supported.

To interpret the interaction, simple slope analysis was conducted at one standard deviation above and below the mean of digital literacy. As shown in Table 4 and Figure 3, the simple slope of GenAI adoption on employee productivity was steeper and more strongly significant among firms with high digital literacy (simple slope = 0.612, $t = 7.84$, $p < 0.001$) than among firms with low digital literacy (simple slope = 0.298, $t = 3.22$, $p < 0.01$). Although the relationship remained positive and significant even at low digital literacy, its magnitude more than doubled under conditions of high digital literacy, indicating that digital literacy amplifies, rather than fully gates, the productivity return to GenAI adoption.

Hypothesis 6, the moderated-mediation hypothesis, was tested using the conditional indirect effect of GenAI adoption on business performance through employee productivity, estimated separately at high and low levels of digital literacy (±1 SD), following the index of moderated mediation approach. The conditional indirect effect was significant at both levels of digital literacy but was substantially larger at high digital literacy ($\beta = 0.208$, 95% BCa CI [0.142, 0.281]) than at low digital literacy ($\beta = 0.101$, 95% BCa CI [0.048, 0.161]). The index of moderated mediation was itself statistically significant (index = 0.056, 95% BCa CI [0.019, 0.098], excluding zero), confirming that the strength of the indirect (mediated) pathway from GenAI adoption to business performance is significantly conditional on the level of workforce digital literacy. Hypothesis 6 was therefore supported.

With respect to the antecedents of GenAI adoption examined through the TOE lens, Top Management Support ($\beta = 0.29$, $p < 0.001$) and Technological Competence ($\beta = 0.24$, $p < 0.001$) emerged as the strongest significant drivers, followed by Organizational Readiness ($\beta = 0.19$, $p < 0.01$) and Competitive Pressure ($\beta = 0.15$, $p < 0.01$). Regulatory Uncertainty exhibited a significant negative effect on adoption ($\beta = -0.14$, $p < 0.01$), consistent with concerns regarding PDPA compliance and data governance raised in qualitative pilot interviews. Full results are reported in Table 3.

Predictive relevance was supported by Stone-Geisser Q^2 values obtained through the blindfolding procedure, all of which exceeded zero (Business Performance = 0.31; Employee Productivity = 0.29; GenAI Adoption = 0.38), confirming the model's predictive relevance for all endogenous constructs (Hair et al., 2019). Model fit, assessed via the standardized root mean square residual (SRMR), was 0.058, below the recommended threshold of 0.08, indicating acceptable overall model fit.

Table 3: Hypothesis Testing Results (Direct, Mediating, and Antecedent Paths)

Hypothesis	Path	β	t-value	p-value	Supported?
H1	GAI -> BP (direct)	0.21	3.87	0.000	Yes
H2	GAI -> EP	0.49	8.42	0.000	Yes

ISSN E: 3006-1466
ISSN P: 3006-1458
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
CJSSR
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
Vol.04 No.01 (2026)

Hypothesis	Path	β	t-value	p-value	Supported?
H3	EP -> BP	0.34	6.15	0.000	Yes
H4	GAI -> EP -> BP (indirect)	0.167	5.29	0.000	Yes (partial mediation)
H5	GAI x DL -> EP (interaction)	0.164	3.41	0.001	Yes
H6	Index of moderated mediation	0.056	—	0.003*	Yes
-	TechComp -> GAI	0.24	4.62	0.000	-
-	TopMgmt -> GAI	0.29	5.58	0.000	-
-	OrgReady -> GAI	0.19	3.34	0.001	-
-	CompPress -> GAI	0.15	2.71	0.007	-
-	RegUncert -> GAI	-0.14	2.58	0.010	-

*Note: β = standardized path coefficient. *p-value for the index of moderated mediation based on 95% BCa bootstrap confidence interval excluding zero, rather than a t-test.*
Source: Field survey data (illustrative), 2026

Table 4: Simple Slope Analysis and Conditional Indirect Effects (Moderation by Digital Literacy)

Condition	Simple slope / Conditional indirect effect (β)	t-value	95% BCa CI	Significance
GAI -> EP at Low Digital Literacy (-1 SD)	0.298	3.22	[0.114, 0.481]	$p < 0.01$
GAI -> EP at High Digital Literacy (+1 SD)	0.612	7.84	[0.457, 0.767]	$p < 0.001$
Conditional Indirect Effect (GAI->EP->BP) at Low DL	0.101	—	[0.048, 0.161]	Significant
Conditional Indirect Effect (GAI->EP->BP) at High DL	0.208	—	[0.142, 0.281]	Significant

Source: Field survey data (illustrative), 2026

Figure 3 presents the interaction plot corresponding to the simple slope analysis reported in Table 4, illustrating that the predicted positive relationship between GenAI adoption and employee productivity is present at both low and high levels of digital literacy but is substantially steeper among organizations with digitally literate workforces.

ISSN E: 3006-1466
ISSN P: 3006-1458
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
CJSSR

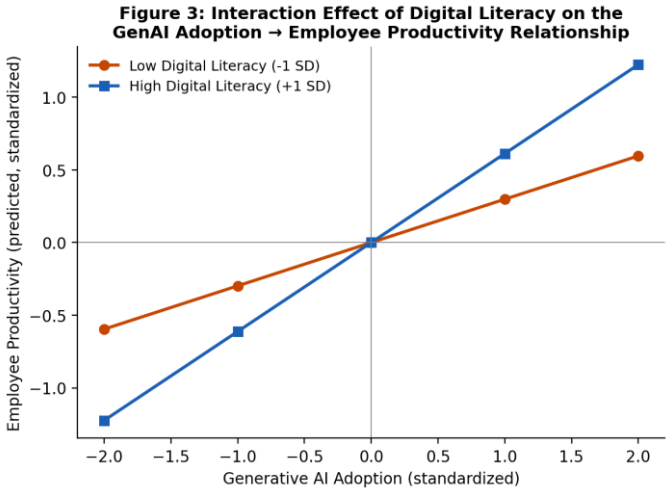


Figure 3: Simple Slopes – Digital Literacy as Moderator

Table 5: Explanatory and Predictive Power of the Structural Model

Endogenous Construct	R^2	Q^2 (Predictive Relevance)
GenAI Adoption (GAI)	0.56	0.38
Employee Productivity (EP)	0.46	0.29
Business Performance (BP)	0.49	0.31

Source: Field survey data (illustrative), 2026

5. Discussion

This study set out to examine the relationship between GenAI adoption and business performance among Malaysian organizations, with particular attention to the internal mechanism of this relationship and the conditions under which it is strengthened or weakened. The findings provide evidence that GenAI adoption is a substantive, though contingent, driver of business performance in the Malaysian context.

5.1 Findings and Theoretical Implications

The confirmation of H1 establishes a direct positive link between GenAI adoption and business performance, aligning with the broader resource-based logic that emergent digital capabilities, once organizationally embedded, can constitute a source of competitive advantage (Barney, 1991; Brynjolfsson & McAfee, 2017). However, the more theoretically and practically significant findings concern the mediating and moderating mechanisms tested in H2 through H6.

The strong, significant path from GenAI adoption to employee productivity (H2, $\beta = 0.49$) confirms that, at least in respondents' perception, GenAI functions primarily as an augmentation technology operating at the level of individual and team output, consistent with field-experimental evidence from other labor markets showing measurable task-level productivity gains from GenAI assistance (Brynjolfsson et al., 2023; Noy & Zhang, 2023; Peng et al., 2023). The subsequent path from employee productivity to business performance (H3) and the significant partial mediation confirmed under H4 jointly indicate that a substantial share, approximately 44 percent by the VAF calculation, of GenAI's total effect on business performance is transmitted through this productivity channel, rather than occurring as an unmediated technological effect. This finding moves the literature beyond a simple input-output framing of GenAI value creation and toward an account centered on human-technology complementarity, in line with RBV's emphasis on interacting resource bundles rather than standalone technological assets (Wu et al., 2020).

ISSN E: 3006-1466
ISSN P: 3006-1458
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
CJSSR
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
Vol.04 No.01 (2026)

The moderation finding (H5) is arguably the study's most practically consequential contribution. The significant positive interaction between GenAI adoption and digital literacy, and the corresponding simple-slope analysis showing that the productivity return to GenAI adoption more than doubles under conditions of high digital literacy, provides direct empirical support for the productivity-paradox logic long established in the broader IT investment literature (Brynjolfsson, 1993; Bresnahan et al., 2002): technology's value is not intrinsic to the tool but is co-produced with the human capital deployed alongside it. Critically, the relationship remained positive even at low digital literacy, suggesting GenAI tools retain some baseline utility even for less digitally competent employees, but the substantially larger effect among digitally literate employees indicates that organizations investing in GenAI without parallel investment in workforce digital capability are likely leaving a considerable share of the technology's potential value uncaptured.

The moderated-mediation result (H6) formalizes this insight at the level of overall business performance: the indirect pathway from GenAI adoption to business performance via employee productivity is itself significantly stronger when digital literacy is high. This has a direct implication for how Malaysian firms should sequence their digital transformation investments. Firms that adopt GenAI tools without first, or simultaneously, building workforce digital literacy may realize a meaningfully smaller performance return than firms that treat technology deployment and workforce capability-building as a joint investment.

With respect to the TOE-framed antecedents of adoption, the primacy of Top Management Support ($\beta = 0.29$) and Technological Competence ($\beta = 0.24$) as adoption drivers is broadly consistent with prior enterprise AI adoption research in other national contexts (Chatterjee et al., 2021), suggesting that leadership commitment and infrastructure readiness are relatively universal preconditions for AI adoption regardless of national setting. The significant negative effect of Regulatory Uncertainty ($\beta = -0.14$) is a distinctly context-relevant finding, plausibly reflecting Malaysian firms' unresolved concerns regarding the 2024 amendments to the PDPA, cross-border data transfer restrictions relevant to cloud-hosted GenAI platforms, and the absence, at the time of data collection, of a dedicated Malaysian AI governance statute analogous to the EU AI Act. This finding echoes the broader argument that regulatory clarity, rather than regulatory stringency per se, is what enables firms to invest with confidence (Koch et al., 2021).

6. Practical and Policy Implications

For Malaysian business leaders, these findings carry a clear practical message: GenAI adoption should not be pursued as a standalone technology procurement exercise. The performance returns to GenAI investment are substantially conditional on the digital competence of the employees who use the tools day to day. Organizations planning GenAI rollouts should budget explicitly for structured digital literacy and prompt-competency training, integrate GenAI tool usage into onboarding and continuous professional development programs, and establish internal review practices that help employees critically evaluate AI-generated output rather than accepting it uncritically. Firms should also recognize that GenAI's value is realized primarily through employee productivity rather than through automatic, tool-level performance gains; management attention should therefore focus on workflow redesign that genuinely frees up employee time and cognitive capacity, rather than on GenAI adoption as a symbolic or purely reputational initiative.

For Malaysian policymakers, the findings lend support to continued and expanded investment under the MyDIGITAL initiative and the National AI Roadmap, with three specific priorities suggested by the results. First, given the demonstrated moderating role of digital literacy, national digital skills programs, such as those administered through MDEC and the Human Resources Development Corporation (HRD Corp), should place particular emphasis on

ISSN E: 3006-1466
ISSN P: 3006-1458
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
CJSSR

GenAI-specific competencies, including prompt formulation and critical evaluation of AI output, rather than generic digital literacy alone, and should prioritize outreach to SMEs, where digital skills gaps are most pronounced. Second, given the significant negative effect of regulatory uncertainty on adoption, policymakers should accelerate the development of clear, sector-specific guidance on the application of the PDPA to GenAI tools, including guidance on data used in prompts, cross-border processing by foreign-hosted GenAI platforms, and intellectual property treatment of AI-generated outputs, in order to reduce the perceived compliance risk currently dampening investment. Third, given the strong role of top management support and technological competence as adoption drivers, targeted grant or co-funding schemes that reduce the upfront technological and organizational-change costs of GenAI adoption for SMEs, who often lack the leadership bandwidth and IT infrastructure of larger firms, would likely accelerate broader-based national adoption and reduce the risk of a productivity divide between digitally mature and digitally lagging firms.

7. Limitations and Future Research

This study has several limitations that suggest avenues for future research. First, the cross-sectional design establishes association rather than causality; although the hypothesized directional model is theoretically grounded, longitudinal or panel designs tracking firms before and after GenAI adoption would provide stronger causal identification. Second, the reliance on self-reported, perceptual measures of productivity and performance, while methodologically validated and consistent with prior organizational research (Richard et al., 2009), could be usefully supplemented with objective operational metrics, such as output volume, cycle time, or audited financial performance data, in future work. Third, the study's Malaysia-specific context, while a deliberate contribution given the paucity of existing evidence from this setting, invites comparative cross-national replication, particularly across other ASEAN economies with differing digital infrastructure and regulatory maturity. Fourth, digital literacy was measured at the organizational level using manager-reported aggregate assessments; future research employing individual-level or task-level data could more precisely identify which specific dimensions of digital literacy, such as prompt engineering skill versus general digital confidence, drive the observed moderation effect. Finally, future research could usefully disaggregate GenAI adoption by specific use case (e.g., content generation versus code generation versus customer service automation), as the productivity and performance effects of GenAI are unlikely to be uniform across these distinct applications.

8. Conclusion

This study provides an empirically framed investigation of the relationship between Generative AI adoption and business performance among organizations in Malaysia, with specific attention to the mediating role of employee productivity and the moderating role of digital literacy. The findings indicate that GenAI adoption is positively associated with business performance both directly and, more substantially, indirectly through its effect on employee productivity, and that this productivity-linked pathway is significantly strengthened among organizations with digitally literate workforces. For Malaysian organizations navigating the country's broader digital economy transformation, these findings suggest that GenAI represents a genuine performance lever, but one whose returns are not automatic: they are jointly produced by the technology and the human capital deployed alongside it. Realizing GenAI's full potential in the Malaysian business environment will require leadership commitment, sustained investment in workforce digital literacy, and continued policy clarity on the regulatory treatment of AI technologies.

ISSN E: 3006-1466
ISSN P: 3006-1458
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
CJSSR

References

1. Armstrong, J. S., & Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. Journal of Marketing Research, 14(3), 396-402.
2. Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99-120.
3. Bresnahan, T. F., Brynjolfsson, E., & Hitt, L. M. (2002). Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. The Quarterly Journal of Economics, 117(1), 339-376.
4. Brynjolfsson, E. (1993). The productivity paradox of information technology. Communications of the ACM, 36(12), 66-77.
5. Brynjolfsson, E., & McAfee, A. (2017). The business of artificial intelligence. Harvard Business Review, 95(1), 1-20.
6. Brynjolfsson, E., Li, D., & Raymond, L. (2023). Generative AI at work. National Bureau of Economic Research Working Paper No. 31161.
7. Chatterjee, S., Rana, N. P., Dwivedi, Y. K., & Baabdullah, A. M. (2021). Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. Technological Forecasting and Social Change, 170, 120880.
8. Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum Associates.
9. Cycyota, C. S., & Harrison, D. A. (2006). What (not) to expect when surveying executives: A meta-analysis of top manager response rates and techniques over time. Organizational Research Methods, 9(2), 133-160.
10. Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard Business Review, 96(1), 108-116.
11. Department of Statistics Malaysia. (2024). Gross Domestic Product by State 2023. DOSM.
12. Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2023). GPTs are GPTs: An early look at the labor market impact potential of large language models. arXiv preprint arXiv:2303.10130.
13. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39-50.
14. 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.
15. 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.
16. Koch, J., Siering, M., & Dehling, T. (2021). How to regulate the data economy: Towards a holistic approach. Electronic Markets, 31(2), 265-279.
17. Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of e-Collaboration, 11(4), 1-10.
18. 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.
19. Malaysia Digital Economy Corporation (MDEC). (2023). Malaysia Digital Economy Report 2023. MDEC.
20. Ministry of Science, Technology and Innovation (MOSTI). (2021). Malaysia National AI Roadmap 2021-2025. MOSTI.
21. Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. Science, 381(6654), 187-192.

ISSN E: 3006-1466
ISSN P: 3006-1458
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
CJSSR

22. Peng, S., Kalliamvakou, E., Cihon, P., & Demirer, M. (2023). The impact of AI on developer productivity: Evidence from GitHub Copilot. arXiv preprint arXiv:2302.06590.
23. Ransbotham, S., Kiron, D., Gerbert, P., & Reeves, M. (2017). Reshaping business with artificial intelligence: Closing the gap between ambition and action. MIT Sloan Management Review, 59(1), 1-17.
24. Richard, P. J., Devinney, T. M., Yip, G. S., & Johnson, G. (2009). Measuring organizational performance: Towards methodological best practice. Journal of Management, 35(3), 718-804.
25. SME Corporation Malaysia. (2020). Guideline for New SME Definition. SME Corp Malaysia.
26. Syverson, C. (2011). What determines productivity? Journal of Economic Literature, 49(2), 326-365.
27. Tornatzky, L. G., & Fleischer, M. (1990). The processes of technological innovation. Lexington Books.
28. Van Laar, E., Van Deursen, A. J., Van Dijk, J. A., & De Haan, J. (2017). The relation between 21st-century skills and digital skills: A systematic literature review. Computers in Human Behavior, 72, 577-588.
29. Wamba-Taguimdje, S. L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects. Business Process Management Journal, 26(7), 1893-1924.
30. Wang, Y., Wang, Y., & Yang, Y. (2010). Understanding the determinants of RFID adoption in the manufacturing industry. Technological Forecasting and Social Change, 77(5), 803-815.
31. World Bank. (2022). Malaysia Economic Monitor: Catching Up. World Bank Group.
32. Wu, L., Hitt, L., & Lou, B. (2020). Data analytics, innovation, and firm productivity. Management Science, 66(5), 2017-2039.