ACADEMICIA: An International Multidisciplinary Research Journal
ISSN: 2249-7137 Vol. 14 Issue 6, June, 2024 SJIF 2022= 8.252
A peer reviewed journal

UNVEILING THE NEXUS: INVESTIGATING ORGANISATIONAL CULTURE, EXTERNAL FACTORS, AND INTERNAL RESOURCES IN AI ADOPTION AMONG SMES IN DELHI-NCR

Abhay Jain*

*Assistant Professor,
Ibmr Group Of Institutions,
Gurgaon, Haryana, INDIA
Orchid id- 0009-0009-3264-0292
Email id- Abhayjaind352@Outlook.Com

DOI: 10.5958/2249-7137.2024.00015.9

ABSTR ACT

Organisational culture (OC) is a crucial factor that every organisation must address in order to thrive in the digital economy. The present study investigates the crucial drivers employing OC, external factors (EF), and organisational internal resources (OR) in adopting artificial intelligence tools by Delhi-NCR small and medium-sized businesses. Extensive scholarly literature forms the foundation of the study's conceptual framework. The study adopts a research philosophy rooted in positivism and utilises a deductive approach to investigate the relationship. The research strategy employed is survey-based. Utilising a straightforward method of random sampling to encompass a diverse range of industries and businesses. The study collected data from 196 SME owner-managers in order to examine the representable factors of the entire Delhi-NCR SMEs that influence their success or failure to adopt AI. We conducted the analysis using Smart-PLS 4 to evaluate the relationship between the endogenous and exogenous variables in the measurement and structural model. The study's findings indicate that OR, OC, and EF have a significant positive influence on AI adoption. This suggests that SMEs can improve their AI outcomes by enhancing their OR, OC, and EF processes. These findings can assist decision-making and resource allocation by emphasising the significance of critical factors in promoting Al outcomes and identifying areas where efforts may not yield desired results. According to the study, a key factor contributing to the limited adoption of AI among SMEs is the absence of support from top management. The study findings will provide valuable insights for policymakers and institutional chambers regarding the role of OC, OR, and EC in information system adoption. These insights can help inform the development of policies that take these important connections into account. Finally, the findings would enhance the understanding of the literature by presenting empirical evidence from the SMEs of Delhi-NCR, India.

KEYWORDS: *SMEs; Business Environment; Artificial Intelligence; Adoption; Emerging Countries.*

INTRODUCTION

The integration of artificial intelligence (AI) has revolutionised business operations across industries, fundamentally altering the competitive landscape (Müller, Fay, and von Brocke, 2018). This paper delves into innovative approaches for uncovering patterns within raw data to enhance decision-making accuracy, productivity, information development, and innovation support (Acharya, Singh, Pereira, and Singh, 2018; de Vasconcelos and Rocha, 2019; Yaqoob et al., 2016). In an era marked by significant change, AI plays a pivotal role, leading exploration into new boundaries and opportunities (Budhwar et al., 2022). Advancements in machine learning and big data analytics have positioned AI as a valuable tool for marketers, enabling a profound understanding of consumer behaviour, improved marketing campaigns, and enhanced business performance.

Small and medium-sized enterprise (SME) marketers, leveraging machine learning and data analytics, gain fresh perspectives on customer behaviour and preferences. This knowledge empowers the creation of more personalised, effective, and efficient marketing campaigns (Ma and Sun, 2020; Boddu et al., 2022; Volkmar et al., 2022). However, a critical question remains unanswered: what are the primary determining factors influencing the adoption of AI in local SMEs?

In today's highly competitive corporate landscape, staying technologically updated, including the integration of AI, is crucial for organisations, including SMEs. AI has the potential to assist significantly in strategic marketing decisions, offering benefits and opportunities for SMEs to optimise operations, enhance decision-making processes, and improve overall business performance (Davenport et al., 2020). Yet, successful AI implementation requires meticulous planning, substantial financial resources, and specialised knowledge (OECD, 2021). Despite these challenges, the potential advantages position AI as a potent instrument for SMEs to stimulate growth, foster innovation, and enhance competitiveness in the digital age (Campbell et al., 2020; Kumar et al., 2021).

Delving into the local economic structure of Delhi-NCR, SMEs contribute significantly, constituting 29.15% of the gross value added (GVA) in the overall Indian GDP for the year 2022 (Press Information Bureau, 2023). However, these SMEs lag in AI adoption due to a limited understanding of AI capabilities and insufficient resources for implementation (Ambad et al., 2020; Jaganathan et al., 2018). Despite their economic contribution, there is a dearth of research on AI and its impact on SMEs in Delhi-NCR. According to the Economic Census 2016–2021, there are 37,047 SMEs in Delhi-NCR (Ministry of Micro, Small, and Medium Enterprises, 2024).

This study aims to fill existing research gaps by investigating the correlation between environmental factors (EF), organisational culture (OC), organisational resources (OR), and AI adoption in SMEs from the perspective of Delhi-NCR's management. Despite previous research on AI adaptability, the distinct ecosystems of SMEs necessitate targeted exploration. Identifying determinants of success or failure in AI implementation in different sectors of Delhi-NCR's SME ecosystem is crucial for effective strategies and frameworks (Lada et al., 2023).

Research gaps in the adoption of AI in Delhi-NCR SMEs include a limited understanding of AI capabilities, resource constraints, and a lack of comprehensive studies specific to Indian region (refer Figure 1 and Figure 2). Additionally, the determinants of AI adoption success or failure in different industries within Delhi SMEs remains unexplored. A targeted study addressing these gaps can provide valuable insights into the factors influencing AI adoption, facilitating the development of customised strategies and frameworks for SMEs in Delhi-NCR.

Figure 1. Trends of researches done in SMEs context with Artificial Intelligence Adoption from year 2008-2024

Source: Author's Own

Figure 2. Emerging and Advanced Country wise research papers ranging from 2018-2024

Source: Author's Own

This study aims to contribute to a more comprehensive understanding of the challenges and advantages of AI implementation in SMEs in Delhi-NCR. By addressing these research gaps, it seeks to assist SMEs in making informed decisions and navigating the complexities of AI adoption. The findings will be instrumental in developing efficient strategies, frameworks, and tools tailored to the unique needs of SMEs in Delhi-NCR, ultimately empowering them to leverage the advantages offered by AI technologies and enhancing their overall competitiveness in the market.

Literature Review

Artificial intelligence (AI)

AI is the study of computer science that centres around developing intelligent machines capable of performing tasks that usually necessitate human intelligence (Joiner, 2018). AI systems are created to analyse and interpret data, acquire knowledge from experiences, make decisions, and solve problems in a manner similar to human cognition. Algorithms, machine learning techniques, and large datasets are utilised to gain knowledge, enhance performance, and adjust to evolving situations (Xu et al., 2021). Artificial intelligence (AI) is a broad field that includes subfields like natural language processing, computer vision, robotics, expert systems, and neural networks. It has applications in various domains such as healthcare, finance, transportation, gaming, small and medium-sized enterprises (SMEs), and marketing strategy. Small and medium-sized enterprises (SMEs) can derive various advantages from incorporating artificial intelligence technology. These include the opportunity to enhance internal processes, improve decision-making, and increase productivity. Prior research has examined the challenges and restrictions of implementing AI in small and medium-sized enterprises (Hansen and Bøgh, 2021; Moradi and Dass, 2022; Ulrich and Frank, 2021). Consequently, the discussion regarding the impact of AI on small and medium-sized enterprises (SMEs) is broadening.

Environmental Factors (EF)

EF evaluates how much a country's or industry's external environment impacts an enterprise. Environmental factors greatly influence SMEs' intention to embrace artificial intelligence for digital transformation, underscoring the importance of external context in driving technological adoption in SMEs (Dwivedi et al., 2021). SMEs frequently lack the skills, funding, and infrastructure to use AI effectively. EF helps SMEs overcome AI implementation obstacles and increase efficiency, decision-making, competitive advantage, and customer service (Rosa et al., 2022; Ragazou, 2023; Sjödin, 2021). Support for AI use boosts SME business performance. ES helps SMEs deploy AI, employ AI technologies, and improve productivity, decision-making, competitive advantage, customer service, data-driven insights, and scalability (Fountaine et al., 2019, OECD, 2021). Together, these characteristics boost SME performance. However, studies have shown that many elements influence the building of external factors in lieu of the purpose of adopting AI for digital transformation; thus, it is necessary to analyse the crucial environmental factors that affect the DV of this study in India. This study operationalizes competitive pressure, regulatory norms, and customer readiness to pressure firms to adopt AI. Companies must improve their products, services, and strategies to compete (Baabdullah et al., 2021). Businesses must handle competition to thrive (Wu et al., 2023). AI enables competitive analysis, tailored marketing, pricing optimisation, customer experience improvement, and predictive analytics. To compete, businesses can gain insights, target customers, optimise pricing, improve customer experiences, and make data-driven decisions. Many empirical studies show that innovation increases competition. Competitive pressure drives SMEs to adopt AI in their daily operations (Trường, 2022). SMEs' clients' AI adoption depends on customer preparedness. SMEs must understand consumer readiness to design AI adoption strategies as they digitise. Technological optimism, insecurity, and discomfort affect this aim (Flavián et al., 2022). Job relevance and perceived utility drive banking industry digital solution adoption (Omrani et al., 2022). According to Davis (1989) and Rogers (2003), consumer readiness is a measure of technology acceptance, digital literacy, and audience openness. For SMEs' digital transformation, customer preparedness and external factors drive AI and digital solution acceptability. Government legislation accelerates SMEs' digital transformation with AI. SMEs in rigorous regulatory environments may need AI technology to comply, according to research (Teo, 2019). Government regulatory pressure forces companies to embrace and implement digital technology standards, norms, and recommendations. According to Damanpur (1991) and Teo (2019), government regulation pressure in the macro environment impacts company behaviour, especially in technology-transformative sectors. Government legislation and environmental considerations also make SMEs understand the necessity of AI adoption for regulatory compliance, competitiveness, and future-proofing. Based on the above literature, the following hypothesis is proposed:

H1:External factors significantly affects the intention to adopt the AI for digital transformation by the Indian Firms.

Organisational Culture (OC)

OC is a comprehensive concept that includes common values, beliefs, customs, and practices that govern an organisation. Strong-focused, adaptable organisations are more likely to adopt new technology (Jung et al., 2003). Successful AI adoption for digital transformation in small and medium enterprises (SMEs) is not merely a technological challenge but also determined by the organisation's culture (Kagumba and Wausi, 2018). Various studies have examined organisational culture in various dimensions, like Valtiner and Reidl (2021). Change resistance, job displacement anxiety, and significant cultural shifts make promoting organisational culture with AI adoption difficult. On the contrary, these challenges allow organisations opportunities to actively shape their culture, invest in staff education, and establish clear communication channels (Zhang et al., 2019; Fernandes et al., 2013; Jung, 2003). Top management commitment is also vital to strategic decision-making. Strategic decisions in SMEs affect the company's long-term orientation and competitiveness (Dubey et al., 2018; Soltani, 2005). These decisions may involve choosing target markets, creating new products or services, forming partnerships, embracing new technologies, or expanding internationally. TMC is crucial to SMEs' strategic AI adoption and implementation decisions (Deepu and Ravi, 2021; Jayashree et al., 2021). Previous research has shown that TMC and AI adoption are linked. Top management commitment is crucial to the SME AI adoption strategy. It promotes AI awareness, integration, change acceptance, and benefits (Lemos et al., 2022; Rosa et al., 2021). Top management commitment is key to using AI to improve SMEs' decision-making, competitiveness, and performance. Organisational culture factors, including control, social control, and customer focus, increase AI adoption (Kagumba and Wausi, 2018). Sharma et al. (2022) revealed that SMEs' AI-based chatbot adoption intention was positively correlated with top management support and employee capabilities. This shows that a supportive and innovative company culture might help AI adoption. Ingalagi et al. (2021) found that top management commitment and organisational readiness affect SME AI implementation. These findings demonstrate the importance of a culture that appreciates and encourages technical innovation in SMEs' AI adoption for digital transformation. However, studies have not clearly highlighted the importance of fostering an organisational culture environment that enables employees willingness and change management to adopt AI for digital transformation. On contrary, Chaudhry (2022), these factors are also significant and may influence the intention to adopt AI as they demonstrate trust in new technologies, firm usefulness, and a firm culture towards ease of use to promote AI adoption among SMEs. Also, cultural factors like willingness to change affect AI adoption (Zhang et al., 2019). Organisations that are more flexible are more likely to use AI technologies. Additionally, innovative and adaptable firms are more likely to adopt new technology (Jung et al., 2003). Change management helps reduce resistance, promote favourable attitudes towards new technology, and ensure a smooth AI-driven process shift (Chaudhry, 2022). SME's adoption of AI requires a testimonial that showcases the impact of change management and employees willingness to use AI and enabled tools, as organisational culture is crucial for mitigating resistance, fostering a positive attitude towards new technologies, and ensuring a smooth transition to AI-driven processes (Savola, 2018). Thus, it becomes imperative to investigate the effect of organisational culture towards intention to adopt the AI for digital transformation in the Indian context. Following hypothesis is proposed:

H2: Organisational culture pushes Indian SMEs significantly for AI adoption.

Organization resource (OR)

Major organisational resources are financial, human, technological, and knowledge-based. AI adoption by SMEs depends on financial and technological resources (Dey et al., 2023). SMEs need resources and expertise to manage and exploit AI technology and infrastructure (Al-Hornai et al., 2023). Lack of IT maturity and concern about losing control over critical company activities to machine-based algorithms prevent SMEs from adopting AI (Schoeman and Seymour, 2022). These organisational components stress resource issues and IT skills and knowledge to encourage SMEs to use AI (Mokhtar and Salimon, 2022).

Budget capacity determines Indian SMEs' digital transformation (Dey et al., 2023). Corporate size and technology investment have an impact on AI adoption (DeStefano et al., 2022). Larger firms and those investing in cloud computing and database systems profit from AI (Gans, 2023). Cost-effectiveness, resource availability, and vendor support drive AI-based technology adoption (Al-Horani et al., 2023). A firm's cost structure improves greatly with AI automation. How augmented AI affects a firm's profit and expense structures is uncertain. The study will assess whether a firm's budgetary capacity impacts its digital transformation and AI adoption ambitions.

Technology maturity of Indian SMEs' infrastructure determines AI adoption. Davenport et al. (2010) say AI applications need robust technology. SMEs with better technology are more likely to adopt AI for digital transformation. Many studies have examined how technology resources affect SME AI adoption. According to these research, SMEs with modern hardware, software, IT infrastructure, and skilled IT personnel are more likely to adopt AI. AI may be integrated into SMEs with the right resources (Abuselidze and Mamaladze, 2021). Technology helps SMEs overcome AI adoption barriers like cost, relative advantage, and organisational readiness.

Indian SMEs need AI competence, training, and development. According to Damanpour (1991), a learning-centric workplace promotes competency, technical efficiency, and technology adoption (Rawashdeh et al., 2023). SMEs with this culture should embrace AI for digital transformation.

AI benefits boost digital transformation. The diffusion of innovation theory (Rogers, 2003) suggests that SMEs will adopt AI if it offers a clear advantage over present practises. McDougall et al. (2022) found that SMEs are more likely to use AI if it improves productivity, cost reductions, and decision-making. Innovations may boost company performance (Rogers, 2003). Its advantages over alternatives help firms accept innovation. Business value drives innovation adoption (Ali Abbasi, 2022). Companies employ useful innovations more often (Chatterjee et al., 2020). Big data, blockchain, social media marketing, and mobile payment adoption intents increase with relative advantage (Park and Kim, 2021; Hashimy et al., 2023). AI helps with business model innovation, sales, operations, and client targeting. AI adoption benefits must be assessed in competitive markets to obtain an edge. Thus, it is vital to establish if Indian SMEs benefit from AI for digital transformation.

SMEs undertaking digital transformation must focus on AI systems; trust is crucial. Mayer et al. (1995) discovered that SME trust in AI technologies is associated to favourable adoption intentions because trust is based on openness, reliability, and security. Trust reduces risks and increases SME AI adoption.

Efficiency gains from AI greatly impact SMEs' digital transformation ambitions. Bughin et al. (2020) believe SMEs that see AI's operational efficiency potential are more inclined to adopt it. Artificial intelligence, process optimisation, and resource use boost efficiency. Machine learning-based AI models boost SME productivity and decision-making (Rawashdeh et al., 2023). Accounting efficiency affects SME AI adoption and projected factors (Polas et al., 2022). Their study found that AI accounting automation saves time and boosts efficiency, making SMEs more open to AI. AI can boost SMEs' inventory, decision-making, and performance.

The ease of implementing AI affects Indian SMEs' goals. Venkatesh et al.'s (2003) TAM links perceived ease of use to adoption. SMEs that prefer user-friendly AI solutions with little training are more likely to adopt. AI technology and their benefits are known before acceptance. Knowing industry trends, market education, and government incentives makes SMEs more likely to employ AI for digital transformation (Gonçalves et al., 2022). Awareness promotes adoption. Also, SMEs seeking digital transformation must assess AI system performance and capacity. Companies who believe AI can boost performance, competitiveness, and efficiency employ it more (Fountaine et al., 2019). AI adoption by SMEs depends on accuracy and reliability.

OR AI adoption substantially influences SME operations and performance. Thus, high OR enhances resource management, trust, efficiency, ease of use, competency, robust data management, cooperation and skill development, awareness, and knowledge by integrating AI deployment with organisational strategy. Operational efficiency, decision-making, resource use, and performance improve SMEs. OR in AI adoption severely affects SMEs' operations and performance, therefore we proposed the following hypothesis.

H3: Organization Resources significantly influences the adoption of AI technologies.

Methodology

The study's philosophy is deemed to be positivism, followed by a deductive approach. The strategy employed for this study is survey-based, followed by a mono-method choice. The study used simple random sampling for the investigation. For analysis of hypotheses and conceptual models to be validated through PLS-SEM. As,in exploratory research, PLS-SEM yields accurate results (Hair et al., 2018). This method also does not limit the survey sample size (Willaby et al., 2015). Data with non-normal distributions cannot be analysed using covariance-based structural equation modelling (SEM). However, PLS-SEM may assess data without a normal distribution (Sarstedt et al., 2017; Khan et al., 2019). Smart PLS 4 analysed structural and measurement data. Smart PLS 4 software was used because it can analyse small data samples and validate theoretical frameworks from a prediction perspective (Hair et al., 2019). Surveying is the first stage in PLS-SEM. Survey participants' replies are analysed using a standard scale. The study used a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). All variables are measured this way. Two academics and one IT specialist face-validated the draft measurement scale. The pilot-phase study questionnaire was refined based on their responses to test understandability, reliability, and validity. The unit of analysis was SME owners. Environmental Factor (EF), Organisational Culture (OC), and Organisational Resources (OR) were the study's three higher-order constructs, 17 lower-order constructs, and the dependent variable AI adoption intention for digital transformation by Indian SMEs formed the model's conceptual foundation. Figure 3 shows the proposed research model as analysed by the theoretical models and main factors.

Sampling and Data Collection

Respondents owned or managed SMEs in the Delhi NCR from industries of services, manufacturing, construction, and agriculture. The company owner or management is chosen because they decide whether to implement new technology like AI. AI-customised knowledge is assumed to be complete. The sampling frame included 37,047 SMEs from Delhi NCR listed and registered with the MSME data portal. After repeated reminders sent twice a week via email and WhatsApp message, 196 responses were obtained. Many Delhi NCR SMEs are small and do not use AI-based solutions, which may explain the poor response rate. This amount is sufficient and meets Hair et al.'s (2016) and 2019 guidelines. This study uses simple random sampling because it covers multiple industries and business sizes. The difference is a crucial aspect of SME AI adoption. The study employed Common Method Bias (CMB) and Harman's single-factor test to authenticate the measurement items of the model. The initial component accounted for 38.6% of the variation. Given that a single component does not account for the majority of the variance, it is concluded that CMB is not significant in this particular situation (Podsakoff et al., 2003).

Figure 3: Conceptual Framework of the study

Respondents Profile

The data distributes SMEs by sector. Table 1 illustrates the number and proportion of SMEs by sector. This survey included 196 SMEs, with each sector contributing a percentage. SME numbers are highest in the services sector, with 84 companies (42.71%). Manufacturing follows with 49 companies, or 25% of the total. The construction sector comprises 41 SMEs, or 20.83% of the total. 22 SMEs, or 11.45% of the total, are in agriculture. The largest age group is 30–40, with 88 replies. The 40–50 age group follows with 62 respondents. The smallest age group is 20–30, with 46respondents. The bulk of responses are male numbers 147, while 49 are female. Moreover, 171 of the respondents were the small scale business owners and the rest 25 were medium scale sized business.

TABLE 1: RESPONDENT'S PROFILE BASED ON SECTOR

SME Sector	**N**	**Percentage**
Services	84	42.85
Manufacturing	49	25.00
Construction	41	20.83
Agriculture	22	11.45
Age		
20-30	46	23.4
30-40	88	44.83
40-50	62	31.6
50 and Above	0	0
Gender		
Male	147	75
Female	49	25
Size of Enterprise		
Small Scale	171	87.25
Medium Scale	25	12.75

Validity of the Measurement Model

Fornell and Larcker (1981) used factor loadings, composite reliability (CR), average variance explained (AVE), and reliability (Cronbach's alpha) to check for construct convergence. CR values of 0.7 or higher, all standardised factor loadings of 0.5 or higher, and AVE values of 0.5 or higher indicate convergent validity (Cheung et al., 2023; Henseler, 2015). Table 2 reveals that the higher-order construct measurement model meets CR, standardised loading, AE, and Cronbach's alpha requirements. This study validates the higher-order concept for measurement model evaluation. Each component was assessed for reliability and convergent validity. The study's LOC latent scores are used to assess HOC discriminant validity, according to Sarstedt et al. (2019). The HOCs (OR, OC, and EF) show reliability and validity. Summarising the results, all other constructs had reliability >.60 and convergent validity >.50 (Table 2).

TABLE 2: HIGHER ORDER CONSTRUCT VALIDITY AND RELIABILITY

Construct	**AVE**	**CR**	**Cronbach's Alpha**
Environmental Factors (EF)	.620	.787	.896
Organisational Culture (OC)	.647	.813	.830

Organisational Resources (OR)	.537	.706	.801

Discriminant Validity

The discriminant validity assessment ensures that a reflective construct has the strongest connections with its own indicators in the PLS path model (Hair et al., 2017; 2019). We check the OC, EF, and OR's discriminant validity with the LOCs (employee willingness, change management, top management commitment, competitive pressure, government pressure, customer readiness, relative advantage, trust, cost, efficiency, ease of use, awareness, knowledge, training and development, competency, budget, and performance). Another thing we look at is their reliability and validity. According to Franke and Sarstedt (2019); Gold, Malhotra, and Segars (2001), Fornell and Larcker's (1981) criterion shows that the construct's square root of AVE is greater than its correlation with all other constructs, and HTMT is less than.90. Table 3 shows that the measuring model has good discriminant validity for the constructs under study. In particular, all values are below 0.85, indicating construct discriminant validity. Each construct's correlations with indicators of other constructs are lower than those of the same construct, showing that they are separate and not significantly overlapping.

TABLE 3: HIGHER ORDER CONSTRUCT DISCRIMINANT VALIDITY: HETEROTRAIT-MONOTRAIT RATIO (HTMT)

Construct	AI	EF	OC	OR
Artificial Intelligence Adoption (AI)				
Environmental Factors (EF)	.678			
Organisational Culture (OC)	.234	.533		
Organisational Resources (OR)	.542	.674	.776	

Assessment of Structural Model

In PLS-SEM, the structural model evaluation focuses on determining the significance and relevance of path coefficients, followed by the model's explanatory and predictive power. Specifically, the structural model reflects the paths hypothesised in the research framework. The hypothesised paths from the research framework are reflected in the structural model. The significance of pathways, as well as the R^2 and Q^2, are used for the evaluation. Based on Figure 2, shows that the R^2 value of a model is 0.381, which means that approximately 38.1% of the variability in the dependent variable can be explained by the independent variables included in the model. In other words, the independent variables (i.e. OC, EF and OR) collectively account for 38.1% of the variation observed in the dependent variable (i.e. AI).

The quality or goodness of the model is measured by the strength of each structural path, which is determined by the R^2 value for the dependent variable, which should be equal to or greater than "0.1" (Falk & Miller, 2014). Table 4 and Figure 4 show that the R^2 value of 0.381 is more than 0.1 which is termed as a substantial value. As a result, predictive capacity is established. Q^2 also confirms the predictive importance of endogenous components. A Q^2 greater than "0" indicates that the model is predictively relevant (Q^2 = 0.109). In addition, the model fit was evaluated using SRMR. The SRMR score was 0.056, which is less than the necessary value of "0.10", indicating an acceptable model fit (Hair et al., 2016).

Figure 4: Structural Model

TABLE 4: HYPOTHESIS TESTING (PATH COEFFICIENT)

Hypothesis	**Original Sample (O)**	**Sample Mean (M)**	**Standard Deviation (ST DEV)**	**T statistics (O/STDEV)**	**P Values**	**Result**
H1 EF -> AI	.085	.077	.069	1.895	.001	Supported
H2 OC -> AI	-.153	-.093	.091	4.325	.002	Supported
H3 OR -> AI	.947	.916	.067	14.090	.000	Supported
Goodness of the model	Estimate	Threshold				
R^2	0.381	More than 0.1				Acceptable
Q^2	0.109	Greater than 0				Acceptable
SRMR	0.056	Less than 0.1				Acceptable

EF, OC, and OR significantly impact AI adoption (EF-AI: β = 0.085, t = 1.895, p < 0.001), OC-AI: β = -.153, t = 4.325, p < 0.001), and OR-AI: β =.947, t = 14.090, p < 0.001). Consequently, H1, H2, and H3 were supported. Results have little impact on AI. The statistically substantial positive connection suggests that EF, OC, and OR approaches could influence Al. To increase Al outcomes, SME organisations may benefit from improving OR, OC, and EF processes. These findings might help decision-making and resource allocation by highlighting the importance of critical factors in promoting Al outcomes and identifying areas where efforts might not be effective.

DISCUSSION

The study showed that Top Management Commitment (TMC) and Organisation Readiness (OR) had a substantial effect on AI adoption, confirming hypotheses H2 and H3. The considerable positive relationship between TMC, OR, and AI adoption implies that investments in these areas may have a major influence on AI outcomes for SMEs. These results may help to guide decision-making and resource allocation by emphasising the relevance of OR and TMC in obtaining desired AI goals and recognising areas where efforts may be ineffective. For strategic decision-making, the significant relationship between OR and Al implies that organizations should focus on optimizing their organisation readiness to improve Al outcomes (Aboelmaged, 2014). This could involve streamlining processes, enhancing efficiency, and investing in technological advancements to leverage the potential benefits of Al. Given the significant relationship between TMC and AI, organizations should prioritize the development and training of employees in relevant technological and managerial competencies. This includes providing opportunities for upskilling and reskilling to ensure that the workforce possesses the necessary skills to effectively utilize AI technologies. However, contradictory results were observed in small and medium-sized enterprises lacking top management commitment (Furuholt&Ørvik, 2006). This study asserts that the lack of support from top management is one of the reasons for the lack of adaptation of AI among SMEs.

Top Management Commitment (TMC) plays a crucial role in influencing AI technology adoption among SMEs (Daoud et al., 2021). Top management, including executives and senior leaders, have the authority and responsibility to set the vision and strategic direction of the organization. When there is a strong commitment from top management to embrace AI technology, it signals to the rest of the organization that AI is a strategic priority (Jayashree et al., 2021; Mikalef et al., 2023). This commitment helps align the efforts and resources of the organization towards AI adoption. Top management commitment is essential for allocating resources, including financial, technological, and human resources, towards AI initiatives (Dubey et al., 2018; Soltani, 2005). Without the support and commitment of top management, it can be challenging to secure the necessary resources to invest in AI technology, infrastructure, and talent acquisition (Deepu& Ravi, 2021; Lemos et al., 2022). TMC ensures that the SME organization allocates adequate resources to support the successful adoption and implementation of AI.

Organisation Readiness (OR) plays a significant role in influencing AI technology adoption among SMEs . AI adoption requires a robust technological infrastructure that can support the implementation and integration of AI systems and applications (Jöhnk et al ., 2021). Organisational Readiness involves evaluating and improving the technological infrastructure to ensure it can accommodate AI requirements, such as processing power, data storage capacity, and network bandwidth. AI adoption often entails changes in work processes, roles, and responsibilities (Hashim et al., 2021; Hradecky et al., 2022). OR involves effectively managing these changes by providing clear communication, training, and support to employees. It is important to engage employees throughout the AI adoption process, addressing any concerns or resistance they may have. Organisation Readiness ensures that employees understand the benefits of AI technology, are equipped with the necessary skills, and are prepared to adapt to new ways of working (Aboelmaged, 2014; Indriastuti and Fachrunnisa, 2021). By addressing these aspects of Organisation Readiness, SMEs can enhance their readiness to adopt AI technologies, overcome potential barriers, and maximize the benefits of AI adoption.

The statistically significant relationships suggests that changes in these variables (i.e. OR, EF, OC) may not have a significant impact on the variable Al (or its demonstration). Practically, this implies that efforts targeting changes in OR, EF, OC may not yield substantial or noticeable effects on Al, and other factors should be considered or explored. The findings of this research are extremely reflected in the actual state of SME activities in NCR-Delhi (Jaganathan et al., 2018). This absence may disproportionately impact SMEs, whose limited financial, technical, and human resources may impede the establishment of a successful digital technology adoption path (Battistoni et al., 2023; Wu et al., 2023). In practice, SMEs' difficulty in embracing AI technology may be caused by various problems. The results above support the findings of previous studies, among others lack of the ability to recognize the benefits that ICT or technology, lack of affordability of ICTs, poor infrastructure, and lack of adequate training and support (Oz and Sosik, 2000; Wei and Pardo, 2022). Even if they (i.e. OR, EF, OC) are statistically significant, organizations may still consider allocating excessive resources towards these areas concerning improving Al outcomes. So that considering other factors they may re-tune the resources more strategically towards OR and TMC initiatives that have demonstrated a significant impact on Al.

CONCLUSION

In conclusion, this study studied the factors influencing Delhi NCR SMEs' AI adoption. The Smart PLS 4 programme analysed data from 196 simple random sample responses. All research instruments and survey data acquired from the measurement model and structural model utilising the "bootstrapping" analysis and the "PLS-SEM” method had values above the benchmark value, as suggested by Hair et al. (2017). According to the findings, organisations should prioritise knowledge, trust, and efficiency in resources, change management, and competitive pressure in culture and environment to improve AI outcomes. Organisational culture and environmental factors were equally important in this study. Advocating for all three HOCs to boost AI adoption. By efficiently planning for training and development and prioritising cost-based AI technologies that may improve competency and efficiency, Indian enterprises can raise their chances of successful AI adoption for digital transformation. Addressing these issues will help firm owners develop effective strategies, frameworks, and tools to help SMEs harness the benefits of AI technologies and improve performance through an enhanced understanding of the opportunities and challenges of AI adoption in SMEs. The result should result in high trust, competency, and relative advantage. Overall, awareness of new AI tools and solutions is required to aid AI technology adoption. Without proper adoption, using AI technologies as supporting tools will be challenging. These obstacles must be overcome for AI to gain widespread acceptability.

Limitations and Future Direction

This study delimits AI technology's widespread implementation to Delhi NCR SME adoption only. More specific studies should be conducted to assess the acceptance of AI technology in product development, customer service, sales, and advertising. Another drawback is the study's sample size (196). The sample results may be less indicative of the population for this study. Moreover, it's harder to capture SMEs' AI adoption experiences, views, and settings with fewer data points. SMEs in different locations may face different AI adoption obstacles and opportunities. Furthermore, age, gender, and business size can be used as moderators to study new dimensions and insights on AI adoption and outcomes. This study may not reflect the experiences or tendencies of SMEs outside Delhi, NCR. Future research should involve SMEs from varied areas to better understand AI adoption and its ramifications and increase external validity. This would enable SMEs in varied contexts to understand their difficulties and possibilities and design more robust and relevant AI adoption plans. Finally, AI use in SMEs may displace workers. A future study should address how AI affects SMEs and micro-enterprises, as well as ways to prevent negative effects such as job losses, lack of opportunities, and re-skilling and upskilling initiatives.

REFERENCES

Aboelmaged, M. G. (2014). Predicting e-readiness at firm-level: An analysis of technological, organizational and environmental (TOE) effects on e-maintenance readiness in manufacturing firms. *International Journal of Information Management*, *34*(5), 639-651.

Abuselidze, G., &Mamaladze, L. (2021, March). The impact of artificial intelligence on employment before and during pandemic: A comparative analysis. In *Journal of Physics: Conference Series* (Vol. 1840, No. 1, p. 012040). IOP Publishing.

Acharya, A., Singh, S. K., Pereira, V., & Singh, P. (2018). Big data, knowledge co-creation and decision making in fashion industry. *International Journal of Information Management*, *42*, 90-101.

Ali Abbasi, G., Abdul Rahim, N. F., Wu, H., Iranmanesh, M., &Keong, B. N. C. (2022). Determinants of SME's social media marketing adoption: competitive industry as a moderator. *Sage Open*, *12*(1), 21582440211067220.

Ambad, S. N. A., Andrew, J. V., & Awang Amit, D. H. D. (2020). Growth challenges of SMEs: empirical evidence in Sabah, Malaysia. *ASEAN Entrepreneurship Journal (AEJ)*, *6*(1), 8-14.

Baabdullah, A. M., Alalwan, A. A., Slade, E. L., Raman, R., &Khatatneh, K. F. (2021). SMEs and artificial intelligence (AI): Antecedents and consequences of AI-based B2B practices. *Industrial Marketing Management*, *98*, 255-270.

Battistoni, E., Gitto, S., Murgia, G., &Campisi, D. (2023). Adoption paths of digital transformation in manufacturing SME. *International Journal of Production Economics*, *255*, 108675.

Boddu, R. S. K., Santoki, A. A., Khurana, S., Koli, P. V., Rai, R., & Agrawal, A. (2022). An analysis to understand the role of machine learning, robotics and artificial intelligence in digital marketing. *Materials Today: Proceedings*, *56*, 2288-2292.

Budhwar, P., Malik, A., De Silva, M. T., &Thevisuthan, P. (2022). Artificial intelligence–challenges and opportunities for international HRM: a review and research agenda. *The International Journal of Human Resource Management*, *33*(6), 1065-1097.

Bughin, J. (2020). Artificial Intelligence, Its Corporate Use and How It Will Affect the Future of Work. In *Capitalism, Global Change and Sustainable Development* (pp. 239-260). Springer International Publishing.

Campbell, C., Sands, S., Ferraro, C., Tsao, H. Y. J., &Mavrommatis, A. (2020). From data to action: How marketers can leverage AI. *Business horizons*, *63*(2), 227-243.

Chatterjee, S., Nguyen, B., Ghosh, S. K., Bhattacharjee, K. K., & Chaudhuri, S. (2020). Adoption of artificial intelligence integrated CRM system: an empirical study of Indian organizations. *The Bottom Line*, *33*(4), 359-375.

Chaudhry, I. S., Paquibut, R. Y., &Chabchoub, H. (2022, November). Factors Influencing Employees Trust in AI & its Adoption at Work: Evidence from United Arab Emirates. In *2022 International Arab Conference on Information Technology (ACIT)* (pp. 1-7). IEEE.

Cheung, G. W., Cooper-Thomas, H. D., Lau, R. S., & Wang, L. C. (2023). Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia Pacific Journal of Management*, 1-39.

Dabbous, A., Aoun Barakat, K., &Merhej Sayegh, M. (2022). Enabling organizational use of artificial intelligence: an employee perspective. *Journal of Asia Business Studies*, *16*(2), 245-266.

Damanpour, F. (2018). Organizational innovation: A meta-analysis of effects of determinants and moderators. In *Organizational Innovation* (pp. 127-162). Routledge.

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.

Davenport, T., Guha, A., Grewal, D., &Bressgott, T. (2020). How artificial intelligence will change the future of marketing. Journal of the Academy of Marketing Science, 48(1), 24–42. https://doi.org/10.1007/s11747-019-00696-0

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340.

De Vasconcelos, J. B., & Rocha, Á. (2019). Business analytics and big data. *International Journal of Information Management*, *46*(C), 320-321.

Deepu, T. S., & 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.

DeStefano, T. J., Teodorovicz, T., Cho, J., Kim, H., & Paik, J. (2022). What Determines AI Adoption?. In *Academy of Management Proceedings* (Vol. 2022, No. 1, p. 14791). Briarcliff Manor, NY 10510: Academy of Management.

Dey, P. K., Chowdhury, S., Abadie, A., Vann Yaroson, E., & Sarkar, S. (2023). Artificial intelligence-driven supply chain resilience in Vietnamese manufacturing small-and medium-sized enterprises. *International Journal of Production Research*, 1-40.

Dubey, R., Gunasekaran, A., Childe, S. J., Papadopoulos, T., Hazen, B. T., &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.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*, 101994.

Falk, R. F., & Miller, N. B. (1992). *A primer for soft modeling*. University of Akron Press.

Fernandes, J., et al. (2013). Designing and implementing collaborative networks: A case study. *Expert Systems with Applications*, 40(6), 1883-1895.

Flavián, C., Pérez-Rueda, A., Belanche, D., &Casaló, L. V. (2022). Intention to use analytical artificial intelligence (AI) in services–the effect of technology readiness and awareness. *Journal of Service Management*, *33*(2), 293-320.

Forbes Advisor (2023). MSME Statistics of 2024. Available at: https://www.forbes.com/advisor/in/business/msme-statistics/

Fornell, C., &Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, *18*(1), 39-50.

Fountaine, T., McCarthy, B., & Saleh, T. (2019). Building the AI-powered organization. *Harvard Business Review*, *97*(4), 62-73.

Franke, G., &Sarstedt, M. (2019). Heuristics versus statistics in discriminant validity testing: a comparison of four procedures. *Internet Research*, *29*(3), 430-447.

Furuholt, B., &Ørvik, T. U. (2006). Implementation of information technology in Africa: Understanding and explaining the results of ten years of implementation effort in a Tanzanian organization. *Information Technology for Development*, *12*(1), 45-62.

Gans, J. S. (2023). Artificial intelligence adoption in a competitive market. *Economica*, *90*(358), 690-705.

Gold, A. H., Malhotra, A., & Segars, A. H. (2001). Knowledge management: An organizational capabilities perspective. *Journal of management information systems*, *18*(1), 185-214.

Gonçalves, M. J. A., da Silva, A. C. F., & Ferreira, C. G. (2022, February). The future of accounting: how will digital transformation impact the sector?. In *Informatics* (Vol. 9, No. 1, p. 19). MDPI.

Hair, J. F., Hult, G. T. M., Ringle, C. M., &Sarstedt, M. (2017). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). Thousand Oaks. *Sage*, 165.

Hair, J.F., Risher, J., Sarstedt, M. and Ringle, C.M. (2018), "When to use and how to report the results of PLS-SEM", European Business Review, Vol. 31 No. 1, pp. 2-24.

Hair, Joseph F, Black, W. C., Babin, B. J., & Anderson, R. E. (2016). *Multivariate data analysis* (8th ed.). Cengage Learning.

Hair, Joseph F, Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.

Hansen, E. B., &Bøgh, S. (2021). Artificial intelligence and internet of things in small and medium-sized enterprises: A survey. *Journal of Manufacturing Systems*, *58*, 362-372.

Hashim, N., Samsuri, A. S., & Idris, N. H. (2021). Assessing Organisations' Readiness for Technological Changes in Construction Industry. *International Journal of Sustainable Construction Engineering and Technology*, *12*(1), 130-139.

Hashimy, L., Jain, G., &Grifell-Tatjé, E. (2023). Determinants of blockchain adoption as decentralized business model by Spanish firms–an innovation theory perspective. *Industrial Management & Data Systems*, *123*(1), 204-228.

Henseler, J., Ringle, C. M., &Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science*, *43*, 115-135.

Horani, O. M., Al-Adwan, A. S., Yaseen, H., Hmoud, H., Al-Rahmi, W. M., &Alkhalifah, A. (2023). The critical determinants impacting artificial intelligence adoption at the organizational level. *Information Development*, 02666669231166889.

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*, 102497.

Indriastuti, D., &Fachrunnisa, O. (2021). Achieving organizational change: Preparing individuals to change and their impact on performance. *Public Organization Review*, *21*, 377-391.

Ingalagi, S. S., Mutkekar, R. R., & Kulkarni, P. M. (2021). Artificial Intelligence (AI) adaptation: Analysis of determinants among Small to Medium-sized Enterprises (SME's). In *IOP Conference Series: Materials Science and Engineering* (Vol. 1049, No. 1, p. 012017). IOP Publishing.

Jaganathan, M., Ahmad, S., Ishak, K. A., Nafi, S. N. M., &Uthamaputhran, L. (2018). Determinants for ICT adoption and problems: Evidence from rural based small and medium enterprises in Malaysia. *International Journal of Entrepreneurship*, *22*(4), 1-13.

Jayashree, S., Reza, M. N. H., Malarvizhi, C. A. N., & Mohiuddin, M. (2021). Industry 4.0 implementation and Triple Bottom Line sustainability: An empirical study on small and medium manufacturing firms. *Heliyon*, *7*(8).

Jöhnk, J., Weißert, M., &Wyrtki, K. (2021). Ready or not, AI comes—an interview study of organizational AI readiness factors. *Business & Information Systems Engineering*, *63*, 5-20.

Joiner, I. A. (2018). *Emerging library technologies: it's not just for geeks*. Chandos Publishing.

Jung, D. I., Chow, C., & Wu, A. (2003). The role of transformational leadership in enhancing organizational innovation: Hypotheses and some preliminary findings. *The Leadership Quarterly*, 14(4-5), 525-544.

Kagumba, F. G., &Wausi, A. N. (2018). The influence of organizational culture on the adoption of ICT innovation following technological disruption: Evidence from Kenyan ICT SMEs. *International Journal of Advances in Scientific Research and Engineering (ijasre)*, *4*(1), 21-33.

Khan, G.F., Sarstedt, M., Shiau, W.-L., Hair, J.F., Ringle, C.M. and Fritze, M.P. (2019), "Methodological research on partial least squares structural equation modeling (PLS-SEM): an analysis based on social network approaches", Internet Research, Vol. 29 No. 3, pp. 407-429.

Khan, N. A., Khan, A. N., Bahadur, W., & Ali, M. (2021). Mobile payment adoption: a multi-theory model, multi-method approach and multi-country study. *International Journal of Mobile Communications*, *19*(4), 467-491.

Kumar, V., Ramachandran, D., & Kumar, B. (2021). Influence of new-age technologies on marketing: A research agenda. *Journal of Business Research*, *125*, 864-877.

Lada, S., Chekima, B., Karim, M. R. A., Fabeil, N. F., Ayub, M. S., Amirul, S. M., ... and Zaki, H. O. (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*, *9*(4), 100144.

Lemos, S. I., Ferreira, F. A., Zopounidis, C., Galariotis, E., & Ferreira, N. C. (2022). Artificial intelligence and change management in small and medium-sized enterprises: an analysis of dynamics within adaptation initiatives. *Annals of Operations Research*, 1-27.

Ma, L., & Sun, B. (2020). Machine learning and AI in marketing–Connecting computing power to human insights. *International Journal of Research in Marketing*, *37*(3), 481-504.

Maroufkhani, P., Tseng, M. L., Iranmanesh, M., Ismail, W. K. W., and Khalid, H. (2020). Big data analytics adoption: Determinants and performances among small to medium-sized enterprises. *International journal of information management*, *54*, 102190

Mayer, R. C., Davis, J. H., &Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of management review*, *20*(3), 709-734.

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*, 1149-1162.

Mikalef, P., Islam, N., Parida, V., Singh, H., &Altwaijry, N. (2023). Artificial intelligence (AI) competencies for organizational performance: A B2B marketing capabilities perspective. *Journal of Business Research*, *164*, 113998.

Ministry of Micro, Small and Medium Enterprises (2024). MSME DASHBOARD. Available at: https://dashboard.msme.gov.in/udyam_dist_wise.aspx?stid=7

Mokhtar, S. S. M., &Salimon, M. G. (2022). SMEs’ Adoption of Artificial Intelligence-Chatbots for Marketing Communication: A Conceptual Framework for an Emerging Economy. In *Marketing Communications and Brand Development in Emerging Markets Volume II: Insights for a Changing World* (pp. 25-53). Cham: Springer International Publishing.

Moradi, M., &Dass, M. (2022). Applications of artificial intelligence in B2B marketing: Challenges and future directions. *Industrial Marketing Management*, *107*, 300-314.

Müller, O., Fay, M., &VomBrocke, J. (2018). The effect of big data and analytics on firm performance: An econometric analysis considering industry characteristics. *Journal of Management Information Systems*, *35*(2), 488-509.

OECD. (2021). Artificial Intelligence, Machine Learning and Big Data in Finance: Opportunities, Challenges, and Implications for Policy Makers. OECD Business and Finance Outlook 2020 : Sustainable and Resilient Finance., 1–72. Available at: https://www.oecd.org/finance/financialmarkets/Artificial-intelligence-machine-learning-big-data-in-finance.pdf

Omrani, N., Rejeb, N., Maalaoui, A., Dabić, M., & Kraus, S. (2022). Drivers of digital transformation in SMEs. *IEEE Transactions on Engineering Management*.

Oz, E., &Sosik, J. J. (2000). Why information systems projects are abandoned: a leadership and communication theory and exploratory study. *Journal of Computer Information Systems*, *41*(1), 66-78.

Park, J. H., & Kim, Y. B. (2021). Factors activating big data adoption by Korean firms. *Journal of Computer Information Systems*, *61*(3), 285-293.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of applied psychology*, *88*(5), 879.

Polas, M. R. H., Jahanshahi, A. A., Kabir, A. I., Sohel-Uz-Zaman, A. S. M., Osman, A. R., & Karim, R. (2022). Artificial intelligence, blockchain technology, and risk-taking behavior in the 4.0 IR Metaverse Era: evidence from Bangladesh-based SMEs. *Journal of Open Innovation: Technology, Market, and Complexity*, *8*(3), 168.

Premkumar, G., & Roberts, M. (1999). Adoption of new information technologies in rural small businesses. *Omega*, *27*(4), 467-484.

Press Information Bureau (2023). Ministry of Micro Small and Medium Enterprises. Available at: https://pib.gov.in/PressReleaseIframePage.aspx?PRID=1985020

Ragazou, K., Passas, I., Garefalakis, A., &Zopounidis, C. (2023). Business intelligence model empowering SMEs to make better decisions and enhance their competitive advantage. *Discover Analytics*, *1*(1), 2.

Rawashdeh, A., Bakhit, M., &Abaalkhail, L. (2023). Determinants of artificial intelligence adoption in SMEs: The mediating role of accounting automation. *International Journal of Data and Network Science*, *7*(1), 25-34.

Rogers, E. M. (2003). Diffusion of innovations, 5th edn London. *UK: Free Press.[Google Scholar]*.

Rosa, A., Bento, T., Pereira, L., Costa, R. L. D., Dias, Á., & Gonçalves, R. (2022). Gaining competitive advantage through artificial intelligence adoption. *International Journal of Electronic Business*, *17*(4), 386-406.

Rosa, I. S., Liliawati, W., Efendi, R., Ingalagi, S. S., Mutkekar, R. R., & Kulkarni, P. M. (2021). Artificial Intelligence (AI) adaptation: Analysis of determinants among Small to Mediumsized Enterprises (SME's). IOP Conference Series: Materials Science and Engineering, 1049(1), 012017. https://doi.org/10.1088/1757-899X/1049/1/012017

Sarstedt, M., Ringle, C.M. and Hair, J.F. (2017), "Partial least squares structural equation modeling", in Homburg, C., Klarmann, M. and Vomberg, A. (Eds), Handbook of Market Research, Springer International Publishing, Chams, pp. 1-40.

Sarstedt, M., Hair Jr, J. F., Cheah, J. H., Becker, J. M., &Ringle, C. M. (2019). How to specify, estimate, and validate higher-order constructs in PLS-SEM. *Australasian marketing journal*, *27*(3), 197-211.

Savola, T., Tuohimaa, T., & Berg, S. (2018). AI-Enhanced Marketing Management–Factors Influencing Adoption in SMEs.

Schoeman, F., & Seymour, L. F. (2022, July). Understanding the Low Adoption of AI in South African Medium Sized Organisations. In *Proceedings of 43rd Conference of the South African Insti* (Vol. 85, pp. 257-269).

Sharma, S., Singh, G., Islam, N., &Dhir, A. (2022). Why do smes adopt artificial intelligence-based chatbots?. *IEEE Transactions on Engineering Management*.

Sjödin, D., Parida, V., Palmié, M., &Wincent, J. (2021). How AI capabilities enable business model innovation: Scaling AI through co-evolutionary processes and feedback loops. *Journal of Business Research*, *134*, 574-587.

Soltani, E. (2005). Top management: A threat or an opportunity to TQM?. *Total Quality Management & Business Excellence*, *16*(4), 463-476.

Teo, T. S. H. (2019). The impact of government support, institutions, and regulations on e-commerce adoption in developing countries. Information Systems Frontiers, 21(6), 1381-1395

Trường, T. N. X. (2022). Adopting digital transformation in small and medium enterprises: An empirical model of Influencing factorsbased on TOE-TAM integrated. *TạpchíNghiêncứuTàichính-Marketing*, 45-57.

Ulrich, P., & Frank, V. (2021). Relevance and adoption of AI technologies in German SMEs–results from survey-based research. *Procedia Computer Science*, *192*, 2152-2159.

Valtiner, D., &Reidl, C. (2021). On change management in the age of artificial intelligence: a sustainable approach to overcome problems in adapting to a disruptive, technological transformation. *Journal of Advanced Management Science Vol*, *9*(3).

Volkmar, G., Fischer, P. M., & Reinecke, S. (2022). Artificial Intelligence and Machine Learning: Exploring drivers, barriers, and future developments in marketing management. *Journal of business research*, *149*, 599-614.

Wei, R., & Pardo, C. (2022). Artificial intelligence and SMEs: How can B2B SMEs leverage AI platforms to integrate AI technologies?. *Industrial Marketing Management*, *107*, 466-483.

Willaby, H.W., Costa, D.S.J., Burns, B.D., McCann, C. and Roberts, R.D. (2015), "Testing complex models with small sample sizes: a historical overview and empirical demonstration of what partial least squares (PLS) can offer differential psychology", Personality and Individual Differences, Vol. 84, pp. 73-78.

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.

Xu, Y., Liu, X., Cao, X., Huang, C., Liu, E., Qian, S., ... & Zhang, J. (2021). Artificial intelligence: A powerful paradigm for scientific research. *The Innovation*, *2*(4).

Zhang, H., et al. (2019). Cultivating innovative behavior in firms: The role of top management transformational leadership, organizational culture, and climate for creativity. *Journal of Business Research*, 97, 37-46.

Yaqoob, I., Hashem, I. A. T., Gani, A., Mokhtar, S., Ahmed, E., Anuar, N. B., &Vasilakos, A. V. (2016). Big data: From beginning to future. *International Journal of Information Management*, *36*(6), 1231-1247.