The Mediating Effects of Process Innovation on AI Adoption and Operational Performance in Malaysia's Electrical and Electronics Small and Medium Enterprise Manufacturers: A Conceptual Framework

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ABSTRACT

The adoption of Artificial Intelligence (AI) has become increasingly prevalent in the Fourth Industrial Revolution, particularly among Electrical and Electronics (E&E) Small and Medium-sized Enterprises (SMEs) in Malaysia. AI has the potential to enhance operational performance of E&E SMEs. Despite the growing potential of AI, the adoption rate in Malaysian SMEs is slow. This is largely due to a lack of readiness and awareness regarding the key factors that influence AI adoption and its impact on operational performance. Previous studies examined various factors to study the AI adoption and there tends to be an empirical gap where none of the study covers all five important factors in a single study. To fill in the empirical gap, this conceptual paper proposes a framework that integrates five important key factors influencing AI adoption in organizations such as human, technological, organizational, environmental, and data management factors within a single study in alignment with the TOE Framework. In addition, in align with dynamic capability theory, this framework also introduces process innovation as a mediating variable to better explain the relationship between AI adoption and operational performance. The proposed conceptual framework aims to provide valuable insights for researchers and practitioners seeking to enhance operational performance through AI adoption in Malaysian E&E SMEs with support of process innovation.

Keywords: AI Adoption factors, Operational Performance, Process Innovation, SMEs

INTRODUCTION

Electrical and Electronics (E&E) Small and Medium Enterprises (SMEs) are the foundation of manufacturing industry in Malaysia as it allows the country to move forward (Othman et al., 2022). According to New Industrial Master Plan 2030 (NIMP), E&E SMEs are the main players in industry with 89.0% of subtotal companies in Electrical and Electronics Industry. E&E SMEs engage in local and global markets by primarily involving in activities such as assembly, test and packaging (Ministry of Investment Trade and Industry, 2023). Malaysia's economic growth is strongly supported by the manufacturing sector, particularly the Electrical & Electronics (E&E) industry. Hence, as the E&E SMEs play a vital role in contributing to the Malaysian economy, it is very important for them to operate effectively and efficiently. This is because the Malaysian E&E industry is more export-oriented, and E&E SMEs also serve both the local and global markets, which demands them to handle high-volume export orders within a short period of time. Therefore, the operational performance of E&E SMEs, in terms of delivery performance, quality performance, and operational flexibility, is essential to contribute to the Malaysian economy as well as the E&E industry. As such, E&E SMEs must adopt emerging technologies like AI to enhance their operational performance.

In the current business environment, AI applications are the most compatible selection for big size organizations and SMEs (Bhalerao et al., 2022). This is because, AI offers various benefits to SMEs by helping them improve their ability to compete, helping to fit into the emerging markets, enhancing their operational performance, product development and in improving their process of decision-making and customer experiences as well

(Ishengoma & John, 2024; Iyelolu et al., 2024). Many countries are striving to lead in the development and adoption of AI, as it has great potential to boost a country's economic growth (Patnaik & Bakkar, 2024). As AI technology continues to evolve, E&E manufacturing SMEs in Malaysia must consider various factors to successfully adopt it and to attain high operational performance.

To attain the Developed Nation Status by 2030 one of the government agency Malaysian Investment Development Authority (MIDA) currently promoting AI among SMEs in Malaysia (Ministry of Digital, 2021). For instance, Malaysian Investment Development Authority (MIDA) in collaboration with two companies which are Intel Malaysia and Malaysia Productivity Corporation conducted a programme called AI4S which stands for AI for SMEs. Hence, it is evident that AI adoption among SMEs is one of the important goal of nation, as the SMEs contribute to the development of Malaysian economy globally. However, AI adoption alone will not significantly contribute to Malaysia's GDP, instead support from process innovation could facilitate AI adoption and operational performance of E&E SMEs. This is because, process innovation positively and significantly affects the operational performance of SMEs (Al-Sa'di et al., 2017; Hazem & Yunhong, 2020; Kim-Soon et al., 2017).

Furthermore, process innovation not only assisting SMEs to improve their operational performance yet it helps SMEs create the perfect environment for AI adoption by streamlining workflows, and by aligning operations with AI technology. For instance, SMEs with outdated or manual processes may find it difficult to adopt AI solutions that require real-time data, digital workflows, or automation readiness yet process innovation creates a structured, flexible, and technologically ready environment which can enable SMEs to integrate AI tools effectively and efficiently which can affect their operational performance. This is because, process innovation involves a notable change in terms of techniques used, equipment and software used (Gunday et al., 2011) to convert knowledge to skills through the whole process (Widya-Hasuti et al., 2018). Process innovation directly affects the AI adoption and performance of a business (Alhosani & Safian, 2024). Therefore, with the support of process innovation SMEs can integrate AI technologies effectively to generate meaningful outcomes to their operational performance.

Generally, Electrical and Electronics (E&E) SMEs in Malaysia must do process innovation to their internal processes to adopt AI and to attain high operational efficiency. Therefore, this paper aims to propose a conceptual framework to investigate the mediating effects of process innovation on AI adoption and operational performance in Electrical and Electronics (E&E) SMEs in Malaysia.

PRIOR RESEARCH ON AI ADOPTION- AN EMPIRICAL GAP

Industry 4.0 has caused a massive shift in the manufacturing sector, where all businesses are compelled to embrace digital transformation regardless of scale, industry, or location (Bettoni et al., 2021). Therefore, AI adoption has become prevalent among organizations to improve efficiency and productivity to survive in the competitive environment. As AI technology evolves, E&E small and medium-sized enterprises (SMEs) often face numerous challenges and opportunities when adopting AI. In Malaysia, SMEs are facing difficulties to adopt and integrate AI technology in their daily operations. Even though, AI technology offers extensive benefits to the manufacturing companies, the adoption rate among bigger manufacturing companies is high compared to small and medium enterprises (Muminova et al., 2024; Peretz-Andersson et al., 2024). This might happen because SMEs lack with employee expertise and skills, IT infrastructure, and are facing financial constraints, costs, and other factors hindering SMEs from successfully adopting AI technology.

According to Malaysia Digital Economy Corporation (2023), Malaysia has scored 2.1 index score in 2022 which indicates that the digital adoption by businesses is in the state of progressing. Business Digital Adoption Index which knows as BDAI defined as the baseline index that used to assess the digital adoption at national level for businesses operating in Malaysia.Therefore, 21 empirical studies have selected from google scholar database. Google Scholar Database's advanced search string was used to find the relevant articles. The keywords used were 'AI adoption determinants in manufacturing industry SMEs'. The search option set to include results where the terms appear anywhere in the article. The date range was limited to publications between 2020 and 2025 to find recent and significant studies. The search generated a total of 17,300 studies in the database. Then the findings were narrow down based on the relevance to the topic and have been analyzed thoroughly to understand

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the factors that lead to AI adoption. The analyzed studies address multiple industries such as manufacturing, agriculture, services, and more with a specific focus on SMEs.

Based on the Table 1, a total of ten influencing factors have been identified from prior studies. Factors that have been identified are human factors, situational factors, individual factor, business structure factors, data management factors, technological factors, organizational factors, business environment, economic environment, regulatory environment factors. These factors serve as fundamental factors that have consistently shown to impact the adoption of AI across various organizational contexts. The identified factors offer a strong foundation for further analysis in exploring SMEs readiness to embrace AI technologies.

There are four prior studies on the human factor (Aish & Noor, 2025; Almashawreh et al., 2024; Naheed et al., 2025; Seah et al., 2023) while individual factor has been discussed in three prior studies (Chaudhuri et al., 2022; Ingalagi et al., 2021; Lada et al., 2023). Next situational factors, business environment factors, economic environment, and regulatory environment are considered and are listed in Table 1. There are two prior studies on situational factors (Chaudhuri et al., 2022; Kabalisa & Altmann, 2021), sixteen studies on business environment factors (Aish & Noor, 2025; Badghish & Soomro, 2024; Chatterjee et al., 2021; Heimberger et al., 2024; Ingalagi et al., 2021; Kabalisa & Altmann, 2021; Kelly et al., 2023; Kinkel et al., 2022; Lada et al., 2023; Masod & Zakaria, 2024; Naheed et al., 2025; Qu & Kim, 2025; Ronaghi, 2023; Solaimani & Swaak, 2023; Soomro et al., 2025; Wang & Su, 2021), three studies on the economic environment (Heimberger et al., 2024; Kabalisa & Altmann, 2021; Kinkel et al., 2022), and four studies on the regulatory environment (Aish & Noor, 2025; Heimberger et al., 2024; Kabalisa & Altmann, 2021; Naheed et al., 2025).

There are twenty prior studies on organizational factors, which is the highest (Aish & Noor, 2025; Almashawreh et al., 2024; Arroyabe et al., 2024; Badghish & Soomro, 2024; Chatterjee et al., 2021; Chaudhuri et al., 2022; Heimberger et al., 2024; Ingalagi et al., 2021; Kabalisa & Altmann, 2021; Kelly et al., 2023; Kinkel et al., 2022; Lada et al., 2023; Masod & Zakaria, 2024; Naheed et al., 2025; Qu & Kim, 2025; Ronaghi, 2023; Seah et al., 2023; Solaimani & Swaak, 2023; Soomro et al., 2025; Wang & Su, 2021), while only one study focused on business and structure factors, conducted by Heimberger et al. (2024).

	Human Factors	Individual Factor	Situational Factors	Business Environment Factors	Economic Environment Factors	Regulatory Environment	Technological Factors	Business Structure Factors	Organizational Factors	Data Management Factors
(Kinkel et al., 2022)					1.√		1.√		1.√	
(Chatterjee et al., 2021)				1. √					2.√	
(Badghish & Soomro, 2024)				2.√			2.√		3.√	
(Ronaghi, 2023)				3.√			3.√		4.√	
(Wang & Su, 2021)				4.√			4.√		5.√	
(Kelly et al., 2023)				5.√					6.√	
(Qu & Kim, 2025)				6.√			5.√		7.√	
(Lada et al., 2023)		1. √		7.√					8.√	
(Ingalagi et al., 2021)		2. √		8.√					9.√	
(Aish & Noor, 2025)	1. √			9.√		1.√	6.√		10.√	
(Masod & Zakaria, 2024)				10.√			7.√		11.√	
(Kabalisa & Altmann, 2021)			1.√	11.√	2.√	2.√			12.√	
(Solaimani & Swaak, 2023)				12.√			8.√		13.√	1.√
(Chaudhuri et al., 2022)		3.√	2.√				9.√		14.√	
(Arroyabe et al., 2024)				13.√					15.√	
(Heimberger et al., 2024)				14.√	3.√	3.√	10.√	1.√	16.√	2.√
(Seah et al., 2023)	2. √								17.√	3.√
(Soomro et al., 2025)				15.√			11.√		18.√	
(Naheed et al., 2025)	3. √			16.√		4.√	12.√		19.√	
(Almashawreh et al., 2024)	4. √						13.√		20.√	
(Jalil et al., 2024)							14.√			
Total Number of studies on Each Factor	4	3	2	16	3	4	14	1	20	3

Table 1 shows summary of empirical study on AI adoption by prior study

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Since some of the factors identified in Table 1 are similar and overlapping, a well-structured proposed table has been developed to provide clearer categorization and to avoid ambiguity. This new table aims to streamline the classification process by grouping related factors together, ensuring that each category is distinct and accurately reflects the concepts. By addressing the overlaps and similarities, the proposed table helps to enhance the precision and consistency of future analyses. Table 2 shows the combination of human factors and individual factors, organizational factors and business structure, business environmental factors, economic environment, regulatory environment, and situational factors.

	Human Factors	Technological Factors	Organizational Factors	Environmental Factors	Data Management Factors
(Kinkel et al., 2022)		1.√	1.√	1. √	
(Chatterjee et al., 2021)			2.√	2.√	
(Badghish & Soomro, 2024)		2.√	3.√	3.√	
(Ronaghi, 2023)		3.√	4.√	4.√	
(Wang & Su, 2021)		4.√	5.√	5.√	
(Kelly et al., 2023)			6.√	6.√	
(Qu & Kim, 2025)		5.√	7.√	7.√	
(Lada et al., 2023)	1. √		8.√	8.√	
(Ingalagi et al., 2021)	2. √		9.√	9.√	
(Aish & Noor, 2025)	3. √	6.√	10.√	10.√	
(Masod & Zakaria, 2024)		7.√	11.√	11.√	
(Kabalisa & Altmann, 2021)			12.√	12. √	
(Solaimani & Swaak, 2023)		8.√	13.√	13.√	1.√
(Chaudhuri et al., 2022)	4. √	9.√	14.√	14.√	
(Arroyabe et al., 2024)			15.√	15.√	
(Heimberger et al., 2024)		10.√	16.√	16.√	2.√
(Seah et al., 2023)	5. √		17.√		3.√
(Soomro et al., 2025)		11.√	18.√	17.√	
(Naheed et al., 2025)	6. √	12.√	19.√	18.√	
(Almashawreh et al., 2024)	7. √	13.√	20.√		
(Jalil et al., 2024)		14.√			
Total Number of studies on Each Factor	7	14	20	18	3

Table 2 presents the summary of the comprehensive analysis of empirical studies on AI.

Based on the summary in Table 2, which presents a comprehensive analysis of empirical studies on AI, an apparent empirical gap is identified. None of the studies cover all five factors which are human factors, technological factors, organizational factors, environmental factors, and data management factors within a single study. Therefore, to address the identified empirical gap, this study aims to cover all five factors such as human factors, technological factors, organizational factors, environmental factors, and data management factors within a single research framework. By doing so, this study seeks to provide a comprehensive understanding of these factors on AI adoption and implementation in any organization.

FACTORS OF AI ADOPTION

Human Factors

Human factors refer to the readiness employees in terms of knowledge, technical skills, and other relevant competencies to effectively handle technology-related challenges during the implementation of new technologies (Aish & Noor, 2025). For instance, according to Lada et al. (2023), employees with strong adaptability skills can easily adjust to changes brought by emerging technologies like AI, where they can successfully utilize and integrate AI into their organization with sufficient knowledge of the technology.

Technological Factors

Technological factors refer to the availability of technology in a company (Badghish & Soomro, 2024; Scupola, 2009), such as IT infrastructure, system compatibility, and the quality of the data (Czarnitzki et al., 2023; Masod & Zakaria, 2024) while Wang et al. (2010) defined the technological context as the technologies aligned with a firm's operation or the current and new technologies related to the organization. The author highlighted that the features of these technologies could affect technology adoption.

Environmental Factors

According to Alraja et al. (2022) environmental factors play a vital role in influencing technology adoption (Almashawreh et al., 2024). In addition, Pai and Chandra (2022) defined environmental context as the situation where organizations operate their business activities, which compasses attributes such as customers, rivals, and vendors too.

Organizational Factors

Organizational factors can be defined as the availability of sufficient resources within an organization to support technology adoption. Characteristics such as organizational size and access to resources may influence the adoption of technology (Chatterjee et al., 2021). In addition, Chaudhuri et al. (2022) stated that organizational characteristics are vital for the integration of AI in the manufacturing and production industries.

Data Management Factors

Jöhnk et al. (2021) classified data management factors as the right data specifically in terms of its availability, quality, accessibility, and flow for the successful implementation of AI within organization. Moreover, Heimberger et al. (2024) highlighted that adoption of AI in organization highly depends on the data. Data is very important for the successful AI implementation as it needs high volume of data and cannot be implemented in the absence of data (Bettoni et al., 2021) because AI has the potential to analyse large number of datasets by identifying knowledge that supports decision-making (Rane et al., 2024) which will assist E&E SMEs to make good decisions.

APPLICATION OF TOE FRAMEWORK IN AI ADOPTION AND OPERATIONAL PERFORMANCE

As a starting point, it is important to thoroughly understand why AI technology adoption has been studied by using TOE framework, and similarly it is important to examine TOE framework's role in studying business performance, particularly operational performance. TOE framework has been widely used by previous scholars to study the relationship of AI adoption and operational performance in the context of SMEs. For instance, Apostoaie et al. (2025), Pillai et al. (2022) and Neumann et al. (2024) has employed TOE framework in their respective studies to examine the adoption of AI. Chatterjee et al. (2021) stated that TOE framework developed by Tornatzky and Fleischer in 1990 is the best to examine adoption of AI in the organizations. Likewise, Mahakittikun et al. (2021) highlighted that their study did not utilize TOE framework to investigate the technology adoption instead used to identify the relationship between TOE framework factors and organization performance. Badghish and Soomro (2024) utilized the TOE framework to examine the adoption of AI in the context of SMEs and the findings indicates the significant relationship.

The selection of the TOE framework in this study can be justified by empirical support and findings from previous studies. Wong and Ngai (2025) highlighted important points in the findings part of the research. Firstly, the researchers emphasized in the findings that the TOE framework has the potential of explanatory strength in explaining AI adoption. Secondly, the authors highlighted that the integrated TOE framework with Dynamic Capability Theory enhances the understanding of AI adoption by connecting technological, organizational, and environmental factors with operational performance. Thirdly, the findings of the research validate that the identified TOE factors are the factors of Dynamic Capability to adopt AI and the vital aspects of operational performance. In addition, the study Badghish and Soomro (2024) utilized the TOE framework to examine the adoption of AI in the context of SMEs and the findings indicates the significant relationship. Therefore, the current research framework discusses five factors to examine the adoption of AI in align with TOE framework.

APPLICATION OF DYNAMIC CAPABILITY THEORY IN THE MEDIATING ROLE OF PROCESS INNOVATION ON AI ADOPTION AND OPERATIONAL PERFORMANCE

Dynamic capability theory is the extended approach of the resource-based view of the organization, where the theory widely used in organizational research to explain the persistent performance differences across the organizations (Piening & Salge, 2015). Galvin et al. (2014) highlighted that dynamic capability theory has been introduced to mitigate the potential limitation of resource-based view theory. According to Teece and Pisano (1994) dynamic capabilities known as the subset of the competences or capabilities which enable the organization to develop new product and process as a respond to changing market conditions. Moreover, the primary goal of dynamic capability framework is that to explain how organizations can attain a long-term competitive advantage and to assist managers to refrain from zero profit situation when similar organizations contend in the fully competitive markets (Teece, 2007). For instance, according to Teece (2014) dynamic capability can enable business to attain high revenue by creating and delivering unique products and services to address existing and growing market demands.

AI has brought changes in how the businesses runs (Ingalagi et al., 2021). This is because the emergence of digital technologies in the fourth industrial revolution has affected the environment of business operations globally (Soomro et al., 2025). Hence, it is essential for all the organizations to adapt the new environment to stay competitive in the market especially for the SMEs. This is because study by Enshassi et al. (2025) highlighted that SMEs are still facing difficulties to adopt new technology due to the budget constraints and the limited understanding on the benefits AI could offer practically. According to the dynamic capability theory as defined by Teece et al. (1997) it is important for firms to integrate, build, and reconfigure internal and external capabilities to adapt to rapidly evolving environments. Weaven et al. (2021) highlighted that dynamic capability theory is applicable to examine small firm's attitude during financial crisis as it severely affects the business environment by damaging infrastructure, raising unemployment rates, lowering customer demand and supply availability, and driving up costs. By referring to the comprehensive lens of the dynamic capability theory this study has used process innovation as a mediator to study the AI adoption and operational performance in the context of E&E manufacturing SMEs in Malaysia. Gao et al. (2025) highlighted that businesses to improve their innovation capability via AI technology has emerged as the key issue theoretically and practically in the continuously changing digital era. Therefore, as the current research focuses on E&E manufacturing SMEs, adopting AI technology alone will not result in high operational performance. To fully understand and utilize the perceived benefits of AI technology in response to evolving market demands, SMEs must reconfigure their internal and external capabilities by integrating process innovation into their operational activities to achieve high operational performance. Zollo and Winter (2002) highlighted that dynamic capability is shown when an organization regularly improves its operations through a consistent focus on process improvement. Process innovation defined as the application of novel or enhanced production and delivery method that benefits the user by Ashok et al. (2016).

Zebec and Indihar Štemberger (2024) conducted study on the AI's potential to develop business value by examining the mediating role of business process management capabilities. The findings of this research confirms that process innovation is one of the significant partial mediators in exploring how AI generates business value. Likewise, previous studies by Abdallah et al. (2021), Al-Sa'di et al. (2017), Expósito et al. (2024), Khalfallah et al. (2022), Möldner et al. (2020), Migdadi (2022), Siew Mui et al. (2022), Turkcan et al. (2023), Purwanto (2016) has discussed the mediating role of process innovation in boosting the operational performance. Therefore, this study integrated process innovation as a mediating variable in the framework to examine the relationship between AI adoption factors and operational performance.

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CONCEPTUAL FRAMEWORK

The presented framework explains the impacts of AI adoption factors such as human factors, technological factors, organizational factors, environmental factors, and data management factors on E&E SMEs' operational performance, while the framework also explains the mediating role of process innovation in facilitating the relationship between AI adoption factors and operational performance. From the developed framework, future researchers can better understand the factors affecting AI adoption and its impact on operational performance in the context of Malaysian SMEs. Scholars can use the findings from this research as a reference point to study AI adoption among SMEs from different industries and the role of process innovation as a mediator in the context of AI and organizational performance.

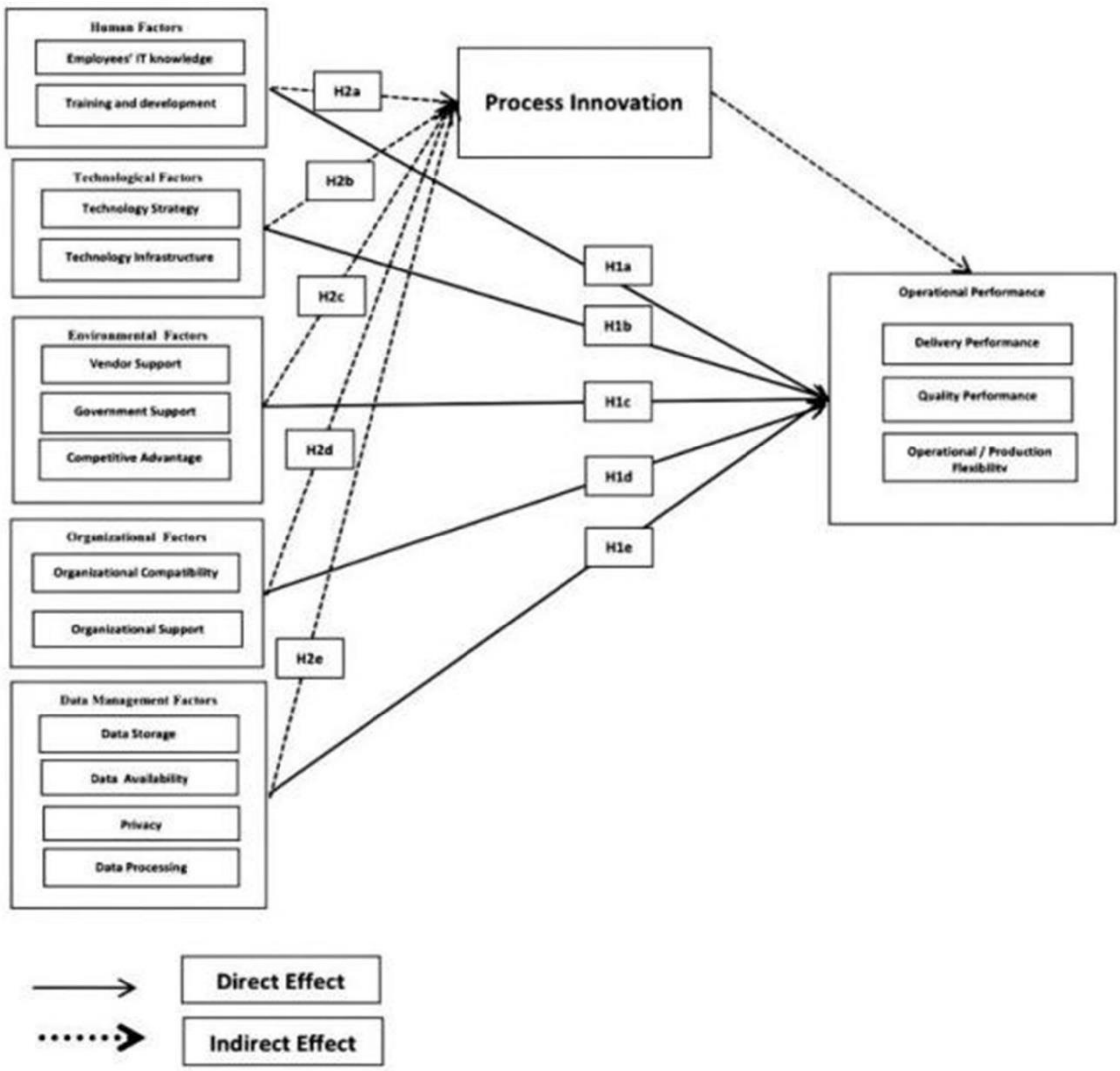

Fig. 1 shows the conceptual framework of this study

CONCLUSION

In summary, this conceptual paper has developed a comprehensive framework that integrates five important factors of AI adoption which has been thoroughly analyzed and identified from the 21 studies which can be used in the context of organization despite of the size of the organization. This framework addresses an existing empirical gap by offering a structured view of the factors affecting AI adoption and their impact on their operational performance in the context of SMEs. In addition, the framework by aligning with the TOE framework and incorporating process innovation as a mediating variable through the lens of Dynamic Capability Theory, the model provides a clearer understanding of how AI adoption can enhance operational performance which can be a foundation for the future researchers to study AI adoption factors, process innovation and operational performance within a single framework within different industries setting.

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