Journal of East European Management Studies

J. East Eur. Manag. Stud. **2026**; 31(3): 46993
https://doi.org/10.31083/JEEMS46993

Article

From Technology Orientation to Performance in Multinational Companies: A Serial Mediation Model

Md Tamzid Parves[1], Md Anamul Haque[1], Md Asadul Islam[2,3], SoonHu Soh[1,*]

[1]Department of Business Administration, Wonkwang University, 54538 Iksan, Republic of Korea
[2]Department of Management and Marketing, KFUPM Business School, 31261 Dhahran, Saudi Arabia
[3]Interdisciplinary Research Center for Finance and Digital Economy, King Fahd University of Petroleum and Minerals, 31261 Dhahran, Saudi Arabia
*Correspondence: soonhu@wku.ac.kr (SoonHu Soh)

Academic Editors: Thomas Steger and Rainhart Lang
Submitted: 28 September 2025 Revised: 17 January 2026 Accepted: 2 March 2026 Published: 30 June 2026

Abstract

This study develops a serial mediation model grounded in the resource-based view to examine how technology orientation, digital technology capability, and generative artificial intelligence adoption influence organizational performance. Using quantitative methods, survey data were collected from 357 managerial-level employees in multinational companies in Bangladesh, an emerging developing nation. Findings suggest that technology orientation alone may not drive organizational performance, while digital technology capability and generative artificial intelligence adoption act as independent mediators. Moreover, these two factors sequentially mediate the relationship between technology orientation and organizational performance. The study introduces a novel sequential capability-building framework based on digital technology and generative artificial intelligence. It also offers managers practical strategies for translating technological direction into performance improvements. The paper further discusses findings, implications, limitations, and directions for future research.

Keywords: technology orientation; digital technology capability; generative artificial intelligence adoption; organizational performance; multinational companies
JEL: M15, O33, F23

1. Background of the Study

Maintaining or improving organizational performance has become increasingly challenging due to factors such as heightened market competition, currency fluctuations, and political instability (Obłój and Voronovska, 2024). However, multinational companies, particularly those operating in developing countries, have shown resilience and continued growth (Divrik, 2024; Haberler, 2024). Therefore, investigating the drivers of organizational performance in multinational companies presents a promising avenue for research. Previous studies have highlighted the positive impact of technology orientation (TO) on organizational performance (Masa'deh et al., 2018; Rezazadeh et al., 2016; Yousaf et al., 2020). TO involves research and development and the adoption of cutting-edge technologies to enhance organizational performance (Sai, 2018). However, conflicting findings have emerged, with some studies suggesting a negative relationship between technology orientation and organizational performance (Al-Ansari et al., 2013). Consequently, the debate regarding the impact of technology orientation on organizational performance remains inconclusive. Recent scholars such as Ali et al. (2016), Gangwani and Bhatia (2024), and Vesterinen et al. (2024) have called for further investigation into the role of technology orientation and its various outcomes, including organizational performance.

Given the contradictory findings in previous studies, we argue that the relationship between TO and organizational performance (OP) in developing countries, particularly in multinational companies, is dynamic and complex, influenced by multiple intervening variables that may either strengthen or weaken the relationship. This perspective aligns with Jaworski's (1988) assertion that the effectiveness of control mechanisms depends on internal and external factors. Additionally, Baron and Kenny, 1986 have suggested that intervening variables should be considered when there is a weak or inconsistent relationship between independent and dependent variables. Therefore, to better understand the relationship between TO and OP, we propose digital technology capability (DTC) and generative artificial intelligence adoption (GAIA) as potential mediators, examining their independent and serial mediation effects in this context.

We draw upon the resource-based view (RBV) to understand the abovementioned complex relationships. RBV suggests that organizational resources and capabilities contribute to enhancing organizational performance (Wu et al., 2006). However, previous findings on this proposition are inconclusive (Al-Ansari et al., 2013; Masa'deh et al., 2018; Sai, 2018; Yousaf et al., 2020). Hence, the proposition of employing both DTC and GAIA to examine the relationship between TO and OP is justified (Lyytinen et al., 2016; Wu et al., 2006; Zhang and Lee, 2023).

In line with the resource-based view of organizations, DTC is conceptualized as a pool of resources including talents, skills, and expertise that support organizations in managing and utilizing technologies to enhance performance (Lyytinen et al., 2016). Moreover, DTC enables organizations to recognize, seize, and coordinate technological opportunities and innovation in the face of external influences such as market competition, political uncertainty, war, and economic crises. Therefore, DTC is a crucial resource that may positively influence the relationship between TO and OP (Li et al., 2022). However, technological advancements have pressured strategic management personnel to adopt new technologies to keep organizations updated for better performance. Many technologies that were useful a year ago are now obsolete with the emergence of generative artificial intelligence (AI) technologies (Feuerriegel et al., 2024; Sætra, 2023; Schwaeke et al., 2025). Therefore, the adoption of generative AI technologies is also considered a crucial resource that enables organizations to perform better (Chen et al., 2022; Gupta et al., 2024).

Based on the above arguments, we posit DTC and GAIA as two intervening variables that may augment the influence of TO on OP. There are no studies in the current literature that have examined the independent and serial mediation roles of DTC and GAIA in the relationship between TO and OP, representing a significant gap in the literature that needs to be addressed (Whetten, 1989; Zhang and Lee, 2023). Moreover, there is a significant paucity of literature on technology orientation and organizational performance in the context of multinational companies in developing countries specially in Bangladesh. Multinational companies are very important to Bangladesh's economy (Alam et al., 2025; Reza and Du Plessis, 2022). It is because these companies help create jobs, transfer technology, bring in money from exports (Ahmmed, 2023; Alam et al., 2025). As a result, these companies help people learn how to manage businesses better. Bangladesh has also been working on a big digital transformation plan in the last few years. It has projects like "Digital Bangladesh" and later AI and Industry 4.0–oriented policy frameworks (Uddin, 2024). These have pushed companies, especially multinational subsidiaries, to use more advanced digital and artificial intelligence technologies. Even though this is strategically important, there isn't much empirical research evidence showing how technology orientation affects the performance of multinational companies in developing countries. This gap is particularly pronounced as numerous emerging economies exhibit analogous institutional limitations, skill deficiencies, and digital infrastructure obstacles. Consequently, the study on the multinational corporations in Bangladesh yields theoretically significant and practically applicable insights in similar emerging and transitional economies. Most studies are skewed toward economically developed countries such as South Korea, the United Arab Emirates, and the United States of America. Thus, insights relating to developing countries are scarce, emphasizing the necessity for more empirical studies to elucidate the mechanisms through which firms' technology orientation may enhance organizational performance. Therefore, we conducted this study to fill this gap in the current literature.

By addressing these gaps, our study contributes to the current literature and practice in several ways. Firstly, it explains how TO influences the OP of multinational companies in a developing country context. Secondly, the study explores the roles of DTC and GAIA as independent mediators in the relationship between TO and OP. Thirdly, this study underscores the sophisticated interplay of predictors of organizational performance by conceptualizing the serial mediation effect of DTC and GAIA in the relationship between TO and OP. Fourthly, the study collects data from managerial-level employees working in multinational companies, whose responses could have significant implications for strategic management stakeholders.

Despite, this research was conducted in relation to Bangladesh, the findings have implications relating to the multinational companies in Central and Eastern Europe (CEE). It is because Bangladesh has a lot in common with many Eastern European countries when it comes to multinational companies, its structure and institutions. It is arguable that multinational companies in Bangladesh confront problems with developing digital skills, limited skills, technological infrastructure, and the strategic use of new technologies like generative artificial intelligence. This is similar to what companies in Central and Eastern Europe face. Moreover, Bangladesh has transitional economic systems, is becoming more integrated into global value chains, depends on multinational companies for technology transfer, and is going through changes in its institutions and regulations. As a result, the mechanisms identified in this study through which technology orientation affects Organizational performance through digital technology capability and generative AI adoption provide transferable insights for managers and scholars investigating technology-driven performance in emerging economies in Eastern Europe. This study enhances the theoretical framework on technology orientation and digital transformation in transitional and post-transition management contexts by incorporating evidence from a similar emerging market.

2. Literature Review

2.1 Resource-Based View and Diffusion of Innovations

This study uses the RBV and Diffusion of Innovations (DOI) theory to investigate the link between technology orientation and organizational performance (Barney, 1991; Peteraf, 1993; Rogers, 1962; Wernerfelt, 1984). According to the RBV, using special resources and competencies helps companies to develop competitive advantage (Barney, 1991; Peteraf, 1993; Wernerfelt, 1984). Within the framework of multinational corporations, technology orientation is a vital tool that affects how businesses leverage generative AI and digital technologies (Chen et al., 2022).

Strong technology orientation helps companies to increase their digital technology capacity, which serves as a mediator between technical investments into better performance (Wu and Chiu, 2015).

By addressing how innovations—such as digital technologies and generative artificial intelligence—are embraced and incorporated into companies—the DOI theory enhances this approach. The DOI framework underlines how much relative benefit, compatibility, and complexity—among other perceived qualities of innovations—have an effect in determining their adoption rates (Rogers, 1962). Digital technologies become increasingly important as companies negotiate the complexity of technology adoption. These features not only help new technologies to be effectively integrated but also help companies to improve operational efficiency and change with the needs of the market.

In this study, we suggest that technology orientation affects digital technology competence, thereby promoting the adoption of generative artificial intelligence. This sequence of interactions emphasizes the serial mediation effect, in which the ability of digital technologies is essential in bridging technology orientation and generative artificial intelligence adoption, thereby influencing organizational performance. By combining RBV and DOI, the study seeks to offer a thorough knowledge of how multinational corporations can strategically use technology orientation to improve their performance by means of the adoption of modern digital technologies (Chen et al., 2022). This theoretical framework not only contributes to the body of knowledge on technology management but also provides useful ideas for scholars and professionals exploring to adapt the fast-changing digital environment.

Moreover, based on the RBV and the DOI theory, this study contends that DTC must logically precede GAIA, thus supporting a sequential mediation structure instead of a parallel or reversed one. From an RBV standpoint, DTC signifies a fundamental, subordinate Organizational competence that includes digital infrastructure, data integration processes, human digital competencies, and technology management proficiency. These skills among employees help companies use, implement, and grow advanced technologies in a way that works. GAIA, on the other hand, is a higher-level, specialized capacity that builds on current digital foundations and needs a lot of data readiness, interoperability, governance systems, and analytical skills. Without earlier development of DTC, organizations may implement AI in a symbolic or fragmented way that doesn't lead to long-term performance gains. The DOI theory further supports this process even more by positing that DTC makes generative AI technologies seem less complicated and more compatible, which makes it easier for people to use them successfully. As a result, even while tech-focused companies may see the strategic potential of generative AI, meaningful use and performance results depend on having already built up digital technology skills.

Moreover, from an RBV standpoint, the adoption of generative AI is fundamentally distinct from conventional IT capabilities. Generative AI is not just a way to automate tasks; it is a higher-order, recombinative resource that lets people learn, create content, and make decisions that change over time. Its worth depends on the quality of the data, the routines for interacting with AI, and the rules for governing AI, which makes it harder to copy and relies on previous digital technology skills.

2.2 Technological Orientation and Organizational Performance

TO is defined as the degree to which organizations prioritize product and service development, acquire and apply new technologies, and engage in research and development (Gatignon and Xuereb, 1997). Moreover, TO also refers to an organization's capability to use technical knowledge to solve technical problems and meet the dynamic needs of customers or clients (Gatignon and Xuereb, 1997). TO has been shown to be effective in enhancing organizational performance from various perspectives. For example, Arthur Solberg and Olsson (2010) reported that TO has a positive and significant impact on the export performance of Norwegian information and communication technology (ICT) companies. Additionally, Trainor et al. (2011) found that technological orientation significantly influences the financial performance of organizations. Furthermore, technological orientation has also been found to boost firm performance in other studies (Ali et al., 2016; Yousaf et al., 2020). However, Lee et al. (2015) reported that TO did not have a direct and positive impact on South Korean technology-inclusive small and medium enterprises (SMEs). Moreover, TO has not been found to have a positive impact on the organizational performance of the Turkish health industry (Mutlu and Sürer, 2016). Therefore, the insights and arguments about the influence of TO on organizational performance are inconclusive and require more empirical evidence. Hence, we hypothesize that:

Hypothesis 1: There is a relationship between technology orientation and Organizational performance.

2.3 Technological Orientation and Digital Technology Capability

DTC is crucial for organizations to leverage digital innovation and achieve sustainable performance while ensuring competitive advantage (Annarelli et al., 2021). In the specific context of organizational development in digital technology capacity, corporate strategies driven by strategic technological orientation have been found to positively and significantly influence DTC (Arias-Pérez et al., 2021; Forliano et al., 2023). Moreover, literature on strategic orientation also supports the idea that technological orientation significantly influences the development of digital capabilities within organizations (Pan et al., 2021). For instance, customer orientation, competitor orientation, and technological orientation have been shown to significantly impact organizations' digital competencies (Yu and Moon, 2021). Although there is no direct empirical evidence on the relationship between technological orientation and digital technology capability, the preceding arguments provide a solid foundation to posit that TO will have a positive and direct relationship with digital DTC. It is reasonable to argue that an organization committed to acquiring new technologies and investing in research and development (R&D) to gain and apply these technologies will enhance its digital technological capability. Therefore, technological orientation is forecasted to have a positive and significant impact on boosting the digital technology capability of organizations to achieve sustainable performance and secure competitive advantage. Therefore, we hypothesize that:

Hypothesis 2: There is a positive relationship between technological orientation and Digital technology capability.

2.4 Technological Orientation and Generative AI Adoption

GAIA has become a crucial requirement for organizations due to its diverse applications and its immense potential to facilitate organizational success in India (Prasad Agrawal, 2023). Generative AI adoption is defined in this study as how much an organisation has officially committed to, put into practice, and incorporated generative AI technology into its processes, decision-making, and ways of working (Islam et al., 2023; Prasad Agrawal, 2023). Scholars have strongly argued that the adoption of technologies is mainly driven by the technological orientation of firms (Li et al., 2022; Mubarak and Petraite, 2020). Few studies have gone beyond general arguments regarding the role of strategic orientation in the adoption of new technologies to link it with specific technological orientations (Richard et al., 2007; Shen et al., 2022). Although these studies have not directly investigated the role of technological orientation in the generative AI adoption of organizations, it is reasonable to assume that such a rational approach to orientation may have a positive and significant impact on generative AI adoption. By extrapolating the theoretical arguments of RBV, we argue that organizations with a robust technological orientation would be more inclined to adopt new technologies, allowing them to actively monitor, recognize, and adopt cutting-edge technologies such as generative AI technologies (Marak et al., 2019; Tortorella et al., 2021). We postulate this expected influence of technological orientation on generative AI adoption in multinational companies in developing country contexts. Therefore, we propose that:

Hypothesis 3: There is a positive relationship between technological orientation and generative AI adoption.

2.5 Digital Technology Capability and Generative AI Adoption

Adopting new technologies in organizations requires digital technology capabilities because these enable organizational workforces to be agile and efficient enough to understand the features and usefulness of new technologies (Slavković et al., 2023; Wang et al., 2022). An organization develops its DTC from the technological environment, innovation, accessibility, scalability, predictability, and integration of knowledge, skills, and tools (Arroyabe et al., 2024; Sebastian et al., 2017). Thus, DTC is considered as the talents, skills, and expertise (Molla et al., 2025). DTC supports organizations not only to manage technologies but also to adopt cutting-edge technologies according to their needs flexibly (Molla et al., 2025). Moreover, DTC helps organizations to recognize, understand, and seize technological innovations to remain competitive in the market (Li et al., 2022; Wang et al., 2022). Hence, Weill and Woerner (2018) argued that DTC is instrumental in transforming traditional business organizations into high-performing ones by adopting the latest technologies. Thus, it is reasonable to argue that DTC would have a significant impact on adopting generative AI technologies, the most essential and crucial technologies at present. Therefore, we postulate that:

Hypothesis 4: There is a positive relationship between digital technology capability and generative AI adoption.

2.6 Digital Technology Capability and Organizational Performance

Digital technology capability is developed based on acquiring, utilizing, integrating, and reconfiguring technologies that support and develop work processes and business strategies (El-Haddadeh, 2020; Heredia et al., 2022). This ability helps organizations recognize and understand changes in the competitive market and provides opportunities to stay responsive and resilient, ensuring greater performance (Chen et al., 2014; Khin and Ho, 2019; Tsou and Chen, 2023). Therefore, scholars unanimously suggest that organizations develop digital technological capabilities that include the integration of updated technologies like AI, generative AI, big data analytics, blockchain, and social media platforms, etc., to ensure greater performance development of firms (Bhatti et al., 2024; Reis and Melão, 2023). According to extant literature (i.e., Cai et al., 2019; Heredia et al., 2022; Reis and Melão, 2023), when an organization successfully integrates digital technologies, these can yield remarkable benefits for the organization, especially in the case of innovation, operations, supply chain management, organizational agility, and the transmission of information needed for both decision-making and collaboration internally and externally. Hence, scholars worldwide overwhelmingly agree that organizations' digital technology capabilities can secure competitive advantage and ensure greater performance (Barba-Sánchez et al., 2024; Chen et al., 2014; Khin and Ho, 2019). Therefore, we propose that:

Hypothesis 5: There is a positive relationship between digital technology capability and Organizational performance.

2.7 Generative AI Adoption and Organizational Performance

Generative AI technologies have been game-changers in producing text, images, video, and other forms/types of content (Gupta et al., 2024; Reddy, 2024). The economic potential of generative AI has been recognized as instrumental because it saves time in producing required information for decision-makers in many cases (Kar et al., 2023). For example, Chatterjee and Chaudhuri (2022) reported that AI integrated Customer Relationship Management (CRM) system has been effective in enhancing customer relationship management in the multinational companies operating in India. Moreover, AI adoption has been effective in the construction-related companies in South Korea and the United Kingdom (UK), as reported by Na et al. (2023). Additionally, AI adoption has also been effective in the banking industry in Malaysia, as examined by Rahman et al. (2023). Therefore, business practitioners and other users are widely using various generative AI tools, such as ChatGPT, Gemini, Bard, Plus AI, DALL-E, GitHub Copilot, DeepMind, Midjourney, etc. Although generative AI technologies have tremendous potential, scholars like Reddy (2024) have provided mixed insights, arguing that GAIA could facilitate billing, treatment, research, and diagnosis in the healthcare industry, resulting in a more efficient, equitable, and effective way. However, the adoption requires meticulous change management and risk mitigation strategies. In line with this, Jindal et al. (2024) have also outlined that the use of generative AI in healthcare has unclear value in the short term, but it has encouraging potential to benefit health systems and patients. Similar mixed findings have been found in other studies relating to the role of generative AI technologies (Feuerriegel et al., 2024). However, Chen et al. (2022) reported that AI adoption has a significant contribution to developing the performance of Chinese e-commerce firms. Moreover, Dubey et al. (2022) also reported that AI technologies positively impact the agility and resilience of organizations that eventually contribute to the development of organizational performance.

Although there are no prior results relating to the role of GAIA and organizational performance, especially concerning multinational companies operating in developing countries, the preceding arguments provide a rigorous foundation to postulate that GAIA will positively impact organizational performance. This is plausible because organizations compete to respond to internal and external market needs while generative AI provides quick insights as required, albeit not without discrepancies always (Gupta et al., 2024). Thus, there is a dire need for updated information regarding the role of GAIA on organizational performance. This necessity is also further strengthened by the recent calls by Gupta et al. (2024), Dwivedi et al. (2024), and Feuerriegel et al. (2024), who urged for further empirical studies to understand the influence of generative AI adoption in the business context. Based on the above arguments and in response to the recent calls to fill the gap in the current literature regarding the influence of GAIA on organizational performance, we hypothesize that:

Hypothesis 6: There is a positive relationship between GAIA on Organizational performance.

2.8 Mediating Effect of DTC and GAIA in the Relationship Between TO and OP

There has been an inconclusive debate regarding the role of TO on OP (Ali et al., 2016; Dinu, 2025; Lee et al., 2015; Trainor et al., 2011; Yousaf et al., 2020). Therefore, scholars have urged the examination of the role of intervening variables in this relationship. In this regard, we firstly posit DTC as a mediator in the relationship between TO and OP. This is supported by previous studies where DTC positively mediated the relationship between digital strategy and the degree of digitalization (Proksch et al., 2024). Moreover, Tirastittam et al. (2020) reported the mediating role of information technology capability in the relationship between strategic leadership, organizational innovativeness, and organizational supply chain performance. Additionally, Bhatti et al. (2024) also reported the mediating role of digital technology capability in the relationship between digital strategy and firm performance. Furthermore, DTC was also found to be a significant mediator in the relationship between digital technology adoption and enterprises' economic and environmental performance (Li et al., 2022). Therefore, it is reasonable to hypothesize that:

Hypothesis 7: Digital technology capability mediates the relationship between technology orientation and Organizational performance.

Moreover, we posit that GAIA may also mediate the relationship between TO and OP, as a number of previous studies have found that technology adoption ignites this relationship. For example, Jalil et al. (2022) reported that technology adoption mediates the relationship between innovation capability and organizational performance. Furthermore, digital technology adoption was also found to positively mediate the relationship between organizational innovativeness and operational efficiency (Susilawati et al., 2023). Hence, we hypothesize that:

Hypothesis 8: Generative AI adoption mediates the relationship between technology orientation and Organizational performance.

In summary, based on the previous two hypotheses and RBV, we propose a serial mediation model outlining the role of TO on OP through DTC and GAIA (see Fig. 1). Organizations with a technology orientation are more likely to possess greater digital technology capability, facilitating the adoption of technologies like generative AI (Gangwani and Bhatia, 2024; Li et al., 2022; Pan et al., 2021). Consequently, these organizations become more responsive to market competition and capable of executing tasks more efficiently, leading to enhanced performance (Barba-Sánchez et al., 2024; Dwivedi et al., 2024; Feuerriegel et al., 2024; Zhani et al., 2021). Therefore, we hypothesize that:

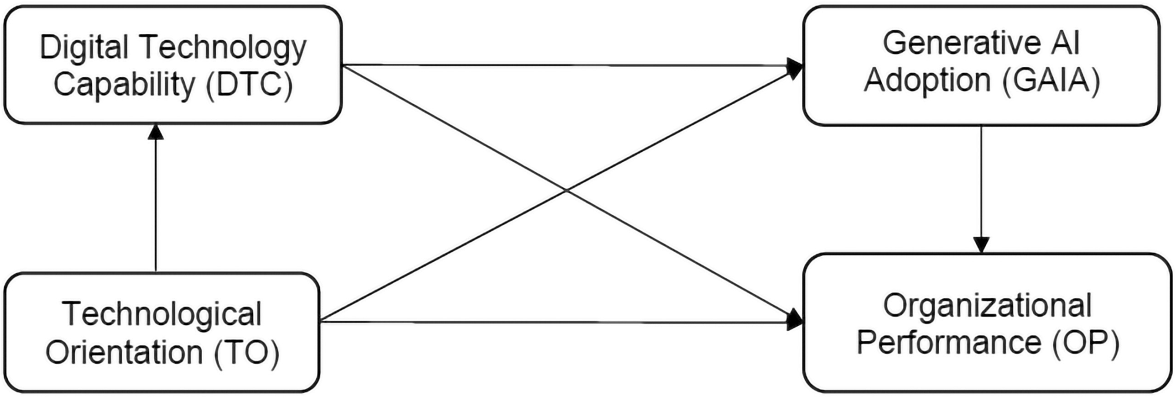

Fig. 1. Conceptual framework.

Hypothesis 9: Digital technology capability and generative AI adoption serially mediate the relationship between technology orientation and Organizational performance.

3. Methods

3.1 Participants and Data Collection

The data analysis for this study utilized a sample comprising participants from various managerial levels within multinational companies across five major industries, such as retail, banking and finance, information and technology, telecommunication and tobacco that were selected based on their economic contribution and presence of multinational companies in those industries. It is important to mention that multinational companies worldwide are pioneers in using AI technology and have been using the generative AI from the inception of this cutting-edge technology (McKinsey & Company, 2023). Furthermore, companies developing and emerging countries have been using the generative AI from 2023 that is identified from the previous studies (i.e., Ahmed and Szczepański, 2023; Ahmmed, 2023; Islam et al., 2023) published in 2023. Data collection took place over three months, from January 2024 to March 2024. However, we conducted a pilot study among 50 participants to ensure that the items of the 4 constructs are comprehensive for the respondents of the multinational companies. Based on the feedback from the pilot study, we implemented changes to the definition and measures of the constructs to enhance their operationalization among respondents from multinational companies.

A total of 600 questionnaires were distributed among managers within these organizations, with permission obtained from the respective authorities beforehand. Participants were randomly selected and provided with information about the research project's objectives and ethical considerations. They were assured of the confidentiality of their identities, and no compensation was offered for participation. Additionally, participants were informed of their ability to withdraw from the study at any time. Details of the participants are provided in Table 1.

Table 1. Demographic details of participants.

Variables	Frequency (N = 357)	Percentage (%)
Gender		
Male	276	77.3
Female	81	22.7
Marital status		
Married	210	58.8
Single	147	41.2
Education		
Undergraduate	89	24.9
Masters	239	66.9
MPhil/PhD/DBA	29	8.1
Position		
HR Manager	55	15.4
FInance Manager	53	14.8
Marketing Manager	45	12.6
Head of Department	59	16.5
General Manager	64	17.9
Operation Manager	43	12.0
Product and Development	38	10.6
Industry		
Retail	69	19.3
Banking and Finance	67	18.8
Information and Technology	85	23.8
Telecommunication	93	26.1
Tobacco	43	12.0

Note: DBA, Doctor of Business Administration; PhD, Doctor of Philosophy; HR, Human Resources.

Of the 371 responses, only 357 were usable. The remaining responses had some different problematic issues, such as zig-zag and straight-line responses, and incompleteness. Therefore, these were dropped. The responses were rated based on a five-point Likert scale.

3.2 Measures

The items used in this study, as shown in Table 2, were adopted from previous research and assessed using a five-

Table 2. Constructs validity and reliability.

Constructs	Items	FL	CA	CR	AVE
Technology Orientation (TO)	The policy of this firm has always been to consider the most up to-date production technology available.	0.763	0.868	0.905	0.655
	We have a long tradition and a reputation in our industry of attempting to be first in trying new methods and equipment.	0.849			
	We spend more than most firms in our industry on new product development.	0.780			
	We devote additional resources to technological forecasting.	0.842			
	The policy of this firm has always been to consider the most up to-date information regarding the changes or upgrades in technology.	0.810			
Digital Technology Capability (DTC)	We can obtain important digital technologies.	0.789	0.911	0.931	0.691
	We can use digital technology to support the enterprise development strategy.	0.847			
	We can use digital technology to develop innovative products/services/processes.	0.834			
	We can use digital technology to discover and respond to new market demands.	0.844			
	We can use digital technology to assess the potential of resource waste and pollutant recovery.	0.842			
	We can use digital technology to improve the efficiency of resource utilization.	0.831			
Generative AI Adoption (GAIA)	Management has given priority in adopting generative AI technologies.	0.859	0.869	0.905	0.657
	A timely GAIA technical implementation and application migration plan has been developed.	0.855			
	The plan has already been endorsed by managers.	0.812			
	A financial budget and a migration schedule have been approved.	0.777			
	Our employees warmly welcome adoption of generative artificial intelligence in the workplace.	0.742			
Organizational Performance (OP)	There has been an increase in total sales revenue.	0.895	0.853	0.91	0.772
	There has been an increased employee and customer satisfaction.	0.878			
	Our market share has been increased.	0.863			

FL, Factor Loading; CA, Cronbach's Alpha; CR, Composite Reliability; AVE, average variance extracted.

point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). However, items were modified in the context of this study. TO was measured using 5 items adopted from Gatignon and Xuereb (1997) and Lee et al. (2015). DTC was assessed with 6 items adopted from Khin and Ho (2019), and Liao et al. (2024). Generative AI Adoption was measured using 5 items adopted from Chau and Tam (1997), Reich and Benbasat (1990), Chen et al. (2021) and Islam et al. (2023). Finally, organizational performance was evaluated with 3 items adopted from Ravichandran et al. (2005) and Lee et al. (2015).

It is important to mention that GAIA in this study is framed as an organizational-level adoption maturity construct rather than an individual-level adoption intention. Consequently, the measurement items encompass tangible indicators of genuine adoption, such as managerial prioritisation, formal approval, implementation planning, budget allocation, and Organizational acceptance. These are broadly acknowledged as valid proxies for adoption in evolving technologies. This operationalisation aligns with previous research on technology adoption (Chen et al., 2021; Islam et al., 2023), which conceptualises adoption as a phased Organizational process involving preparedness, commitment, and deployment. In the cover letter for data collection, we mentioned on widely used enterprise-level generative AI applications like ChatGPT, GitHub Copilot, DALL·E, Gemini, and AI tools. These are built into the company and used in areas like operations, marketing, human resources, and analytics. Hence, we provided instructions on the generative AI applications. Additionally, as previously stated, multinational corporations around the world and in Bangladesh had already started using generative AI by 2023. This meant that the people who answered the questions had enough expertise and exposure to give accurate and useful answers.

4. Results

To assess the measurement and structural model, we employed for specifying the outer and inner model (Bajaba et al., 2021).

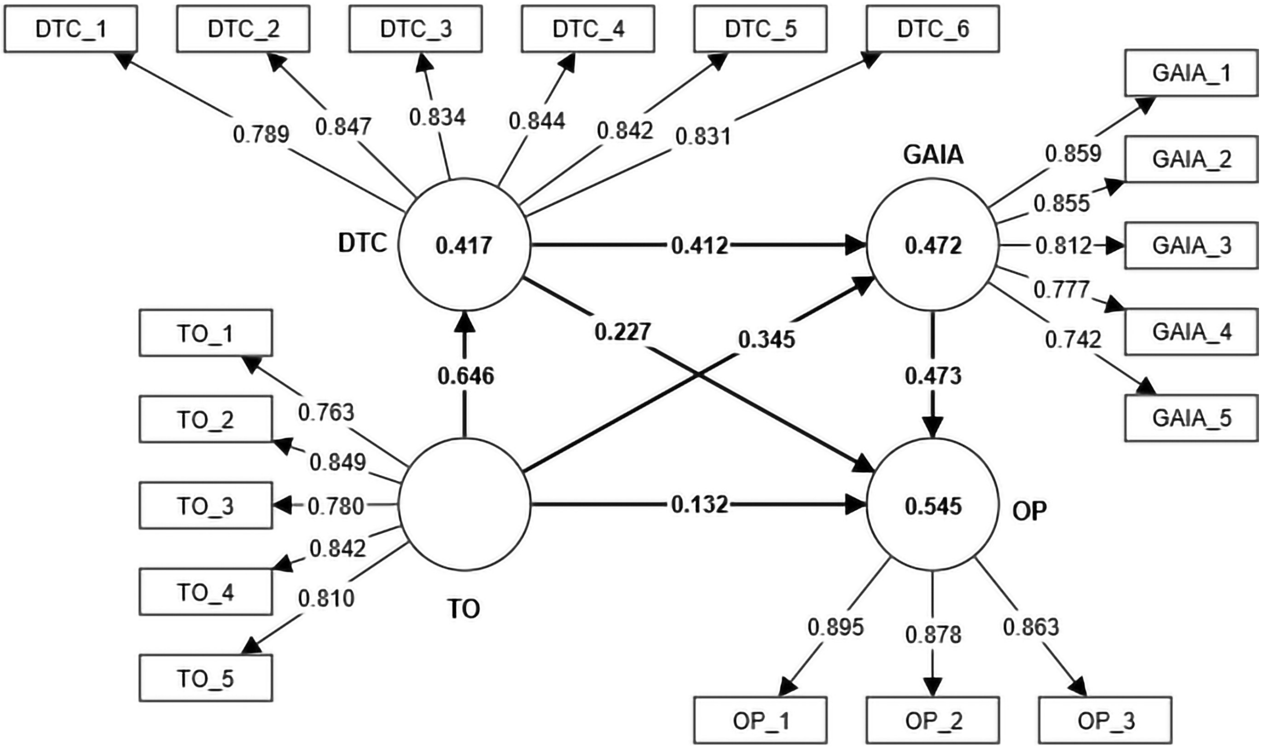

Fig. 2. Measurement model. Note: DTC, Digital Technology Capability; OP, Organizational Performance; GAIA, Generative Artificial Intelligence Adoption; TO, Technology Orientation.

4.1 Common Method Bias

Given that all measures were self-reported, concern arose regarding the potential influence of Common Method Bias (CMB). To mitigate or eliminate CMB, we followed the recommendations of Podsakoff et al. (2003). To assess the potential threat of CMB, we employed a single-factor test of Harman and found that one factor accounted for only 46.88% variance, below the recommended threshold of 50% (Podsakoff et al., 2012). Furthermore, the variance inflation factor (VIF) scores ranged from 1.769 to 2.673, indicating that CMB is not a significant issue as these values are lower than the cutoff of 3.3 (Kock, 2015). Thus, we conclude that CMB is not a significant threat to our research.

4.2 Evaluation of Measurement Model

For a rigorous evaluation of the reliability and consistency of variables, we employed a comprehensive methodology recommended by Hair et al. (2021), including Cronbach's Alpha (CA) and Composite Reliability (CR). As shown in Table 2, both CA and CR values exceed 0.7 for all variables, indicating strong internal consistency. To assess convergent validity, we strictly followed the criteria outlined by Hulland (1999) and Hair et al. (2021), which require a factor loading above 0.40 for each item and an average variance extracted (AVE) greater than 0.50. Results presented in Table 2 and Fig. 2 demonstrate that all items in this study exceed the Factor Loading (FL) and AVE criteria (Hair et al., 2021).

To assess the discriminant validity of the measurements in this study, two techniques were employed: the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT). According to Table 3, which presents the Fornell-Larcker criterion, the AVE square roots, depicted as diagonal values, were compared with the correlation values. The diagonal values (in bold) exceeded the correlated values, indicating a strong level of discriminant validity in line with the criteria established by Fornell and Larcker (1981).

Table 3. Fornell larcker.

Constructs	DTC	OP	GAIA	TO
DTC	**0.831**			
OP	0.613	**0.879**		
GAIA	0.635	0.698	**0.81**	
TO	0.646	0.568	0.611	**0.809**

Note: DTC, Digital Technology Capability; OP, Organizational Performance; GAIA, Generative Artificial Intelligence Adoption; TO, Technology Orientation.

Additionally, discriminant validity was assessed using the HTMT ratio, which compares correlations between different constructs against those within the same construct. Following the recommendations of Henseler et al. (2015), correlations among the latent variables consistently remained below the 0.9 cutoff value, as outlined in Table 4.

Therefore, these results assure that our measurement constructs exhibit satisfactory discriminant validity.

Table 4. Heterotrait-monotrait (HTMT).

Constructs	DTC	OP	GAIA	TO
DTC				
OP	0.692			
GAIA	0.692	0.808		
TO	0.721	0.655	0.69	

Note: DTC, Digital Technology Capability; OP, Organizational Performance; GAIA, Generative Artificial Intelligence Adoption; TO, Technology Orientation.

4.3 Goodness of Fit (Model's Predictive Capabilities)

To ensure the goodness of fit, the coefficient of determination (R^2), effect size (f^2) and the predictive relevance were examined in this study. The analysis shows that R^2 value for the OP is 0.546 that shows a 54.9% variance in the OP can be attributed to TO, DTC and GAIA. In line with the suggested 0.10 cutoff value (Falk and Miller, 1992), our findings outlined that the model gained acceptable R^2 for OP is substantial. Moreover, in our study, the influence on OP is also evaluated through several predictor variables that include TO, DTC and GAIA. In line with Hair et al. (2013), it is suggested that f^2 effect size should be outlined f^2 effect size statistic stipulates if exclusion of an independent variable from the model can have a significant influence on the dependent variable. The results based on the analysis of f^2 statistic outline that in the context of this study, the exclusion of the TO will have a significant influence on the OP as outlined in the Table 5 below:

Table 5. Effect size for independent variable.

	DTC	GAIA	OP	TO
DTC		0.187	0.056	
GAIA			0.260	
OP				
TO	0.714	0.132	0.020	

Note: DTC, Digital Technology Capability; OP, Organizational Performance; GAIA, Generative Artificial Intelligence Adoption; TO, Technology Orientation.

Q^2 value higher than zero outlines the predictive relevance of the endogenous construct. In line with the recommendations of Henseler et al. (2016) and Hair Jr et al. (2014), this is a standard procedure to investigate whether the model can predict the reflective indicators. The Stone-Geisser's Q^2 investigates the models' out-of-sample predictive power. The path model predictive relevance Q^2 for Organizational performance has a value of 0.297, showing that the model has a large predictive relevance for the construct.

4.4 Hypotheses Testing

The analysis was conducted using Model 6 in the PROCESS macro (Hayes, 2017), with 5000 samples used to create a 95% bias-corrected confidence interval (CI) to examine the significance of indirect effects.

The results, presented in Table 6 and Fig. 3, indicated that TO did not have a direct impact on OP (β = 0.139, $p > 0.055$), leading to the rejection of H1. However, H2, proposing a direct relationship between TO and DTC, was found to be positive and significant (β = 0.750, $p > 0.000$). Similarly, H3, suggesting the relationship between TO and GAIA, was also supported (β = 0.390, $p > 0.000$).

Furthermore, H4, proposing the relationship between DTC and GAIA, was also supported (β = 0.377, $p > 0.001$). Additionally, H5, regarding the relationship between DTC and OP, was accepted based on the results (β = 0.215, $p > 0.001$). Moreover, the results supported H6, indicating a significant relationship between GAIA and OP (β = 0.432, $p > 0.000$).

The indirect effect of DTC in the relationship between TO and OP demonstrated that it is a significant mediator, leading to the acceptance of H7 (β = 0.161, $p > 0.001$). Similarly, H8 was accepted as GAIA fully mediated the relationship between TO and OP (β = 0.168, $p > 0.001$). Furthermore, H9, proposing the serial mediation of DTC and GAIA in the relationship between TO and OP, was also supported (β = 0.122, $p > 0.004$).

4.5 Importance Performance Map Analysis (IPMA)

The IPMA is important as it extends the general Partial Least Squares Structural Equation Modeling (PLS-SEM) results by considering average values of the latent scores. In this study, we conducted IPMA for Organizational performance as a particular endogenous variable along with exogenous constructs i.e., DTC, GAIA and TO on the x-axis and Organizational performance on the y-axis (Hair Jr et al., 2014). The Fig. 4 outlines IPMA guide of Organizational performance. The IPMA shows that all critical factors, for example, DTC, GAIA and TO are substantial in determining Organizational performance. Among the mediators, GAIA has the most noteworthy worth, for example, 67.880 among all.

5. Discussion

The results of H1 highlight that TO alone may not necessarily lead to improved OP, echoing findings from previous studies such as Al-Ansari et al. (2013), Lee et al. (2015), and Mutlu and Sürer (2016). This underscores the importance of considering intervening variables in understanding the relationship between TO and OP. The insignificant direct influence of technology orientation on performance may indicate resource limitations that prevent com-

Table 6. Hypotheses testing result.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T	*p*	Decision	Mediation
H1: TO → OP	0.139	0.14	0.073	1.919	0.055	Not Supported	
H2: TO → DTC	0.750	0.75	0.061	12.311	0.000	Supported	
H3: TO → GAIA	0.390	0.389	0.105	3.702	0.000	Supported	
H4: DTC → GAIA	0.377	0.377	0.112	3.365	0.001	Supported	
H5: DTC → OP	0.215	0.218	0.063	3.386	0.001	Supported	
H6: GAIA → OP	0.432	0.427	0.076	5.711	0.000	Supported	
H7: TO → DTC → OP	0.161	0.163	0.049	3.287	0.001	Supported	Full mediation
H8: TO → GAIA → OP	0.168	0.166	0.052	3.259	0.001	Supported	Full mediation
H9: TO → DTC → GAIA → OP	0.122	0.12	0.042	2.885	0.004	Supported	Full mediation

Note: DTC, Digital Technology Capability; OP, Organizational Performance; GAIA, Generative Artificial Intelligence Adoption; TO, Technology Orientation.

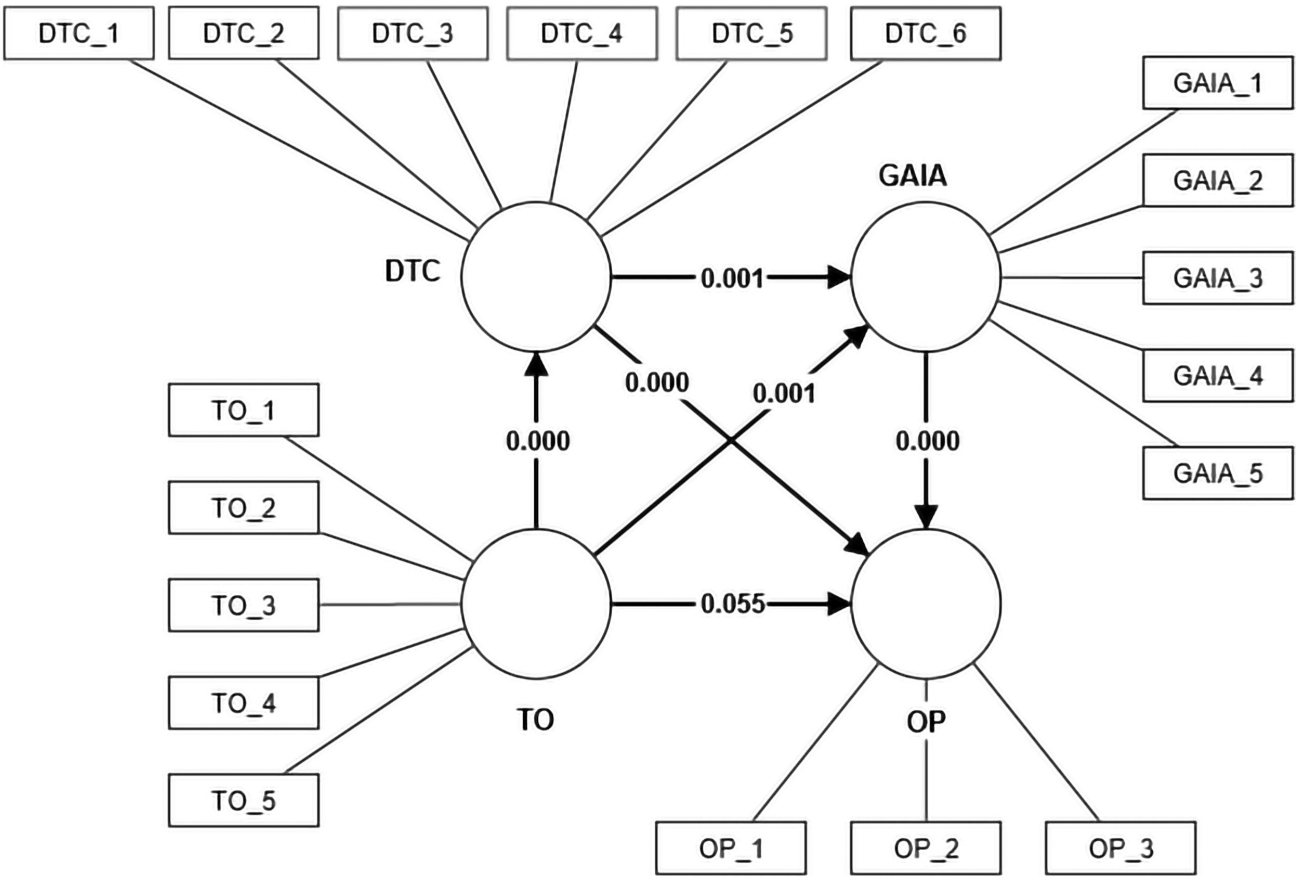

Fig. 3. Structural model. Note: DTC, Digital Technology Capability; OP, Organizational Performance; GAIA, Generative Artificial Intelligence Adoption; TO, Technology Orientation.

panies from turning strategic goals into real-world capabilities. In situations with limited resources, orientation alone may not be enough unless it is backed up by enough money, people, and infrastructure expenditures.

H2, which proposed a positive relationship between TO and DTC, aligned with prior research by Arias-Pérez et al. (2021), Pan et al. (2021) and Forliano et al. (2023), further supporting the relationship. Similarly, H3, suggesting a positive relationship between TO and GAIA, was supported by our results and consistent with arguments from scholars such as Marak et al. (2019) Tortorella et al. (2021) and Arroyabe et al. (2024).

Moreover, H4 revealed a positive relationship between DTC and GAIA, in line with previous studies by Sebastian et al. (2017), Li et al. (2022), and Wang et al. (2022), which emphasize the role of digital capability in fa-

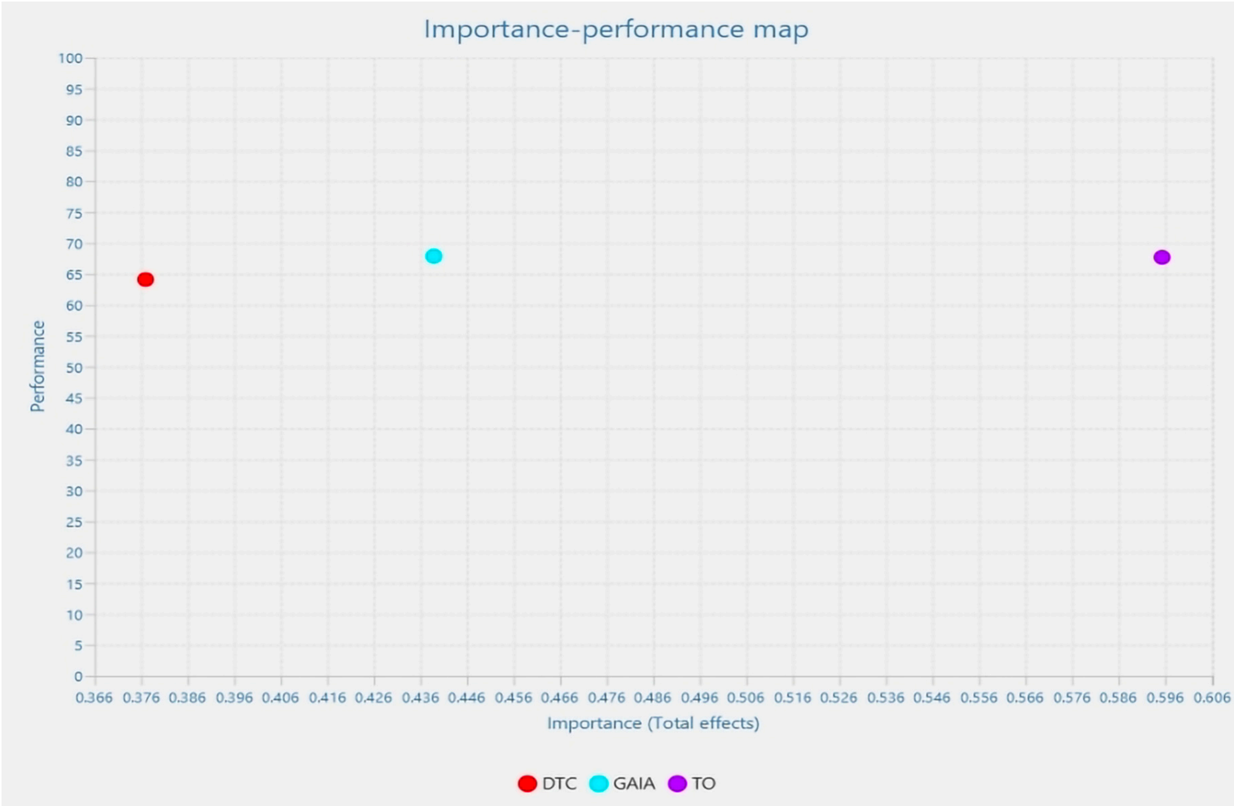

Fig. 4. PLS-SEM importance performance map analysis (IPMA). Note: DTC, Digital Technology Capability; GAIA, Generative Artificial Intelligence Adoption; TO, Technology Orientation; PLS-SEM, Partial Least Squares Structural Equation Modeling.

cilitating technology adoption such as generative AI. H5, indicating a positive relationship between DTC and OP, was supported by previous research by Cai et al. (2019), Heredia et al. (2022), and Reis and Melão (2023) further substantiating this link.

Similarly, H6 demonstrated a positive relationship between GAIA and OP, consistent with findings from Kar et al. (2023), and Feuerriegel et al. (2024), despite mixed results reported by some scholars.

H7 proposed the mediating role of DTC on the relationship between TO and OP, suggesting that TO can enhance OP when organizational digital technology capability is improved. This aligns with prior studies that identified the mediating role of DTC (Dinu, 2025; Li et al., 2022; Tirastittam et al., 2020). Similarly, the results of H8 indicated that GAIA can mediate the relationship between TO and OP, highlighting the independent mediating roles of both DTC and GAIA in this relationship.

Finally, H9 revealed that both DTC and GAIA sequentially mediate the relationship between TO and OP. This aspect of serial mediation has not been extensively examined in previous studies, which often focused on single mediators such as digital technology capability (Li et al., 2022) or generative AI adoption (Jalil et al., 2022; Susilawati et al., 2023). Thus, our study contributes to disclosing these two variables as significant intervening factors in the relationship between TO and OP.

The model is mostly based on the Resource-Based View, but the results can also be understood in a meaningful way using the DOI point of view. The serial mediation finding indicates that digital technology competency is essential in the Organizational innovation-decision process related to generative AI adoption. From a DOI perspective, improved digital capabilities may augment perceived relative advantage, promote interoperability with current systems, and diminish the perceived complexity of generative AI, so promoting adoption. In this context, digital technological proficiency serves as a facilitating factor that aids Organizational advancement through the stages of knowledge acquisition, persuasion, and implementation in the spread of innovation. These results enhance DOI theory by demonstrating how Organizational capacities influence the dissemination of intricate digital technologies throughout global corporations.

Overall, this study enhances the current literature on information technology (IT) competence and digital transformation in numerous significant aspects. Previous studies have predominantly concentrated on overarching IT capabilities or digital transformation as expansive factors intrinsically associated with performance results. Conversely, our findings indicate that technology orientation affects Organizational performance via a sequential capability-building process, with digital technology competence functioning as a fundamental facilitator for generative AI adoption. This study demonstrates that generative AI is distinct from conventional digital technologies, indicating that advanced AI applications constitute a superior capacity whose performance impacts emerge only subsequent to the establishment of foundational digital competencies. Additionally, in contrast to the predominant literature focused on developed economies, this study presents evidence from multinational corporations operating within a developing-country framework, thereby contributing unique perspectives on the dynamics of digital transformation amid institutional and resource limitations.

6. Implications

This study offers several theoretical implications for the current literature. Firstly, it showcases that the role of TO doesn't necessarily translate to OP; rather, it can play a crucial role in OP through intervening variables such as DTC and GAIA. Secondly, the study examines the role of TO on both DTC and GAIA, which hasn't been previously investigated, especially in the context of multinational companies operating in Bangladesh. Thirdly, it explores the serial mediation of DTC and GAIA as joint mechanisms through which TO can influence OP, a novel contribution to the strategic management literature. In this regard, it has been identified that GAIA has a greater influence in igniting Organizational performance. Fourthly, the study makes a methodological contribution by theorizing and testing a serial mediation model to assess the sequential influence of DTC and GAIA on the relationship between TO and OP. This approach highlights the joint influence of these constructs in achieving organizational performance based on the RBV.

The study also offers practical implications for stakeholders and practitioners of multinational companies and other organizations in developing countries like Bangladesh. Firstly, it underscores that TO alone cannot ignite organizational performance; other intervening factors must be considered. Secondly, managers must ensure they have sufficient DTC to adopt and leverage fast-moving yet useful technologies like generative AI, ensuring updated operations and sustained performance amid technological changes. Managers in contexts with limited resources should regard the development of digital capabilities and the use of generative AI as incremental, capital-intensive endeavours rather than immediate performance enhancers. Before moving on to more advanced AI applications, it may be required to focus on building basic digital infrastructure, developing skills, and setting up governance systems. This is especially true in institutional settings in emerging economies.

Managers can turn these insights into actions by starting customised capability-building programs that fit the needs of their organizations. For instance, investing in cloud-based corporate systems, data integration platforms, and organised digital upskilling programs like analytics training, AI literacy seminars, or cross-functional digital innovation laboratories can help improve digital technology skills. Generative AI can then be used in specific ways, such as large language models for managing knowledge and making decisions, generative tools for making marketing content, code-generation systems to speed up software development, or AI-enabled chatbots for customer and employee services. By adopting generative AI solutions in phases, organizations can make sure that their digital skills are up to par while also aligning them with their strategic goals.

Finally, the study emphasizes DTC and GAIA's independent and serial mediating roles in developing organizational performance. It urges organizational practitioners to prioritize the development of digital technology capability and the adoption of technologies like generative AI to remain competitive. Furthermore, as IPMA results show that the GAIA has a maximum worth in elucidating Organizational performance, the practitioners should give importance to the adoption of generative artificial intelligence in the multinational companies to secure greater performance. Given the tough competition in developing countries, both multinational and local companies should invest in enhancing their technological capabilities. Therefore, organizations should invest in developing digital technology capability and fostering generative AI adoption to improve performance.

7. Limitations and Directions for Future Research

While this study contributes significantly to theory and practice, it is not without limitations. Firstly, the data collection method was limited to a cross-sectional survey, meaning the insights gained may not be fully representative as they were collected at a single point in time. Therefore, future research could benefit from longitudinal studies to provide a more comprehensive understanding of the relationships examined. Secondly, the study was conducted exclusively in Bangladesh, which may limit the generalizability of the findings to other contexts. Future researchers could explore the proposed model in different countries, particularly in other poor and developing countries where multinational companies are active due to economic opportunities. This would help understand how the relationships between technological orientation, digital technology capability, generative AI adoption, and organizational performance vary across diverse socio-economic and cultural contexts. Moreover, this study was conducted in the context of multinational companies; therefore, there are limitations in terms of generalizing the results to local companies in Bangladesh and other countries. Therefore, we recommend that future researchers focus their studies on local companies. Moreover, future researchers can include inter-organizational cooperation in digital green supply chains aspects in the generative AI-related studies in the future

(Wang and Zhang, 2024). Furthermore, future researchers can also conduct comparative studies on both multinational and local companies.

Moreover, this study utilises data from several industries; nevertheless, the methodology does not specifically investigate sector-specific variations in the claimed correlations. The influence of technology orientation, digital technology proficiency, and generative AI implementation may differ among industries characterised by varying levels of technical intensity and innovation pathways. Subsequent research may utilise multi-group analysis or industry-specific models to investigate how sectoral contexts influence the serial mediation effects reported in this study.

Furthermore, this study posits a serial mediation mechanism. Nonetheless, its cross-sectional design constrains causal conclusions. The concurrent measurement of all constructs prevents the exclusion of backward or reciprocal linkages, such as Organizational performance facilitating increased technology orientation or post-adoption justification of AI utilisation. Thus, although the suggested ordering is logically based on RBV and DOI, causal conclusions must be approached with caution. Subsequent studies ought to utilise longitudinal, experimental, or time-lagged methodologies to corroborate temporal sequencing and evaluate alternative causal frameworks that elucidate the observed correlations. The operationalisation of Organizational performance was confined to established market-based and perceptual indicators; augmenting performance parameters retrospectively was not methodologically viable within the current study framework.

This study does not explicitly include resource availability as a boundary condition. In underdeveloped economies, financial limits, talent deficits, infrastructure inadequacies, and legal ambiguity may influence enterprises' capacity to convert technology orientation into digital proficiency and AI integration. Future studies should investigate the influence of financial, human, and infrastructural resources on the hypothesised linkages and their impact on the viability of sequential capability-building routes in resource-limited contexts. Moreover, the gender and education profile mirror the management workforce composition of multinational corporations in Bangladesh. Still, this distribution might cause sample selection bias. Thus, the results should be considered and used carefully and should not be generalised. We recommend that future study ought to utilise more demographically balanced samples to improve generalisability.

Availability of Data and Materials

Data available on request.

Author Contributions

MTP, MAH, MAI and SS designed the research study. MTP and MAH performed the research and collected the data. MTP, MAH and MAI conducted the formal analysis and interpreted the results. MAI and SS provided critical feedback, review, and intellectual input throughout the study. Moreover, they work to complete the project before submission and also during revision. All authors put mostly similar efforts into the revision stage. SS supervised the overall project. All authors contributed to the critical revision of the manuscript for important intellectual content. All authors read and approved the final manuscript. All authors have participated sufficiently in the work and agreed to be accountable for all aspects of the work.

Acknowledgment

This paper was supported by Wonkwang University in 2025.

Funding

This research received no external funding.

Conflicts of Interest

The authors declare no conflicts of interest.

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