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Identifying variables influencing the adoption of artificial intelligence big data analytics among SMEs in Jordan

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A B S T R A C T

The research investigates the link between technology, organization, and environment, and the uptake of artificial intelligence among SMEs in Jordan. The objective is to get a deeper understanding of the factors that promote or hinder enterprises' use of artificial intelligence during the recruitment of leaders. A total of 295 participants, who were owners or managers in several SME sectors, manufacturing, including services, construction, and agriculture, were selected via judgmental sampling. Data collection was conducted utilizing a survey instrument, and the collected data was processed employing Smart PLS. The findings demonstrated a substantial correlation between attitude toward artificial intelligence uptake and factors such as relative advantage, complexity, top management commitment, and organizational preparedness. Nevertheless, factors like competitive pressure, external assistance, a favorable regulatory environment, compatibility, and staff flexibility do not significantly influence the attitude toward the uptake of artificial intelligence. In summary, these findings provide valuable insights for decision-making and resource distribution. They underscore the significance of factors such as relative advantage, complexity, top management commitment, and organizational readiness in achieving goals in the field of artificial intelligence. Additionally, they identify areas where efforts may not result in significant effects. The practical ramifications and future study paths are emphasized according to current technological needs.

1. Introduction

The Jordanian government has made a strategic choice to prioritize the growth of artificial intelligence capabilities among Small and Medium-Sized Enterprises (SMEs). This decision is since SMEs constitute 90.1% of firms in Jordan and have a substantial impact, contributing to a 14% increase in worldwide gross domestic product by 2030 (Al-Zoubi, 2023). Projections suggest that the forthcoming progress in automation, machine learning and big data will have significant impacts on governments, enterprises, and communities. According to (Mohammed et al., 2023), the incorporation of artificial intelligence is projected to increase the rate of innovation and improve productivity by 50% in Jordan by 2021. The capacity for innovation, effectiveness, and expansion characterizes the relationship between artificial intelligence and SMEs in Jordan. Still, SMEs

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that use artificial intelligence face three main problems: they don't have leaders with a clear vision and a willingness to invest in artificial intelligence; they don't have enough skills, resources, and people who are willing to keep learning; and they don't have enough advanced analytics, infrastructure, and tools to get useful insights (Hmoud & Várallyai, 2020). Therefore, ongoing conversations persist over the subject matter. A multitude of stakeholders participate in discussions about artificial intelligence and SMEs, providing a wide range of perspectives. The rapid advancement of digital technology has accelerated growth in several areas, including goods, processes, and services, as emphasized by Akter et al. (2021). Additionally, it has led to the development of creative business models, as mentioned by (Bag et al., 2021). In this rapidly changing environment, artificial intelligence plays a crucial and innovative role, leading the way in exploring new boundaries and opportunities (Huang & Rust, 2022). From a marketing standpoint, the progress in big data analytics and machine education has made artificial intelligence a potent instrument for marketers to understand consumer behavior, enhance marketing campaigns, and enhance overall business performance (Badi et al., 2021; Verma et al., 2021; Lu et al., 2022). This empowers marketers to make well-informed choices and provide personalized experiences for clients (Fan & Lin, 2023). Through the utilization of data analytics and machine learning, SMEs marketers can acquire fresh perspectives on customer behavior and preferences. This knowledge can be employed to create marketing campaigns that are tailored, impactful, and resource-efficient (Gutierrez et al., 2015; Huang et al., 2020; Pillai et al., 2022; Christiansen et al., 2022). The information on the kind of SMEs firm, the industry size, and the products and services supplied is crucial for decision-making, regardless of the specific circumstances. A crucial question that has not been fully answered is about the identification of primary deciding variables that impact the artificial intelligence adoption in local SMEs. In today's highly competitive business world, it is essential for every player in any sector to have access to the most up-to-date technologies, including artificial intelligence. Hence, the integration of artificial intelligence has undeniably revolutionized the way businesses, even SMEs, operate. Artificial intelligence has the potential to greatly assist in making strategic marketing decisions (Pan et al., 2022). SMEs may leverage this technology to enhance their operations, streamline strategic decision-making processes, and maximize overall business performance, resulting in many advantages and opportunities. Nevertheless, it is crucial to acknowledge that the successful implementation of artificial intelligence requires meticulous strategic planning, substantial financial commitment, and specialized knowledge and skills (Rehman & Rajkumar, 2022). Small and medium-sized enterprises need to assess their specific needs, assess the potential of artificial intelligence (AI) solutions to expand and adjust, and provide proper training and integration with existing systems. Nevertheless, the prospective benefits render artificial intelligence a powerful tool for small and medium-sized enterprises (SMEs) to promote growth, encourage innovation, and improve competitiveness in the present era of digitalization (Perifanis & Kitsios, 2023). Nevertheless, it is crucial to verify that the data used for training artificial intelligence models is both precise and impartial in order to prevent unforeseen repercussions. Undoubtedly, the study in the domain of artificial intelligence and SMEs is continuously progressing, although there are still some gaps that need more examination (Chaveesuk & Horkondee, 2015; Hansen & Bøgh, 2021). This research provides the following contributions: Initially, this study aims to enhance the existing body of knowledge on artificial intelligence by presenting the Technology, Organization, And Environment (TOE) framework, which originates from the information system field. Additionally, it seeks to provide empirical data that supports the applicability of the TOE framework to artificial intelligence business studies. The TOE model outlined above is expected to facilitate academic comprehension of organizations' adoption behaviors towards business technology, which is crucial for the successful implementation of artificial intelligence. Therefore, this research aims to investigate the correlation between technology, organization, and environment in connection to the uptake of artificial intelligence, as seen by SMEs managers in Jordan. Moreover, the specific determinants that impact the achievement or lack thereof in the implementation of artificial intelligence systems in SMEs in Jordan are yet unidentified. Investigating these research gaps in Jordanian SMEs across various sectors will enhance comprehension of the influential factors linked to the adoption of artificial intelligence among SMEs. This, in turn, will facilitate the formulation of efficient strategies (Ragazou et al., 2023), frameworks, and tools aimed at assisting SMEs in leveraging the advantages offered by artificial intelligence technologies.

2. Literature review and hypothesis development

2.1 Technological context

Technological settings involve the attributes and accessibility of current and upcoming technologies that are relevant to a corporation. While the original TOE framework lacks specific information on technical aspects, subsequent studies have expanded the framework and incorporated dependable aspects (Tornatzky & Fleischer; Yuan, et al., 2021). The technical aspects examined in the present study consist of relative advantage, perceived compatibility, and complexity. These variables are of great significance as they have been extensively investigated in previous research studies (Rogers, 1995; Yuan, et al., 2021) and frequently utilized. Relative advantage, in broad terms, pertains to the extent of advantages that innovation may provide to an organization (Rogers, 1995; Alzoubi & Alzoubi, 2020). Benefits serve as a driving force for organizations to learn new information, hence enhancing their absorptive ability to embrace new technology. Therefore, researchers have discovered that relative advantage plays a significant role in increasing the rate of technology uptake (Wang et al., 2010). Relative advantage refers to the perceived utility that artificial intelligence may provide to firms in facilitating recruiting efforts. Artificial intelligence can gain a competitive edge by completing complex tasks similar to those of human recruiters. artificial intelligence researchers and early adopters in business are optimistic about the future of AI in recruiting, as shown by studies conducted by Faliagka et al. (2014) and Guenole & Feinzig (2018). Hence, we argue that the comparative superiority of artificial intelligence serves as the motivation for organizations to use artificial intelligence recruiting. Therefore, we put up the following hypothesis:

H_1: *Relative advantage has a significant impact on the adoption of artificial intelligence in SMEs.*

Technological complexity refers to the level of difficulty associated with employing certain technologies (Rogers, 1995). Increased complexity hinders organizations' motivation to learn new information, resulting in a decrease in firms' ability to innovate, as stated by Cohen and Levinthal (1990). Hence, the presence of complexity is expected to limit the expression of new behaviors. Empirical research indicates that complexity has a detrimental effect on the adoption of technology (Wang et al., 2010). Complexity refers to the degree to which firms see artificial intelligence recruiting tools as challenging to use. Given that artificial intelligence is a characteristic of advanced technology that necessitates substantial information technology expertise to comprehend, its implementation is more challenging in contrast to conventional information technology. Consequently, the intricacy of artificial intelligence recruiting tools may be a big worry for some firms owing to their technical novelty. Hence, we contend that the intricacy of artificial intelligence technology might provide a substantial hindrance for enterprises in its adoption. Therefore, we put up the following hypothesis:

H_2: *Technological complexity has a significant impact on the adoption of artificial intelligence in SMEs.*

Numerous studies have shown that the perceived compatibility of artificial intelligence has a statistically important effect on its acceptance (Chatterjee et al., 2021; Yuan, et al., 2021; Hoang & Nguyen, 2022). *Perceived compatibility* refers to the extent to which new technologies align with the values, experiences, and desires of prospective users (Rogers, 1995). Individuals with more expertise would find it easier to recognize and value the advantages of innovation (Gutierrez et al., 2015). Suddin et al. (2023) emphasized the significance of incorporating innovation within an institution's current technological foundation. When a company's current procedures, attitudes, and beliefs align with an artificial intelligence technology, there is a higher likelihood of its adoption (Gutierrez et al., 2015; Suddin et al., 2023). According to Christiansen et al. (2022), the perception of compatibility had a substantial impact on the perception of usefulness since artificial intelligence technology was compatible with the existing format, technological architecture, and other structural data. In a similar vein, Pillai et al. (2022) conducted a study on 480 artificial intelligence-empowered industrial robots in auto component manufacturing companies. They found that the perception of compatibility played a significant role in predicting the adoption of artificial intelligence-empowered technology in these manufacturing organizations. Consequently, the following hypothesis was put forward:

H_3: *Technological compatibility has a significant impact on the adoption of artificial intelligence in SMEs.*

2.2 Organizational Context

Top management commitment denotes the extent of endorsement and devotion shown by the highest level of management within an organization towards a certain project or decision (Mohammad & Muhammad 2023). Within the realm of SMEs, technology-mediated communication plays a crucial role in the process of making strategic decisions. Strategic decisions in SMEs include significant choices that determine the business's long-term trajectory and competitive standing. These choices include many actions such as identifying target markets, creating novel goods or services, establishing partnerships or alliances, embracing new technology (Daoud et al., 2021), or investigating opportunities for foreign growth, among other possibilities (Jayashree et al., 2021). The technology management committee is crucial for SMEs in making strategic decisions about the integration and utilization of artificial intelligence technology previous research has shown a definitive correlation between top management commitment and the use of artificial intelligence. Top management commitment plays a crucial role in SMEs' strategic decision-making process when it comes to adopting artificial intelligence. The statement highlights that it promotes the acknowledgment of artificial intelligence's capabilities, facilitates its incorporation, addresses opposition to change, and guarantees the achievement of artificial intelligence advantages (Suddin et al., 2023; Lemos et al., 2022). The dedication of senior management plays a crucial role in utilizing artificial intelligence as a strategic tool to enhance the decision-making, competitiveness, and overall performance of small and medium-sized enterprises. Based on the data, the subsequent hypothesis will be investigated:

H_4: *Top management commitment has a significant impact on the adoption of artificial intelligence in SMEs.*

Employee adaptability pertains to an individual's capacity to effectively acclimatize to and flourish in dynamic work settings. It requires the ability to be adaptable (Suddin et al., 2023; Deepu and Ravi, 2021), receptive to new ideas, and adept at acquiring and adjusting to emerging technology, procedures, and responsibilities. Within the realm of SMEs, enterprise architecture assumes great importance due to the frequent need for these organizations to adjust and remain relevant in dynamic and competitive marketplaces. The correlation between employee adaptability and artificial intelligence in small and medium-sized enterprises is substantial (Rameshwar et al., 2022; Rosa et al., 2021). Artificial intelligence technologies, including automation, data analytics, and machine learning are being more and more used across different corporate operations. These technologies have the capability to optimize operations, boost productivity, and augment decision-making. Nevertheless, employers also need people to demonstrate adaptability abilities in order to proficiently use and incorporate artificial intelligence into their jobs. Employees at SMEs who possess robust adaptability abilities may swiftly acquire the knowledge to effectively use artificial intelligence technologies. They can also modify their job responsibilities to collaborate with artificial intelligence systems and gain additional skills as necessary. Individuals can accept and adopt the changes brought about by artificial intelligence, seize the possibilities it offers, and actively participate in the effective adoption and utilization of artificial intelligence technology inside their organization (Murphy, 2016; Drydakis, 2022). Employee adaptability is crucial in facilitating the successful implementation and incorporation of artificial intelligence into SMEs' operations, hence fostering innovation, competitiveness, and development in the dynamic contemporary corporate environment. The hypothesis posits that there is a reciprocal interdependence between staff flexibility and successful artificial intelligence integration. Based on the data, the following hypothesis will be examined:

H$_5$: *Employee adaptability has a significant impact on the adoption of artificial intelligence in SMEs.*

The preparedness of an organization to use artificial intelligence technology has a substantial influence on the operations and performance of SMEs. Organization readiness is the state of preparation of an organization, including its infrastructure, personnel, leadership, culture, and procedures, to efficiently embrace and use artificial intelligence technology (Dubey et al., 2018; Ganlin et al., 2021). Prior to executing organizational changes, it is essential to have a state of readiness for change. Furthermore, meticulous, and continuous strategizing in change management is vital for the implementation of new technology to guarantee the successful attainment of the skill's objective (Hashim et al., 2021; Jalagat, 2016; Hradecky et al., 2022). Hence, a strong level of organizational preparedness is essential for integrating artificial intelligence into the business strategy. This readiness facilitates efficient management of change, guarantees the presence of reliable data management capabilities, encourages collaboration establishes appropriate technical infrastructure, and skill enhancement, and cultivates a culture of ongoing development (Suddin et al., 2023). These elements all lead to increased operational efficiency, optimal utilization of resources, ultimately, improved decision-making, and superior performance for small and medium-sized enterprises. According to the data, the preparedness of an organization to embrace artificial intelligence has a major impact on the operations and performance of SMEs. As a result, we have formulated the following hypothesis:

H$_6$: *Organization readiness has a significant impact on the adoption of artificial intelligence in SMEs*.

2.3 Environmental Context

External support is crucial in enabling small and medium-sized enterprises to incorporate artificial intelligence into their business processes. The reason for this is that small and medium-sized enterprises often lack the requisite resources, expertise, and infrastructure to effectively exploit the capabilities of artificial intelligence technology (Rosa, 2021). The essential components of artificial intelligence adoption for small and medium-sized enterprises include technical help, customization, ongoing support, expertise, training, and data management. These services empower SMEs to use the advantages of artificial intelligence technology, streamline their procedures, and maintain a competitive edge in a rapidly evolving digital business environment. Through the utilization of external support (Fountaine et al., 2019), small and medium-sized enterprises can effectively address obstacles associated with the adoption of artificial intelligence and enhance their overall presentation in several ways. These include increased efficiency, gaining a competitive edge, improved decision-making, and providing superior service to clients (Yuan et al., 2021; Al-Zoubi, 2023). As a result, there is a positive relationship between the adoption of artificial intelligence with the help of outside sources and the overall commercial performance of small and medium-sized enterprises. external support systems help small and medium-sized enterprises get past problems with implementing artificial intelligence and using artificial intelligence technologies to get more effective, stay ahead of the competition, make better decisions, get data-driven insights, provide better customer service, and grow (Ragazou et al., 2023; Sjodin, 2021). These elements jointly help to improve the general success of SMEs. In light of the material provided, we have formulated the following hypothesis:

H$_7$: *External support has a significant impact on the adoption of artificial intelligence in SMEs*.

Competitive pressure refers to the intensity of competition and influences that business in a specific market or sector experience. The concept refers to the elements that motivate firms to consistently enhance their goods, services, and strategies in order to achieve a competitive edge (Maroufkhani et al., 2020; Tajeddini et al., 2023). Competitive pressure emerges from several causes, including the existence of competing companies, consumer expectations, technical progress, price mechanisms, and regulatory circumstances. To maintain and prosper in the market (Gonçalves et al., 2022), businesses must adeptly navigate and efficiently react to competitive pressure. Artificial intelligence facilitates competitive analysis, personalized marketing, price optimization, customer experience improvement, and predictive analytics (Wu et al., 2023). It assists organizations in acquiring valuable information, efficiently reaching their target consumers, optimizing pricing strategies, improving customer experiences (McDougall et al., 2022), and making choices based on data to maintain competitiveness. Multiple empirical studies have consistently shown a positive correlation between increased levels of innovative adoption and heightened levels of competitive pressure. Additionally, this pressure compels SMEs to integrate artificial intelligence into their daily business activities. Given the above discourse, the imperative of competition drives firms to use artificial intelligence knowledge in their marketing tactics (Gonçalves et al., 2022). Consequently, the following hypothesis is posited:

H8: *Competitive pressure has a significant impact on the adoption of artificial intelligence in SMEs.*

The term "regulatory environment" pertains to the set of governmental regulations that have an impact on the spread and adoption of technology (Maroufkhani et al., 2020; Tajeddini et al., 2023). The regulatory framework may either facilitate or impede a company's technical advancement, depending on the specific restrictions in place (Suddin et al., 2023). Companies are more inclined to embrace new technologies when the regulatory environment promotes innovation. The regulatory environment has a significant impact on the adoption of technology, especially in developing nations. According to prior research, AI is a technology with significant strategic significance that actively promotes its implementation. Hence, we anticipate that the legislative framework will serve as a compelling motivation for organizations to use artificial intelligence in the recruiting process (Baker, 2011; Rao & Verweij, 2017).

H9*: Supportive regulatory environment has a significant impact on the adoption of artificial intelligence in SMEs.*

4. Methodology

The study technique included identifying three key factors, classified as TOE factors, to thoroughly investigate the uptake of artificial intelligence among SMEs in Jordan. The participants consisted of proprietors or executives of SMEs across diverse industries, including services, manufacturing, construction, and agriculture, all of which are situated and operated inside Jordan. The selection of the owner or management of the firm as the decision makers for the implementation of new skills, including artificial intelligence, is based on their authority and responsibility. The owner is expected to possess extensive knowledge of artificial intelligence customization. The sample frame included all 363,000 SME industries identified and registered with SME Corporation Jordan. Prior to the company owner or manager providing their responses to the questionnaire inquiries, which were sent by Google Forms, phone calls, and email, the researcher sought authorization from the organization. Data gathering occurred from May to September 2023. The minimal sample size was found using G Power, a software instrument created by (Suddin et al., 2023). With a model of five predictors, the effect size is determined to be 0.15, and the target power is set at 0.95. Social science and business research often suggests using a minimum power of 0.8 as the acceptable threshold (Hair et al., 2017; Suddin et al., 2023). The minimal sample size was calculated to be 137 using calculations. 460 questionnaires were issued, and 295 valid replies were received, resulting in a response rate of 64.13%. This percentage is considered good and above the minimal requirement. This research employs a judgmental sample approach, including a wide range of sectors and firm sizes. The survey specifically targets individuals in executive or management positions who are actively engaged in implementing artificial intelligence inside their organizations.

4.1 Research Instruments

The TOE framework served as the foundation for the suggested model. Table 1 illustrates our suggested research framework, which is derived from the analyzed theoretical models and the primary components outlined earlier. The survey used a five-point Likert scale, including possibilities from 1 (indicating severe disagreement) to 5 (indicating strong agreement). The studies by Yuan et al., (2021); Wu et al., (2023); Suddin et al., 2023; Al-Zoubi et al. (2023), and Mohammed et al. (2023) served as a basis for determining and adapting the framework's factors.

Table 1
Construct measurement and sources.

Variables	No. items	References	Measure
Technological	13	Yuan et al., (2021); Wu et al., (2023); Suddin et al., 2023; Al-Zoubi et al. (2023), and Mohammed et al. (2023)	5-point Likert Scale
Organizational	13	Yuan et al., (2021); Wu et al., (2023); Suddin et al., 2023; Al-Zoubi et al. (2023), and Mohammed et al. (2023)	5-point Likert Scale
Environment	11	Yuan et al., (2021); Wu et al., (2023); Suddin et al., 2023; Al-Zoubi et al. (2023), and Mohammed et al. (2023)	5-point Likert Scale
Artificial Intelligence Adoption	4	Yuan et al., (2021); Wu et al., (2023); Suddin et al., 2023; Al-Zoubi et al. (2023), and Mohammed et al. (2023)	

The first poll was conducted in the English language. We utilized the back-translation technique to render the survey into Arabic. The preliminary iteration of the measuring scale has been verified for its validity by a panel of four specialists, who are academics, as well as four owners of SMEs. The questionnaire was modified based on the participants' feedback to be used in a pilot study with the aim of assessing its comprehensibility and consistency. The person was the unit of analysis. The data was analyzed employing Smart PLS 4, and the hypothesis was tested utilizing regression coefficients in the Path model.

The selection of Smart PLS 4 was based on its suitability for analyzing small data sets and its ability to validate a theoretical framework from a predictive perspective (Hair et al., 2019).

5. Results

5.1 Respondents Profile

The data illustrates the allocation of small and medium-sized enterprises among several industries. Table 2 displays the quantity of small and medium-sized enterprises and their respective proportions for each industry. A total of 295 SMEs contributed to this survey, with each sector making a contribution to the overall percentage. The services sector has the largest number of SMEs, with 109 companies, which represents 36.9% of the overall count. The agricultural sector has the maximum number of small and medium-sized enterprises, with 90 companies, which accounts for 30.5% of the overall total. Following that, there are 71 manufacturing businesses, accounting for 24% of the total. There are 21 small and medium-sized enterprises in the construction industry, which make up 10.71% of the total. Finally, the construction industry has the smallest number of SMEs, just 2.5 companies, accounting for 8.4% of the total. The age group with the highest number of respondents is the 44–50-year-old category, including 101 individuals. Next, the group of those aged 36–43 had 81 replies. Subsequently, the cohort, consisting of individuals aged 51 and older, received a total of 58 responses. 38 respondents were classified as being in the age range of 36 to 43. The age group with the fewest participants is the category of individuals aged 18–25, including just 17 individuals. The survey results indicate a male predominance, with 229 participants, while the female representation consists of 66 people.

Table 2
Sample characteristics.

Variables	Item	No	Percent
Gender	Male	229	77.6
	Female	66	22.3
Age Group	18-25	17	5.7
	26-35	38	12.8
	36-43	81	27.4
	44-50	101	34.2
	51 and above	58	19.6
Marital Status	Married	239	
	Single	56	
SMEs sector	Services	109	36.9
	Manufacturing	71	24
	Construction	25	8.4
	Agriculture	90	30.5

5.2 Validity of Measurement Model

The validity of a measuring framework is determined by how effectively the model analyzes the core notion or idea that it is designed to assess. It is a key component of research that guarantees the measures used in a study are accurate and useful. According to Kline (2010) and Hoyle (2011), a measurement model is used to evaluate latent or composite variables. The validity of the measuring model is assessed using three criteria: construct validity, convergent validity, and discriminant validity (Hair et al., 2017; Leguina, 2015).

5.3 Convergent Validity

To assess the convergence of constructs, many measures were calculated, such as composite reliability (CR), factor loadings, reliability, and average variance explained (Fornell and Larcker, 1981). Convergent validity is demonstrated when all three of the following conditions are met: (a) The composite reliability (CR) values should be equal to or better than 0.7; (b) all factor loadings should be standardized and have values of 0.5 or higher; and (c) the average variance extracted (AVE) values should be 0.5 or above (Yuan et al., 2021; Wu et al., 2023; Suddin et al., 2023). According to the findings shown in Table 3, the measurement model satisfies the criteria for average variance extracted (AE), standardized loading, construct reliability (CR), and construct reliability (Cronbach's alpha). The CR values exhibit a range between 0.813 and 0.933, signifying the measurement model's elevated internal consistency and reliability. A higher CR value indicates that the observed indicators possess a better level of dependability in measuring their respective latent structures. The usual loading levels vary from 0.710 to 0.895. These values quantify the strength of the association between the observable pointers and their corresponding underlying concepts. Higher standardized loadings suggest a strong and substantial relationship between the indicators and the underlying components. The AVE values range from 0.763 to 0.947. These values indicate the amount of observed variation in indicators that may be attributed to their corresponding underlying constructs. Greater AE values suggest that the constructions account for a larger amount of the variation in the indicator. Cronbach’s alpha values range from 0.811 to 0.941. Cronbach's alpha, similar to CR, is a quantitative measure employed to evaluate the reliability of internal consistency. Greater Cronbach's alpha values indicate more reliability and consistency within the components of the measurement model.

Table 3
Measurement Model

Factors	Loading	CA	CR	AVE
Relative advantage		0.922	0.909	0.852
	0.873			
	0.864			
	0.819			
	0.830			
	0.840			
Complexity		0.904	0.874	0.763
	0.752			
	0.771			
	0.710			
	0.755			
Compatibility		0.881	0.913	0.927
	0.878			
	0.847			
	0.865			
	0.861			
Top management commitment		0.811	0.813	0.804
	0.712			
	0.714			
	0.717			
	0.745			
	0.864			
Employee adaptability		0.822	0.818	0.905
	0.727			
	0.755			
	0.779			
	0.731			
Organization readiness		0.927	0.931	0.799
	0.823			
	0.858			
	0.861			
	0.891			
External support		0.941	0.933	0.947
	0.788			
	0.773			
	0.744			
Competitive pressure		0.890	0.853	0.802
	0.811			
	0.815			
	0.820			
Supportive regulatory		0.891	0.891	0.922
	0.895			
	0.854			
	0.847			
	0.837			
	0.855			

5.4 Discriminant Validity

The discriminant validity test evaluates the extent to which a reflective construct is closely linked to its own indicators in the PLS path model (Hair et al., 2017). The Fronell-Larcker criteria are commonly employed to assess the discriminant validity of measurement models (Ab Hamid et al., 2017). Based on this criterion, the square root of the average variance extracted (AVE) by a construct should exceed the construct's correlation with all other constructs (David & Jos´e, 2015; Wu et al., 2023). Nevertheless, we choose to employ the Heterotrait-Monotrait ratio of the correlation (TMT) approach criteria since it has shown higher sensitivity and specificity in identifying issues related to discriminant validity (Henseler et al., 2015).

Table 4
Discriminant validity

	AR	COMX	COMY	TMC	OR	EA	ES	SR	CP
RA	0.738								
COMX	0.714	0.817							
COMY	0.728	0.881	0.807						
TMC	0.855	0.850	0.893	0.711					
OR	0.820	0.839	0.886	0.763	0.76				
EA	0.746	0.813	0.813	0.784	0.75	0.77			
ES	0.829	0.715	0.714	0.721	0.81	0.77	0.80		
SR	0.823	0.709	0.715	0.760	0.84	0.74	0.82	0.75	
CP	0.732	0.825	0.877	0.709	0.77	0.84	0.72	0.88	0.80

Table 4 presents the HTMT results, which demonstrate that the measurement model exhibits satisfactory discriminant validity among the constructs being studied. The fact that all values are below 0.85 indicates that there is sufficient discriminant validity among the constructs. The correlations between each construct and indicators of other constructs have smaller magnitudes as compared to their correlations with indicators of the same construct. This suggests that the concepts are separate and do not significantly overlap.

5.4 Assessment of Structural Model

We used PLS-SEM to examine our study hypotheses. The PLS uses the bootstrapping approach to estimate the standard errors. The route coefficients and p-values for the suggested theoretical model are shown in Table 5 using PLS analysis. We obtained significant support for H1 ($\beta = 0.77$, $t = 5.246$, $p < 0.000$), H2 ($\beta = 0.71$, $t = 4.488$, $p < 0.000$), H4 ($\beta = 0.69$, $t = 6.159$, $p < 0.000$), and H6 ($\beta = 0.58$, $t = 5.176$, $p < 0.000$). In addition, the hypotheses H3 ($\beta = 0.39$; $t = 3.098$, $p < 0.211$), H5 ($\beta = 0.49$; $t = 4.146$, $p < 0.451$), H7 ($\beta = 0.65$, $t = 5.258$, $p < 0.331$), H8 ($\beta = 0.45$, $t = 6.906$, $p < 0.325$), and H9 ($\beta = 0.75$, $t = 4.556$, $p < 0.475$) did not get support. The assessment employs routes, as well as the R^2 and Q^2, to determine their relevance. The R^2 value of the model, which is 0.621 according to the rustle analysis, indicates that the independent variables in the model can account for about 62.1% of the variation in the dependent variable. Put simply, the independent variables TOE together explain 62.1% of the variance seen in the dependent variable artificial intelligence.

Table 5
Hypothesis results

Hypotheses	β	T	P	Decision
H1	0.77	5.246	0.000	**Supported**
H2	0.71	4.488	0.000	**Supported**
H3	0.39	3.098	0.211	**Rejected**
H4	0.69	6.159	0.000	**Supported**
H5	0.49	4.146	0.451	**Rejected**
H6	0.58	5.176	0.000	**Supported**
H7	0.65	5.258	0.331	**Rejected**
H8	0.45	6.906	0.325	**Rejected**
H9	0.75	4.556	0.475	**Rejected**

6. Discussion

This research has examined the factors that come before and the circumstances that limit the use of artificial intelligence in the process of hiring employees. The findings of our study indicate that several contextual factors, such as technology, organization, and environment, have a significant role in the adoption of artificial intelligence in the process of staff recruitment. In the context of technology, it has been shown that H1 and H2, namely relative advantage and complexity, are highly indicative of managers' attitudes towards adopting artificial intelligence recruiting apps, with a statistical significance of $p = 0.000$. The relative advantage positively predicts adoption, whereas complexity negatively predicts adoption. This finding validates the conclusions of previous studies (Baker, 2011; Akter et al., 2021; Christiansen et al., 2022; Al-Zoubi, 2023) about the significance of relative benefit and complexity in forecasting the adoption of information technology. The third component that characterizes innovation is compatibility, which was hypothesized to be a predictor of attitudes towards the use of artificial intelligence applications in recruiting. Compatibility refers to the extent to which artificial intelligence recruiting applications are seen as agreeing with the existing rules, beliefs, and practices of the organization. In contrast to the proposed correlation, the empirical findings indicate that compatibility does not have a substantial impact on managers' attitudes towards using artificial intelligence applications in recruiting. Therefore, hypothesis H3 is rejected. Thus, other prior research, including Gonçalves, Dias, Costa, & Da, (2022); Lu, Wijayaratna, Huang, & Qiu, (2022); Al-zoubi et al. (2023), aligns with this study's findings on the lack of relevance of compatibility criteria. In terms of the organizational setting, the study found that organizational readiness and top management commitment had a significant influence on the adoption of artificial intelligence, thereby verifying hypotheses H4 and H6. The significant correlation between top management commitment, organization readiness, and artificial intelligence adoption suggests that expenditures in these domains might greatly impact the results of AI implementation for SMEs. These findings may assist in informing resource distribution and decision-making by highlighting the position of organization readiness and top management commitment in achieving intended artificial intelligence objectives and identifying areas where labors may not yield desired outcomes. To make strategic decisions, it is important for organizations to recognize the strong connection between organization readiness and artificial intelligence. This means that organizations should prioritize enhancing their preparedness to get better results in artificial intelligence implementation (Tajeddini et al., 2023). This may include optimizing procedures, improving productivity, and allocating resources towards technical improvements to capitalize on the potential advantages of artificial intelligence. Due to the strong correlation between top management commitment and artificial intelligence, it is crucial for organizations to give high priority to the advancement and education of their personnel in these important areas. This entails offering chances for reskilling and upskilling to guarantee that the staff has the essential expertise to proficiently use artificial intelligence technology. In SMEs, when senior management engagement was absent, conflicting outcomes were seen (Mohammad & Muhammad, 2023). This research posits that the absence of endorsement from senior executives is a contributing factor to the limited adoption of artificial intelligence among SMEs (Alibraheem et al., 2024). The adaptability of employees does not seem to have any impact on the use of artificial intelligence, maybe since major organizations do not necessarily allocate resources towards adopting artificial intelligence, therefore rejecting H5. This outcome validates previous findings about the significance of top management commitment and organization readiness in forecasting information technology adoption. In terms of the environmental context, the impact of external assistance, favorable regulatory regimes, and competitive pressure on the adoption of artificial intelligence was found to be negligible. There was no evidence to support or refute hypothesis H7, H8, and H9. The absence of statistically significant connections implies that changes in these factors may not have a substantial influence on the variable artificial intelligence. Essentially, this means that focusing on altering external support, regulatory settings, or competitive pressure may not result in significant or observable impacts on artificial intelligence. Other aspects should be taken into account or investigated instead. The study results strongly correlate with the current situation of SME operations in Jordan (Alzoubi & Alzoubi, 2020). The lack of these resources may have a greater effect on SMEs, as their human resources, limited financial, and technical resources may hinder their ability to successfully implement digital technology (Wu et al., 2023). One potential explanation for the lack of impact of competitive pressure on the adoption of AI is the existence of industry-specific or organizational qualities that create difficulties in effectively incorporating artificial intelligence. These issues may stem from the intrinsic attributes of their operating methods or the qualities of the data they manage. Due to artificial intelligence's relatively limited advantages in these circumstances, competitive pressure may have less of an impact. Furthermore, the integration of artificial intelligence often requires significant expenditures in several areas, including technical infrastructure, data collection and management, the employment of qualified individuals, and ongoing system maintenance. When an organization has financial or resource constraints, the decision to invest in artificial intelligence may be deprioritized due to more immediate and critical concerns (Akter et al., 2021; Huang & Rust, 2022). This finding validates the findings of Lemos et al., (2022); Battistoni et al., (2023) on the significance of top management commitment and organization readiness in forecasting the adoption of information technology.

7. Conclusion

This research investigated the variables that influence the adoption of artificial intelligence among SMEs in Jordan. The data was analyzed via Smart PLS, employing a sample of 295 respondents obtained by a judgmental sampling approach. The survey data and research tools that were gathered from the structural model and measurement model using “bootstrapping” analyzes and the "PLS-SEM" method are valid and can be trusted. Based on the TOE model, we created and conducted an empirical examination of a model that explores the factors that influence the use of artificial intelligence in the process of hiring employees. The survey results from Jordan indicate that several factors in the domains of technology, organization, and environment directly influence the use of artificial intelligence. Considering the comprehensive results, it is recommended that technology and organizations allocate resources to prioritize investments in top management commitment and organization readiness in order to improve the outcomes of artificial intelligence. Although environmental influences may still be relevant, their influence on the adoption of artificial intelligence may not be as substantial. To enhance the likelihood of effective adoption and use of artificial intelligence, technology and organizations should carefully allocate resources and tackle the unique problems encountered by SMEs. Taking care of these issues will help us understand the pros and cons of implementing artificial intelligence in Small and Medium-sized Enterprises. This will lead to the creation of frameworks, effective strategies, and tools that will help Small and Medium-sized Enterprises take advantage of artificial intelligence technology's benefits. In general, there is an ongoing need for the implementation of sustainable development practices in Jordan, and the integration of artificial intelligence technology might potentially assist in achieving this objective. Adopting artificial intelligence technologies as auxiliary tools will be challenging if they are not fully acknowledged, and these challenges must be solved for artificial intelligence to achieve widespread adoption. This study only focuses on the overall utilization of artificial intelligence technology since Small and Medium-sized Enterprises in Jordan are still in the early phases of implementation. Hence, further investigations need to scrutinize the acceptability of artificial intelligence technology via a more focused lens, including areas like artificial intelligence implementation in advertising, customer service, product development, and sales. The limited number of participants in the sample also places restrictions on the research. The results and conclusions derived from a limited sample size may not accurately reflect the characteristics or behaviours of the whole population or Small and Medium-sized Enterprises as a whole. The study's results are less generalizable and have reduced external validity due to the limited sample size. In addition, the limited number of samples may restrict the range of data, thereby affecting the strength and dependability of the conclusions. Having a smaller number of data points makes it more difficult to include the whole spectrum of experiences, views, and settings associated with the deployment of artificial intelligence in Small and Medium-sized Enterprises. Small and Medium-sized Enterprises in various locations may have distinct obstacles and advantages when it comes to adopting artificial intelligence. Regional disparities in local rules, market circumstances, cultural norms, and available resources may significantly influence the implementation and results of AI efforts. Hence, the conclusions drawn from this research may not accurately represent the knowledge or trends found in Small and Medium-sized Enterprises outside the borders of Jordan. In order to improve the generalizability of the paper, future research should aim to broaden the range of Small and Medium-sized Enterprises included in the study, including various locations. This will provide a more thorough comprehension of the variables that impact the adoption of artificial intelligence and the resulting consequences. This will enhance the understanding of the difficulties and possibilities encountered by Small and Medium-sized Enterprises in various situations and assist in the creation of stronger and more practical plans for the use of artificial intelligence. Finally, as this study is based on quantitative data and depends on the viewpoints of participants rather than firsthand observations of artificial intelligence deployment and acceptance in enterprises, it is advisable for future research to utilize a qualitative research methodology or undertake case studies. This will provide a deeper understanding of the key drivers and challenges that impact organizations' choices to use artificial intelligence in their technological, organizational, and environmental settings.

References

Akter, S., Wamba, S., Mariani, I., & Hanu, I. (2021). How to build an AI climate-driven service analytics capability for innovation and performance in industrial markets? *Industrial Marketing Management, 97*, 258–273.

Alzoubi, S., & Zoubi, M. (2023). Exploring the relationship between robot employees' perceptions and robot-induced unemployment under COVID-19 in the Jordanian hospitality sector. *International Journal of Data and Network Science, 7*(4), 1563-1572.

Alzoubi, S. I., & Azloubi, S. (2020). Determinants of E-Learning Based on Cloud Computing adoption: Evidence from a Students' Perspective in Jordan. *International Journal of Advanced Science and Technology, 29*(4), 1361-1370.

Badi, S., Ochieng, E., Nasaj, M., & Papadaki, M. (2021). Technological, organizational and environmental determinants of smart contracts adoption: UK construction sector viewpoint*. Construction Management and Economics, 39*(1), 36–54.

Bag, S., Gupta, S., & Kumar, S. (2021). Industry 4.0 adoption and 10R advance manufacturing capabilities for sustainable development. *International Journal of Production Economics, 231*, 107844.

Baker, J. (2011). The technology-organization-environment framework. In Y. K.Dwivedi, M. R.Wade, & S. L. Schneberger (Eds.), Information systems theory: Explaining and predicting our digital society (Vol. 1, pp. 231–245). Springer Science & Business Media.

Battistoni, E., Gitto, S., Murgia, G., & Campisi, D. (2023). Adoption paths of digital transformation in manufacturing SME. *International Journal of Production Economic, 255* (October 2022), 108675 https://doi.org/10.1016/j.ijpe.2022.108675.

Chaveesuk, S., & Horkondee, S. (2015). An integrated model of business intelligence adoption in Thailand logistics service firms. Proceedings - 2015 7th International Conference on Information Technology and Electrical Engineering: Envisioning the Trend of Computer, Information and Engineering.

Christiansen, V., Haddara, M., & Langseth, M. (2022). Factors Affecting Cloud ERP Adoption Decisions in Organizations. *Procedia Computer Science, 196*, 255–262.

Cohen, W., & Levinthal, D. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly, 35*(1), 128–152. https://doi.org/10.2307/2393553.

Daoud, L., Marei, A., Al-Jabaly, S., & Aldaas, A. (2021). Moderating the role of top management commitment in usage of computer-assisted auditing techniques. *Accounting, 7*(2), 457–468. https://doi.org/10.5267/j.ac.2020.11.005.

David, A., & Jos´e, A. (2015). Assessing convergent and discriminant validity in the ADHD-R IV rating scale. In: Proceedings of the Spanish STATA Meeting 2015, 1–39. https://www.stata.com/meeting/spain15/abstracts/materials/spain15_ alarcon.pdf.

Deepu, T., & Ravi, V. (2021). Exploring critical success factors influencing adoption of digital twin and physical internet in electronics industry using grey-DEMATEL approach. *Digital Business, 1*(2), 100009 https://doi.org/10.1016/j.digbus.2021.100009.

Drydakis, N. (2022). Artificial intelligence and reduced SMEs' business risks. A dynamic capabilities analysis during the COVID-19 pandemic. *Information and System Frontier, 24*(4), 1223–1247. https://doi.org/10.1007/s10796-022 10249-6.

Dubey, R., Gunasekaran, A., Childe, S., Papadopoulos, T., Hazen, B., & Roubaud, D. (2018). Examining top management commitment to TQM diffusion using institutional and upper echelon theories. *International Journal of Production Research, 56*(8), 2988–3006. https://doi.org/ 10.1080.

Faliagka, E., Iliadis, L., Karydis, I., & Rigou, M. (2014). On-line consistent ranking on e-recruitment: Seeking the truth behind a well-formed CV. *Artificial Intelligence Review, 42*(3), 515–528. https://doi.org/10.

Fan, Y., & Lin, T. (2023). Identifying university students' online academic help-seeking patterns and their role in Internet self-efficacy. *The Internet and Higher Education, 56*, 100893.

Fountaine, T., Mccarthy, B., & Saleh, T. (2019). Building the AI-powered organization. Harv. Bus. Rev. 97 (4), 62–73.

Ganlin, P., Qamruzzaman, M., Mehta, A., Naqvi, W., & Karim, S. (2021). Innovative finance, technological adaptation and SMEs sustainability: the mediating role of government support during covid-19 pandemic. *Sustainability, 13*(16). https://doi. org/10.

Gonçalves, R., Dias, A., Costa, R., & Da, Q. (2022). Gaining competitive advantage through artificial intelligence adoption. *International Journal of Electronic Business, 1*(1), 1. https://doi.org/10.1504/ijeb.2022.10044363.

Guenole, N., & Feinzig, S. (2018). The business case for AI in HR: With insights and tips on getting started. IBM Smarter Workforce Institute, IBM. 2018.

Gutierrez, A., Boukrami, E., & Lumsden, R. (2015). Technological, organizational and environmental factors influencing managers' decision to adopt cloud computing in the UK. Journal of Enterprise Information Management, 28(6), 788-807.

Hair. (2017). A primer on partial least squares structural equation modeling (PLS-SEM).

Hansen, E., & Bøgh, S. (2021). Artificial intelligence and internet of things in small and medium-sized enterprises: a survey. *Journal of Manufacturing System, 58*(October 2019), 362–372. https://doi.org/10.1016/j.jmsy.2020.08.009.

Hashim, N., Samsuri, A., & Idris, N. (2021). Assessing organizations' readiness for technological changes in construction industry. *International Journal of Sustainable Construction Engineering Technology, 12*(1), 130–139. https://doi.org/10.30880/ijscet.2021.12.01.013.

Hmoud, B., & Várallyai, L. (2020). Artificial Intelligence in Human Resources Information Systems: Investigating its Trust and Adoption Determinants. *International Journal of Engineering and Management Sciences, 5*(1), 749–765.

Hoang, T., & Nguyen, H. (2022). Towards an economic recovery after the COVID-19 pandemic: empirical study on electronic commerce adoption by small and medium-sized enterprises in Vietnam. Management & Marketing. Challenges for the Knowledge Socie.

Hoyle, R. (2011). *Structural equation modeling for social and personality psychology*. Sage, London.

Hradecky, D., Kennell, J., Cai, W., & Davidson, R. (2022). Organizational readiness to adopt artificial intelligence in the exhibition sector in Western Europe. *International Journal of Information Management, 65*(February), 102497 https://doi.org/10.1016/j.ijinfomgt.2022.102497.

Huang, C., Wang, H., Yang, C., & Shiau, S. (2020). A derivation of factors influencing the diffusion and adoption of an open-source learning platform. *Sustainability, 12*(18), 7532.

Huang, M., & Rust, R. (2022). A framework for Collaborative Artificial Intelligence in Marketing. *Journal of Retailing, 98* (2), 209–223. https://doi.org/10.1016/j. jretai.2021.03.001.

Jalagat, R. (2016). The impact of change and change management in achieving corporate goals and objectives: organizational perspective. International Journal of Science and Research, *5*(November), 1233–1239. https://doi.org/10.21275/ART20163105.

Jayashree, S., Reza, M., Malarvizhi, C., & Mohiuddin, M. (2021). Industry 4.0 implementation and triple bottom line sustainability: an empirical study on small and medium manufacturing firms. *Heliyon, 7*(8), e07753. https://doi.org/10.1016/ j.heliyon.

Kline, R. (2010). *Principles and practice of structural equation modeling*. Guilford Press, New York.

Kumar, V., Ramachandran, D., & Kumar, B. (2021). Influence of new-age technologies on marketing: a research agenda. *Journal of Business Research, 125*(January 2020), 864–877. https:// doi.org/10.1016/j.jbusres.2020.01.007.

Leguina, A. (2015). *A primer on partial least squares structural equation modeling* (PLS-SEM).

Lemos, S., Ferreira, F., Zopounidis, S., Galariotis, E., & Ferreira, N. (2022). Artificial intelligence and change management in small and medium-sized enterprises: an analysis of dynamics within adaptation initiatives. *Annals of Opererations Research*. https://doi.org/10.1007/s10479-022-05159-4.

Lu, X., Wijayaratna, K., Huang, Y., & Qiu, A. (2022). AI-enabled opportunities and transformation challenges for SMEs in the post-pandemic era: a review and research agenda. *Frontier in Public Health, 10*(April), 1–11. https://doi.org/10.3389/ fpubh.2022.885067.

Maroufkhani, P., Tseng, M., & Iranmanesh, M. (2020). Big data analytics adoption: determinants and performances among small to medium-sized enterprises. *International Journal of Information Management, 54*, 102190 https://doi.org/10.1016/j. ijinfomgt.2020.

McDougall, N., Wagner, B., & MacBryde, J. (2022). Competitive benefits & incentivisation at internal, supply chain & societal level circular operations in UK agri-food SMEs. *Journal of Business Research, 144*(November 2020), 1149–1162. https://doi.org/10.1016/j. jbusres.2022.

Mohammad, N., & Muhammad, T. (2023). The effects of the internal and the external factors affecting artificial intelligence (AI) adoption in e-innovation technology projects in the UAE? Applying both innovation and technology acceptance theories. *International Journal of Data and Network Science, 7*, 1321–1332.

Mohammed, A., Algerafi, M., Yueliang, Z., Hind, A., & Tommy, T. (2023). Understanding the Factors Influencing Higher Education Students' Intention to Adopt Artificial Intelligence-Based Robots. *IEEE Acess, 11*(5), 99752-99764.

Murphy, S. (2016). 2016. Individual adaptability as a predictor of job performance. Dissertation Abstracts International Section A: Humanities and Social Sciences, 77(4-A(E), No-Specified. 〈 http://ovidsp.ovid.com/ovidweb.cgi?T=JS&PAGE=reference &D=psyc13&NEWS=psyc13&NEWS=N&A.

Pan, Y., Froese, F., Liu, N., Hu, Y., & Ye, M. (2022). The adoption of artificial intelligence in employee recruitment: The influence of contextual factors. *The International Journal of Human Resource Management, 33*(6), 1125–1147.

Perifanis, N., & Kitsios, F. (2023). Investigating the influence of artificial intelligence on business value in the digital era of strategy: a literature review. *Information, 14*(2). https://doi.org/10.3390/info14020085.

Pillai, R., Sivathanu, B., Mariani, M., Rana, N., Yang, B., & Dwivedi, Y. (2022). Adoption of AI-empowered industrial robots in auto component manufacturing companies. *Production Planning & Control, 33*(16), 1517-1533.

Ragazou, K., Passas, I., Garefalakis, A., & Zopounidis, C. (2023). Business intelligence model empowering SMEs to make better decisions and enhance their competitive advantage. *Discovery Analysis, 1*(1) https://doi.org/10.1007/s44257-022-00002-3.

Rameshwar, D., J, D., Bryde, B., & Yogesh, K. (2022). Impact of artificial intelligence-driven big data analytics culture on agility and resilience in humanitarian supply chain: A practice-based view. *International Journal of Production Economics ,25*(9), 1-15.

Rao, D., & Verweij, G. (2017). Sizing the prize: What's the real value of AI for your business and how can you capitalise? PwC Publication.

Rehman, M., & Rajkumar, M. (2022). Overcoming the Complexities in Decision-Making for Enterprise Software Products: Influence of Technological Factors. In Information and Communication Technology for Competitive Strategies (ICTCS 2020) (pp. 393–410). Spri.

Rogers, E. (1995). *The diffusion of innovations* (5th ed.). The Free Press.

Rosa, I., Liliawati, W., Efendi, R., Ingalagi, S., Mutkekar, R., & Kulkarni, P. (2021). Artificial intelligence (AI) adaptation: analysis of determinants among small to medium-sized enterprises (SME's). *IOP Conf. Ser.: Mater. Sci. Eng. 1049* (1), 0120.

Suddin, L., Brahim, C., Mohd, R., & Noor, F. (2023). Determining factors related to artificial intelligence (AI) adoption among Malaysia's small and medium-sized businesses. *Journal of Open Innovation: Technology, Market, and Complexity, 24*(11), 1-10.

Tajeddini, K., Gamage, T., Tajeddini, O., & Kallmuenzer, A. (2023). How entrepreneurial bricolage drives sustained competitive advantage of tourism and hospitality SMEs: The mediating role of differentiation and risk management. *International Journal of Hospitality Management, 111*.

Tornatzky, L., & Fleischer, M. (1990). *The process of technology innovation*. Lexington Books.

Verma, S., Sharma, R., Deb, S., & Maitra, D. (2021). Artificial intelligence in marketing: Systematic review and future research direction. *International Journal of Information Management Data Insights, 1*(1), 100002.

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. https://doi.org/10.1016/j.techfore.2010.03.006.

Wu, Q., Yan, D., & Umair, M. (2023). Assessing the role of competitive intelligence and practices of dynamic capabilities in business accommodation of SMEs. *Economic Analysis and Policy*, *77*, 1103-1114. https://doi.org/10.1016/j.eap.2022.11.024.

Yuan, P., Fabian, F., Ni, L., Yunyang, H., & Maolin, Y. (2021). The adoption of artificial intelligence in employee recruitment: The influence of contextual factors. *The International Journal of Human Resource Management, 19*(15), 1-24.