Journal of Infrastructure, Policy and Development 2025, 9(1), 9498.
https://doi.org/10.24294/jipd9498

Article

The AI revolution: Identifying the internal capabilities to AI-powered innovation among manufacturing small and medium enterprises

R. I. David Pooe*, Watson Munyanyi*

University of Johannesburg, Johannesburg 2006, South Africa
*** Corresponding authors:** David Pooe, dpooe@uj.ac.za; Watson Munyanyi, wmunyanyi@hotmail.com

CITATION

Pooe RID, Munyanyi W. (2025). The AI revolution: Identifying the internal capabilities to AI-powered innovation among manufacturing small and medium enterprises. Journal of Infrastructure, Policy and Development. 9(1): 9498. https://doi.org/10.24294/jipd9498

ARTICLE INFO

Received: 8 October 2024
Accepted: 13 November 2024
Available online: 8 January 2025

Abstract: The ongoing fourth industrial revolution has undoubtedly had a significant impact on virtually all aspects of society and business, and in this disruptive digital landscape. This study investigates the critical internal capabilities that enable small and medium enterprises to effectively adopt AI-driven innovations in the South African context. By examining key factors such as AI readiness, organizational learning capacity, strategic flexibility, and data management capabilities, the research provides a comprehensive analysis of their impact on AI-powered innovation performance. Using structural equation modelling to analyse data from SME owners and managers, the findings reveal significant positive correlations between these internal capabilities and innovation success. The results highlight the importance of investing in technological infrastructure, fostering a learning-oriented culture, and enhancing data management systems to ensure sustained competitiveness in the rapidly evolving AI landscape. These insights are crucial for SMEs aiming to leverage AI technologies for business growth and for policymakers seeking to support technology-driven sector development in emerging markets.

Keywords: artificial intelligence; innovation; disruptive digital landscape; innovation performance

1. Introduction

The massive diffusion of digital technologies, such as the Internet of Things (IoT), cloud computing, blockchain, big data, artificial intelligence, algorithms, and virtual reality, is forcing firms to confront an external environment characterized by unprecedented levels of complexity and velocity (Crupi et al., 2022; Troise et al., 2022). The ongoing fourth industrial revolution (4IR) has undoubtedly had a significant impact on virtually all aspects of society and business, and in this disruptive digital landscape, Artificial Intelligence (AI) has emerged as a transformative force. AI and machine learning, its immediate subset, have been defined as computational and mathematical algorithmic models that execute trained data and humanoid experiences input in making decisions a human being who is an expert in the field would make when provided with similar information (Alhashmi et al., 2019, Yorks et al., 2020). The adoption of AI has reshaped the way businesses interact, forcing them to redefine their business models (Kohtamäki et al., 2022). AI has been depicted as a game-changer, a transformative force that has the potential to make businesses more sustainable and competitive (Chauhan et al., 2022a; Iansiti and Lakhani, 2020). The change in business models has been proven by the rise in businesses like Airbnb, Uber, eBay, Amazon, and numerous other business enterprises that have incorporated AI-powered business models (Fountaine et al., 2019; Mishra and Tripathi, 2020). Other examples of successful implementation of AI deep learning technology that are more visible include Google Assistance, Alexa, and Siri (Mishra and Tripathi, 2020). There has been consensus in the literature on the transformative nature of AI and its capacity to ignite significant changes in business processes as well as its likelihood to intensify in coming years (Jarrahi, 2018; Jarrahi et al., 2023). According to Cooper (2023a), most AI early adopter firms have demonstrated that AI has been remarkably useful in areas such as new product development, offering significant payoffs in many business processes. In the case of Small and Medium Enterprises (SMEs), AI presents a unique opportunity to enhance productivity, streamline operations, and innovate in ways that were previously unimaginable.

Generally, firms largely rely on their capabilities to attain and maintain a sustainable competitive advantage in the face of intensified competition and rapid technological advancement (Kraus et al., 2020). This development necessitates the need for collaboration and co-creation of products and services (Bogers et al., 2018; Jasimuddin and Naqshbandi, 2019; Sengupta and Sena, 2020). The significance of innovation among SMEs cannot be over-elaborated, as it is central to their ability to sustain a competitive advantage, respond to environmental changes, and drive growth (Teoh et al., 2023). As momentum grows in the adoption of 4IR technologies, SMEs face increasing pressure to innovate and remain competitive in an era marked by rapid technological advancements. While there is a consensus that the advent of AI poses several transformative opportunities for SMEs to enhance their operations, products, and services, many SMEs still struggle to harness its capabilities effectively. Notably, while large corporations often have the resources and expertise to leverage AI effectively, SMEs frequently struggle to identify and develop the internal capabilities required to fully realize the benefits of AI-powered innovation. The challenge lies in identifying and developing these critical internal capabilities that enable SMEs to successfully implement AI-driven innovations. Without a clear understanding of these enablers, SMEs risk falling behind in the competitive landscape and fail to leverage the full potential of AI. In this regard, there exists a critical gap between potential and actualisation among SMEs, stemming from inadequate organisational capabilities, such as AI readiness, organizational learning capacity, strategic flexibility and data management capabilities.

The South African National Development Plan (NDP) 2030 highlights that technologies associated with the 4IR hold the potential to enhance economic growth and productivity in South Africa (Gonese and Ngepah, 2024). However, similar to many other nations, South Africa struggles with the challenge of transitioning to an era where SMEs can generate employment opportunities and deliver benefits to all its citizens (Olaitan et al., 2021; Sutcliffe and Bannister, 2020). Understanding and identifying these internal capabilities is vital, not only for guiding SMEs in their AI adoption journey but also for informing policymakers and industry stakeholders seeking to support SME growth through technology-driven innovation. In addition, although in recent years, the focus has increasingly shifted toward understanding how internal capabilities enable successful technology adoption and innovation (Shen et al., 2022; Sony et al., 2023a), there remains a gap in understanding the specific internal capabilities that are most critical for SMEs to harness AI for innovation. This gap is particularly pronounced in emerging markets, where SMEs face additional challenges related to infrastructure, skills, and financial resources. Unfolding AI technology as the promoter of innovation and grounded on the dynamic capabilities framework (DCF), this study aims to bridge this gap by investigating the internal capabilities that influence AI-powered innovation among SMEs in the South African context. By identifying these key enablers, the study seeks to provide actionable insights that can help SMEs navigate the complexities of AI adoption, thereby enhancing their competitiveness and contributing to broader economic growth. This study seeks to address this gap by investigating the key internal capabilities that influence AI-powered innovation in SMEs, thereby providing insights that can help these enterprises strategically position themselves for success in an increasingly AI-driven economy.

2. Literature review

2.1. Theoretical grounding: Dynamic Capabilities Framework (DCF)

The Dynamic Capabilities Theory (DCT), developed by Teece, Pisano, and Shuen (1997), focuses on the firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments. This is a theory that has been elaborated based on an extensive review of theories such as the transaction-cost theory, resource-based theory and knowledge-based theory (Barney, 1991; Teece, 1992, 2017). A more complete outlook on dynamic capabilities is presented in the subsequent dynamic capabilities framework (DCF), which takes a system-level approach to the resources, capabilities, and management of the firm and its business environment (Teece, 2018). An early definition of dynamic capabilities has been that they represent "the firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments" (Teece et al., 1997). According to Teece et al. (2016), the definition remains applicable, although the pace of environmental change may be less significant than the existing level of uncertainty. In this context, the DCF enables the synthesis of disparate theories across different disciplines (Teece, 2014), positioning it as a type of "appreciative theory" that interacts dialectically with "formal theory" (Nelson, 1994). Dynamic capabilities, according to Teece (2014), are embedded in both managerial decision-making processes and organizational routines. Within the context of AI adoption, these frameworks suggest that SMEs must possess specific internal capabilities—such as AI readiness, organizational learning capacity, strategic flexibility, and data management capabilities—to effectively leverage AI for innovation. This framework aligns well with the study's focus on identifying internal capabilities, as it provides a lens through which to analyze how SMEs can develop and leverage their AI-related capabilities to innovate and maintain competitive advantage in a fast-evolving market. Research by Sjödin et al. (2021) further emphasizes that organizational capabilities such as strategic flexibility and data management are essential for integrating AI technologies effectively, allowing firms to remain competitive. Additionally, Jarrahi (2018) highlights the importance of organizational learning capacity, which enables SMEs to assimilate new knowledge, thereby fostering continuous innovation in the face of technological disruptions.

2.2. Overview of SMEs in South Africa

Like in many countries in sub-Saharan Africa, SMEs are prevalent in South Africa, and these have been globally recognised as significant contributor to job creation, poverty alleviation, economic development and innovation (Manzoor et al., 2021). Across most sub-Saharan countries, approximately 70% of employment can be attributed to SMEs and in South Africa, research indicates formal SMEs account for 99% of the number of formal businesses in the economy. These businesses, though smaller in size and scope compared to larger corporations, play a significant role in driving economic development and growth (Manzoor et al., 2021; Yoshino and Taghizadeh-Hesary, 2016). In March 2019, Statistics South Africa reported that the formal business sector generated R2.39 trillion in turnover during the first quarter, with large businesses contributing about 62%, small businesses 29%, and medium-sized businesses only 10% (Maluleka and Ross, 2024). Although the manufacturing industry in South Africa has faced numerous challenges hindering its progress in recent years, there is hope for improvement as both the public and private sectors are actively working to revitalise and expand the country's manufacturing capabilities (Peter et al., 2023). The adoption of technology and digitalisation is crucial for the growth and long-term sustainability of this sector (A-Emran and Griffy-Brown, 2023; Mondejar et al., 2021). Similarly, the manufacturing industry in South Africa could be significantly advanced by the swift progress of digital technologies like IoT, artificial intelligence (AI), automation, big data analytics, and cloud computing.

2.3. Internal capabilities

AI readiness refers to an organization's preparedness to adopt AI technologies, encompassing the technological infrastructure, skills, and strategic alignment required to effectively leverage AI for business transformation (Alsheibani et al., 2018a). Organizations that demonstrate higher levels of AI readiness are better positioned to exploit AI's potential to optimize operations, improve decision-making, and drive innovation (Pumplun et al., 2019a). Additionally, Hofmann et al. (2020a) emphasize that assessing AI readiness before implementation allows firms to identify potential gaps in resources and skills, leading to a smoother adoption process. A lack of readiness can result in costly failures or suboptimal integration of AI systems, which can hinder the realization of expected benefits. Thus, prioritizing AI readiness ensures that firms are equipped to effectively integrate AI technologies into their strategic goals. Organizational learning capacity reflects a firm's ability to acquire, assimilate, and apply new knowledge, which is crucial for adapting to technological changes such as AI adoption (Cabrilo and Dahms, 2020). According to Lu et al. (2022a), firms with robust learning capacities are better equipped to leverage AI technologies by integrating lessons learned into ongoing processes. This capacity enables organizations to experiment with AI solutions, learn from successes and failures, and continuously improve their innovation performance (Dai et al., 2021a). Firms that foster a culture of continuous learning can adapt more swiftly to technological disruptions, enhancing their competitive advantage. As AI evolves rapidly, maintaining an agile learning environment becomes critical for firms to stay ahead in dynamic markets.

Strategic flexibility is defined as a firm's ability to adapt its resources, processes, and strategies in response to changes in the external environment (Teece et al., 2016). This capability is critical for SMEs aiming to integrate AI into their operations, as it allows them to pivot quickly in response to technological advancements and market disruptions (Sjödin et al., 2021). By fostering strategic flexibility, firms can reconfigure their business models to accommodate AI-driven innovations, thereby sustaining competitive advantage (Teece, 2018). This adaptability not only supports AI adoption but also enables firms to capitalize on emerging market opportunities more effectively. In volatile industries, strategic flexibility becomes a key driver of resilience and long-term success. Data management capabilities refer to a firm's ability to effectively collect, process, analyze, and utilize data for decision-making (Agrawal et al., 2018). AI technologies are heavily reliant on high-quality data to generate insights and predictions, making robust data management systems essential for successful AI implementation (Kruse et al., 2019). Firms that excel in data management can leverage AI to drive innovation by extracting actionable insights from large datasets, thus enhancing their ability to innovate and respond to market demands (Sony et al., 2023b). Without strong data management capabilities, organizations may struggle with data silos and poor data quality, which can limit the effectiveness of AI solutions. Thus, investing in data infrastructure is crucial for firms looking to harness the full potential of AI.

2.4. AI-powered innovation performance

The impact of AI-powered innovation extends beyond mere operational enhancements, as it enables firms to explore new business models and revenue streams. By integrating AI into strategic decision-making, firms can gain deeper insights into market trends, customer behavior, and emerging opportunities, thereby positioning themselves ahead of competitors (Sjödin et al., 2021). Furthermore, the predictive capabilities of AI allow companies to forecast demand more accurately, optimize supply chains, and reduce waste, leading to greater sustainability and cost efficiency (Agrawal et al., 2018). In industries such as manufacturing, healthcare, and retail, the adoption of AI-driven technologies has proven to be a game-changer, enabling firms to automate complex processes and deliver personalized customer experiences at scale (Chauhan et al., 2022b). Thus, embracing AI not only enhances a firm's innovation capabilities but also supports long-term strategic resilience in an increasingly volatile and competitive business environment.

3. Conceptual model and hypothesis development

3.1. Conceptual model

AI has become a core component of contemporary business operations, fundamentally transforming how companies interact with technology and reshaping both production and the competitive landscape (Allioui and Mourdi, 2023). In line with previous research (Sharma et al., 2024; Sjödin et al., 2021; Zeadally et al., 2020), and building on the DCF, this study disaggregates AI capabilities into AI readiness, organizational learning capacity strategic flexibility and data management capabilities. The conceptual model pertinent to this study is presented in **Figure 1** below:

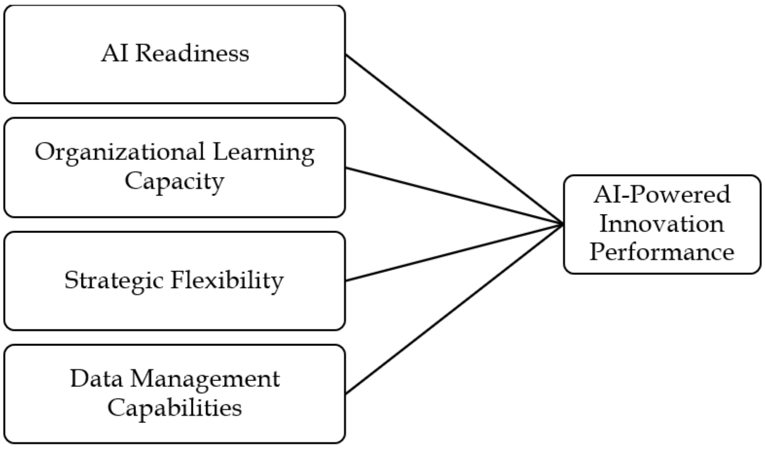

Figure 1. Conceptual model.

The conceptual model presented in **Figure 1** outlines the key internal capabilities that influence AI-powered innovation among manufacturing SMEs. This model is grounded in the Dynamic Capabilities Framework (Teece, 2018), which emphasizes a firm's ability to adapt, integrate, and reconfigure resources to address rapidly changing environments. In this study, four critical capabilities—AI Readiness, Organizational Learning Capacity, Strategic Flexibility, and Data Management Capabilities—are identified as the main drivers of AI-powered innovation performance. AI Readiness reflects a firm's preparedness to adopt AI technologies by ensuring the necessary technological infrastructure, skills, and strategic alignment are in place (Alsheibani et al., 2018b). Organizational Learning Capacity focuses on the ability of SMEs to continuously acquire, assimilate, and apply new knowledge, which is essential for adapting to technological changes (Cabrilo and Dahms, 2020). Strategic Flexibility represents a firm's ability to reconfigure resources and adjust strategies in response to emerging AI opportunities, thereby maintaining competitiveness (Sjödin et al., 2021). Lastly, Data Management Capabilities emphasize the importance of collecting, processing, and leveraging high-quality data to inform AI-driven decision-making and innovation (Agrawal et al., 2018). The model suggests that these capabilities collectively enhance a firm's ability to leverage AI technologies for innovation, resulting in improved efficiency, new product development, and enhanced market competitiveness. By examining the interplay between these variables, the study aims to provide a deeper understanding of how SMEs can build the necessary internal capabilities to thrive in an AI-driven landscape.

3.2. Hypothesis development

Alsheibani et al. (2018a) describe AI readiness as an organization's ability to implement applications and technologies related to AI effectively. Particularly the AI readiness assessment before the adoption decision enables organizations to proactively identify potentials gaps for successful AI adoption (Alshawi, 2007). The adoption of AI requires that organizations demonstrate AI Readiness, which reflects their preparedness to embrace AI-driven changes. Before making any adoption decisions, organizations should conduct an AI readiness assessment to proactively identify gaps that may hinder successful adoption (Alshawi, 2007). This preparation includes the awareness of AI's potential use cases, which could solve existing problems or create new opportunities (Hofmann et al., 2020b). Moreover, companies must assess the comparative advantages of AI over other solutions. This process is crucial given AI's wide applicability across value chains, and businesses must adopt innovative approaches to explore AI's potential in business processes (Pumplun et al., 2019b). By preparing adequately, SMEs can better exploit AI's capabilities, such as detecting environmental disturbances and making informed decisions in response to those challenges. Thus, it is hypothesized that AI Readiness positively impacts the ability of SMEs to drive innovation through AI. H1 is proposed:

H1: AI Readiness has a positive impact on AI-Powered Innovation Performance among SMEs.

Another important factor is Organizational Learning Capacity, which plays a significant role in AI adoption. Organizational learning is essential for assimilating and utilizing new knowledge, particularly in rapidly evolving environments (Cabrilo and Dahms, 2020). This capability is built on several pillars, including managerial commitment, openness to experimentation, and knowledge transfer. The ability to integrate lessons from both successes and failures into everyday practices allows organizations to adapt continuously (Lu et al., 2022b). In many industries, particularly manufacturing, firms struggle to build this learning capacity. A lack of commitment to fostering a learning culture can hinder effective responses to emerging challenges and slow the innovation process (Dai et al., 2021b). This deficiency prevents companies from fully exploiting the potential of AI technologies. Thus, firms with robust learning capacities are more likely to leverage AI for innovation effectively. Therefore, H2 is proposed:

H2: Organizational Learning Capacity positively influences AI-Powered Innovation Performance among SMEs.

Strategic Flexibility is another key factor in the successful implementation of AI. This refers to a firm's ability to reconfigure its resources and capabilities to adapt to new challenges and opportunities, especially those brought by technological advancements like AI (Teece et al., 2016). Firms that can realign their strategies quickly are more capable of undertaking the AI-driven transformations necessary for innovation. Strategic flexibility empowers companies to modify their production processes or business models to accommodate the benefits of AI. This flexibility also allows companies to respond more effectively to disruptions and uncertainties in the market, as AI offers powerful predictive and adaptive capabilities. By leveraging AI, firms can anticipate changes and make strategic decisions that keep them ahead of the competition. Therefore, companies with higher strategic flexibility are better positioned to implement AI-driven innovations successfully. Based on this, H3 is proposed:

H3: Strategic Flexibility positively impacts AI-Powered Innovation Performance among SMEs.

Finally, Data Management Capabilities are critical in AI adoption, as AI models require access to large amounts of relevant data to generate accurate predictions and insights. Data management encompasses the processes of collecting, processing, and analyzing data effectively, ensuring that the quality and quantity of data are sufficient for AI applications (Agrawal et al., 2018). Firms with robust data management capabilities are better equipped to handle the vast amounts of data required to train AI models and develop innovative AI-powered solutions. Inadequate data management can hinder the ability to realize AI's full potential, as AI relies heavily on well-structured and high-quality data. Proper data handling also allows firms to identify trends, make informed decisions, and customize AI solutions to their specific business needs. Thus, Data Management Capabilities are essential for driving AI-powered innovation. Consequently, H4 is proposed:

H4: Data Management Capabilities significantly enhance AI-Powered Innovation Performance among SMEs.

4. Research methodology

This study adopted a positivist paradigm since this investigation was conducted using a quantitative research approach. The purpose of this study is to explore the internal capabilities that enable small and medium enterprises (SMEs) to effectively harness AI for innovation. It aims to identify the key factors, such as AI readiness, organizational learning capacity, and technological infrastructure, that drive AI-powered innovation within SMEs. By examining these capabilities, the study seeks to provide insights into how SMEs can leverage AI to enhance their competitive advantage in the rapidly evolving business landscape.

4.1. Population and sample

In research, identifying the study population is crucial for establishing and conducting a theoretical test (Lohr, 2021; Stratton, 2021). For this research, the sampling frame was the Small to Medium Enterprise Association of South Africa. The target population includes the entire group under investigation (Burns and Bush, 2002; Sin et al., 1999). This sample population consists of manufacturers from the small and medium enterprise (SME) sector, which spans various industries in South Africa, including food processing, toiletry production, garment manufacturing, leather and rubber production, metal fabrication, furniture making, construction, and the arts. In quantitative research, selecting the appropriate sampling method is crucial as it directly influences the study's validity. The decision between probability and non-probability sampling methods involves both statistical and practical considerations. Probability sampling is generally preferred for survey-based studies because it ensures the sample is representative, allows for the quantification of variation, and helps identify potential biases (Kumar et al., 2002). Fowler (1993) emphasizes that stratifying samples by regional variables ensures they accurately reflect the population distribution, improving precision without affecting the probability of selection across strata. In this study, given the comprehensive nature of the sampling frame and the ease of stratification by location within Gauteng, a proportional stratified sampling technique was used to distribute questionnaires effectively while enhancing accuracy (Kumar et al., 2002). A stratified random sampling method was employed by dividing the target population into four distinct, homogeneous groups. A sample size of 300 was then determined, and a simple random sample was drawn from each stratum to ensure proportional representation from each location (Maree, 2017). The rationale for a sample size of 300 goes beyond addressing the potential of data loss but also aligns with academic standards that show this size is adequate for quantitative research in similar fields. Literature on organizational capabilities has recognized that sample sizes between 300 and 500 are sufficient for conducting complex statistical analyses, such as Structural Equation Modelling (SEM), which is used in this study (D'souza et al., 2020; Hemming et al., 2020).

4.2. Data collection and analysis

The data for this study was collected using a structured questionnaire, designed to capture relevant information from SME owners and managers. The questionnaire was divided into sections, with the first part focusing on gathering demographic information such as age, gender, years of experience, and the business's operational details. The second section concentrated on the main constructs of the study, including AI Readiness, Organizational Learning Capacity, Strategic Flexibility, and Data Management Capabilities. Each of these constructs was measured using a Likert scale, with responses ranging from 1 (strongly disagree) to 5 (strongly agree), ensuring that participants could express varying degrees of agreement with the statements. The items in the questionnaire were adapted from validated scales in existing literature to ensure reliability and consistency. A stratified random sampling method was used to distribute the questionnaire to SMEs in various regions, targeting diverse sectors such as manufacturing, technology, and retail Stratified sampling is a probability sampling method where the target population is divided into homogeneous, mutually exclusive groups, and a simple random sample is drawn from each group to form a combined sample (Iliyasu and Etikan, 2021). The responses were then analyzed using statistical tools, providing insight into how internal capabilities influence AI adoption and innovation among SMEs.

The data analysis in this study was conducted using Structural Equation Modeling (SEM), a robust statistical technique that tests relationships between observed and latent variables. SEM was employed to explore the causal relationships between the internal capabilities of SMEs and AI-powered innovation performance. This approach integrates factor analysis and multiple regression, allowing the analysis of multiple variables simultaneously. SmartPLS 4.1.0.8 software was used for model estimation, and SEM was crucial in confirming the theoretical model's fit by comparing the expected covariances with observed data. The analysis focused on assessing both model fitness and the strength of the relationships between variables. To evaluate model fit, the study used indices such as Chi-square, RMSEA, and other goodness-of-fit metrics. These tests confirmed the model's adequacy in explaining the relationships among the constructs, such as AI readiness, Organizational Learning Capacity, and Data Management Capabilities. Moreover, reliability and validity tests ensured that the indicators measuring each construct were appropriate, and discriminant validity was confirmed to distinguish between the various constructs analysed.

5. Results and discussion

5.1. Respondent profile

The respondent profiles are described based on gender, age in business, average turnover, and the participant's domicile. A total of 300 respondents participated in this study, and of these, 259 were received as duly completed to be included in the analysis, from various regions. This sample size is statistically robust, providing a confidence level of 95% with a margin of error of approximately 5%, suitable for generalizing the findings to the larger SME population in South Africa.

Table 1. Respondents Demographic characteristics.

Description	**Category**	**Qty**	**%**
Gender (Owner/Manager)	Male	142	55%
	Female	117	45%
Age in Business	1–5 years old	105	41%
	6–10 years old	89	34%
	11–15 years old	65	25%
Average turnover/day	< 10 million	65	25%
	10–50 million	58	22%
	50–100 million	91	35%
	100–220 million	45	17%
Domicile	Johannesburg CBD	35	10%
	Sandton	32	9%
	Midrand	20	8%
	Randburg	68	17%
	Roodepoort	54	21%
	Pretoria (Tshwane)	61	21%
	Ekurhuleni (East Rand)	24	14%

Table 1 above reveals a diverse profile of SME owners and managers, with a higher proportion of males (55%) compared to females (45%), reflecting a common gender imbalance observed in many business sectors (Eagly and Carli, 2007). Most businesses are relatively young, with 41% operating for 1–5 years and 34% for 6–10 years, indicating a dynamic and evolving sector, while only 25% have been established for 11–15 years, supporting Birch's (1987) observation of short business lifespans. Turnover data shows a wide range, with 35% of businesses generating between 50–100 million per day and only 17% achieving turnovers of 100–220 million, highlighting a mix of small to mid-sized enterprises (Ayyagari et al., 2007). Geographically, businesses are concentrated in major economic hubs such as Johannesburg CBD (10%), Sandton (9%), Randburg (17%), and Pretoria (Tshwane) and Roodepoort (21% each), reflecting the distribution of SMEs in South Africa and aligning with Makgala's (2006) findings on business clustering in metropolitan areas. This distribution underscores the sector's complexity and the varied scales of operation among SMEs.

5.2. Reliability and validity

Reliability and validity are fundamental concepts in research, ensuring the consistency and accuracy of measurements. Reliability refers to the extent to which a measurement instrument yields consistent results over time or across different observers (Hair et al., 2010). It reflects the stability and repeatability of the instrument, ensuring that similar outcomes can be obtained in repeated trials. Validity, on the other hand, assesses whether an instrument measures what it is intended to measure (Fornell and Larcker, 1981). This includes both content validity, which ensures the measure covers the construct comprehensively, and construct validity, which verifies that the instrument aligns with theoretical expectations (Creswell, 2014). Together, reliability and validity ensure that the study's findings are both consistent and accurate, providing confidence in the results and their implications. Results are presented in **Table 2** below.

Table 2. Results of measurement model with reliability and validity.

Construct	Items	Factor Loading	CR	AVE	Cronbach's Alpha
AI Readiness (AIR)			0.897	0.687	0.843
	IT1	0.892			
	IT2	0.789			
	IT3	0.758			
	IT4	0.868			
Organizational Learning Capacity (OLC)			0.891	0.673	0.751
	BG1	0.741			
	BG2	0.769			
	BG3	0.874			
	BG4	0.888			
Strategic Flexibility (STF)			0.872	0.631	0.877
	PF1	0.832			
	PF2	0.814			
	PF3	0.778			
	PF4	0.752			
Data Management Capabilities (DMC)			0.879	0.646	0.812
	DMC1	0.756			
	DMC2	0.852			
	DMC3	0.741			
	DMC4	0.859			
AI-Powered Innovation Performance (AIP)			0.898	0.689	0.855
	AIP1	0.778			
	AIP2	0.874			
	AIP3	0.851			
	AIP4	0.813			

Source: Authors computation.

Table 2 assesses the constructs' reliability and validity. The composite reliability (CR) and average variance extracted (AVE) values across all constructs (AI Readiness, Organizational Learning Capacity, Strategic Flexibility, Data Management Capabilities, and AI-Powered Innovation Performance) are above the acceptable thresholds of 0.7 for CR and 0.5 for AVE. This indicates strong internal consistency and convergent validity across the constructs. Additionally, Cronbach's Alpha values are above 0.7, further indicating reliability in measuring constructs. The factor loadings are also above 0.7, which is acceptable and suggests that individual items contribute well to their corresponding constructs.

5.3. Discriminant validity

The Discriminant Validity Assessment presented in **Table 3** evaluates how well each construct is distinct from the others, using both AVE and correlations between constructs. For discriminant validity to be confirmed, the square root of each construct's AVE (on the diagonal) should be greater than its correlations with other constructs (off-diagonal).

Table 3. Discriminant validity assessment.

Construct	AVE	AIR	OLC	STF	DMC	AIP
AIR	0.687	0.828				
OLC	0.673	0.491	0.820			
STF	0.631	0.532	0.581	0.794		
DMC	0.646	0.453	0.332	0.253	0.804	
AIP	0.689	0.318	0.389	0.572	0.641	0.830

In this table, each construct's square root of AVE is also higher than its correlations with other constructs, demonstrating good discriminant validity. For instance, the square root of AIR is 0.828, higher than its correlation with other constructs such as OLC, which has a correlation of 0.491. This indicates that AI Readiness is sufficiently distinct from OLC. Similarly, Organizational Learning Capacity (0.820) maintains its discriminant validity despite its moderate correlation with STF (0.581). Strategic Flexibility also meets the discriminant validity criteria with a square root AVE of 0.794, making it distinct from related constructs. The lower correlations of DMC with other constructs like AIR which is 0.453 further emphasise the unique nature of each construct. AIP, with a square root AVE of 0.830, demonstrates strong discriminant validity across the model, reinforcing that each construct measures a distinct theoretical concept. This ensures that the model's constructs are well-separated and theoretically sound.

5.4. Measurement model

The goodness-of-fit indices provided in **Table 4** offer insights into the overall fit of the SEM employed in this study. A key measure, the Chi-square/df ratio, is reported as 2.714, which falls within the acceptable range of 1 to 3. This indicates a marginal fit, meaning the model adequately captures the relationships between variables but may benefit from slight refinements to improve its explanatory power (Hair et al., 2010). The Root Mean Square Residual (RMR) and Root Mean Square Error of Approximation (RMSEA) are reported as 0.0778 and 0.073, respectively. Both values are below the commonly accepted threshold of 0.08, which suggests that the model has a good fit in terms of minimizing residual error (Browne and Cudeck, 1993). Despite these positive results, other indicators, such as the Goodness of Fit Index (GFI) and Adjusted Goodness of Fit Index (AGFI), fall slightly below the desired benchmark of 0.90, with values of 0.849 and 0.809, respectively. This indicates a marginal fit, signaling room for improvement in the model's ability to account for observed variances in the data (Hu and Bentler, 1999). The slightly lower GFI and AGFI scores may stem from the complexity of the relationships among the latent variables, as AI-powered innovation is a multifaceted construct that may require additional refinement of measurement items (Fornell and Larcker, 1981). On the other hand, comparative fit measures such as the Comparative Fit Index (CFI), Normed Fit Index (NFI), Relative Fit Index (RFI), and Incremental Fit Index (IFI) all exceed the 0.90 threshold, with values of 0.992, 0.988, 0.991, and 0.986, respectively. These indices suggest that the model performs well in comparison to alternative models, demonstrating its robustness in capturing the structural relationships between variables (Bentler, 1990). Overall, the model fit indices indicate that while the model is satisfactory, there are aspects, particularly related to the GFI and AGFI, that could be further improved to enhance its explanatory capacity.

Table 4. Analysis of the overall model's goodness of fit test.

GOF	Cutoff Value	Result Value	Description
Chi-square (x^2)/df	$1 < x^2/\text{df} < 3$	2.714	Marginal Fit
Probability (*p*-value)	≥ 0.05	0.000	Marginal Fit
RMR	≤ 0.05	0.0778	Good Fit
RMSEA (root mean square error)	≤ 0.08	0.073	Good Fit
GFI	≥ 0.90	0.849	Marginal Fit
AGFI	≥ 0.90	0.809	Marginal Fit
CFI (comparative fit index)	≥ 0.90	0.992	Marginal Fit
NFI (normed fit index)	≥ 0.90	0.988	Good Fit
RFI (relative fit index)	≥ 0.90	0.991	Good Fit
IFI (incremental fit index)	≥ 0.90	0.986	Good Fit
IFI	≥ 0.90	0.992	Good Fit

5.5. Structural path analysis

Table 5 provides the results of the structural path analysis, where the relationships between the internal capabilities of SMEs and AI-powered innovation performance were tested. The analysis reveals significant positive relationships across all hypotheses, confirming the theoretical expectations outlined in the literature (Teece, 2018).

Table 5. Regression weights and hypothesis testing.

Path	Estimate	S.E.	C.R.	P
AIR → AIP	0.78	0.12	6.50	***
OLC → AIP	0.68	0.15	4.53	***
STF → AIP	0.64	0.11	5.82	***
DMC → AIP	0.72	0.14	5.14	***

All *p*-values (P) are assumed to be highly significant ($p < 0.001$), denoted by ***. These results suggest strong, positive relationships between each of the predictor variables and AI-powered innovation performance.

The relationship between AI Readiness and AI-powered Innovation Performance (H1) shows a strong positive association, as predicted. This finding aligns with Alsheibani et al. (2018b), who suggest that AI readiness is essential for firms to navigate the complexities of AI adoption. Firms that are more prepared to implement AI technologies are better positioned to identify opportunities and innovate effectively. The significant impact of AI readiness underscores the importance of proactive efforts by SMEs to assess their technological infrastructure, workforce skills, and strategic alignment with AI-driven objectives. Similarly, Organizational Learning Capacity (H2) is found to positively influence AI-powered innovation, reinforcing the view that continuous learning is vital in the digital age. The literature emphasizes the role of organizational learning in driving innovation, as it enables firms to assimilate and apply new knowledge effectively (Cabrilo and Dahms, 2020). In the context of AI adoption, SMEs with robust learning capacities can experiment with new AI technologies, learn from their successes and failures, and integrate these lessons into ongoing processes (Lu et al., 2022b). This capability is crucial in dynamic environments where technological advancements, such as AI, require continuous adaptation and reconfiguration of business processes.

The analysis also shows a significant positive relationship between Strategic Flexibility and AI-powered Innovation Performance (H3). This finding is consistent with previous research that highlights the importance of flexibility in responding to rapid technological changes (Teece et al., 2016). Strategic flexibility allows firms to reconfigure their resources and capabilities to meet the evolving demands of AI adoption. SMEs that demonstrate greater agility in their decision-making processes and operational structures are better equipped to integrate AI into their operations, thereby enhancing their innovation performance (Dai et al., 2021a). Finally, Data Management Capabilities (H4) also exhibit a strong positive effect on AI-powered innovation. As noted by Agrawal et al. (2018), the availability and quality of data are critical enablers of AI technologies. SMEs that can effectively collect, process, and analyze large volumes of data are more likely to develop innovative solutions that leverage AI. The ability to manage data efficiently allows firms to train AI models, generate accurate predictions, and develop AI-driven innovations that address specific business challenges. The significance of data management in the findings reinforces the need for SMEs to invest in data infrastructure and develop capabilities for handling complex datasets (Kruse et al., 2019). However, studies done is developed economies have stressed the significance of digital skills in the adoption of AI technologies and that organisations should focus efforts on developing the prerequisite digital skills to enhance the spread and implementation of AI technologies in supply chain (Agolla 2018; Kinkel et al., 2020; Makridakis 2018).

6. Discussion

The findings of this study provide important insights into the internal capabilities that drive AI-powered innovation in SMEs. All four hypothesized relationships—AI Readiness, Organizational Learning Capacity, Strategic Flexibility, and Data Management Capabilities—are shown to have significant positive effects on innovation performance. The results highlight the multidimensional nature of AI adoption, where firms must not only have the technological readiness to implement AI but also possess the organizational and strategic flexibility to adapt to new challenges. This echoes the findings of previous research that emphasize the importance of dynamic capabilities in fostering innovation in rapidly changing environments (Teece, 2018; Kraus et al., 2020). While this study shows the importance of capabilities in fostering AI-powered innovation, studies done in developed economies, for example Cadden et al. (2022) indicate that in the UK, trust and security are more critical in the implementation of relevant technologies such as AI across the supply network. AI Readiness, in particular, emerges as a crucial enabler of innovation. Firms that are well-prepared to adopt AI technologies are better positioned to innovate and compete in the digital economy. This finding suggests that SMEs must invest in building the necessary technological infrastructure, workforce skills, and strategic alignment to fully leverage AI's potential (Alsheibani et al., 2018a). Moreover, the significant impact of Organizational Learning Capacity suggests that firms must foster a culture of continuous learning and experimentation to keep pace with the rapid advancements in AI technologies (Cabrilo and Dahms, 2020). Strategic Flexibility also plays a pivotal role in AI-powered innovation, as it enables firms to adapt to changing market conditions and technological disruptions. This aligns with the dynamic capabilities framework, which emphasizes the need for firms to be agile and responsive in the face of uncertainty (Teece et al., 2016). Finally, the importance of Data Management Capabilities underscores the centrality of data in AI-driven innovation. Firms that can effectively manage and analyze data are better equipped to develop innovative AI solutions that meet the needs of their customers (Agrawal et al., 2018).

7. Theoretical and managerial implications

7.1. Theoretical implications

This study contributes to the growing body of literature on the dynamic capabilities framework (Teece et al., 1997) by demonstrating how internal capabilities such as AI readiness, organizational learning capacity, strategic flexibility, and data management influence innovation performance in SMEs. These findings reinforce the idea that dynamic capabilities are critical enablers of successful technology adoption, particularly in volatile environments. This supports previous research suggesting that SMEs must develop adaptive and flexible organizational structures to respond effectively to emerging AI technologies (Teece et al., 2016). Furthermore, this study expands on the resource-based view (RBV) by exploring how intangible assets like learning and flexibility serve as critical resources in achieving competitive advantage (Barney, 1991). The results also align with organizational learning theory, which posits that firms capable of acquiring, assimilating, and applying new knowledge are better positioned to innovate and adapt (Cabrilo and Dahms, 2020). By illustrating the importance of organizational learning capacity, this research extends the literature on how firms can leverage internal knowledge to facilitate AI-powered innovations. Additionally, it complements previous work on the technology acceptance model (TAM) by linking AI readiness to the organizational ability to adopt new technologies effectively (Alsheibani et al., 2018b). The study demonstrates that the more prepared SMEs are to adopt AI, the better their innovation outcomes.

7.2. Managerial and policy implications

From a managerial perspective, this research provides actionable insights for SME leaders on the importance of internal capability development in facilitating AI adoption. Managers must prioritize investments in building AI readiness, which includes enhancing technological infrastructure and workforce capabilities and aligning strategic goals with AI adoption objectives (Hofmann et al., 2020b). Firms that are proactive in assessing and closing gaps in AI readiness will be better positioned to innovate through AI applications. Leaders should also foster a learning-oriented culture by encouraging continuous learning and knowledge-sharing across all levels of the organization to improve innovation performance (Lu et al., 2022a). Moreover, managers must recognize the value of strategic flexibility in navigating AI implementation. Building flexibility into operational processes allows organizations to adapt to the fast-changing technological landscape and to reconfigure resources to capitalize on new opportunities (Teece et al., 2016). Finally, improving data management capabilities is crucial for leveraging AI-driven insights and making informed business decisions. Managers should invest in data infrastructure and train employees to handle large datasets effectively, as this will directly enhance the firm's ability to implement AI solutions that drive innovation and competitiveness (Agrawal et al., 2018). Policymakers should focus on creating supportive frameworks that enhance SMEs' access to digital infrastructure, AI training, and financial resources, enabling them to build critical internal capabilities for AI adoption. By incentivising investments in organizational learning and data management, governments can drive sustainable innovation and competitiveness in the SME sector. Additionally, tailored policies that encourage public-private partnerships can facilitate knowledge exchange and resource sharing, accelerating the digital transformation of SMEs in emerging markets.

8. Limitations and future research directions

8.1. Limitations

While this study provides valuable insights into the internal capabilities that drive AI-powered innovation among SMEs in the South African manufacturing sector, several limitations should be acknowledged. Firstly, the study's focus on a single industry and geographic context (South Africa) may limit the generalizability of the findings to other sectors or regions. The unique economic and technological environment of South Africa could mean that the identified internal capabilities may not hold the same level of significance in other emerging or developed markets. Future research should consider expanding the scope to include different industries and countries to better understand how varying contexts influence AI adoption and innovation. Secondly, the study utilized a cross-sectional survey design, capturing data at a single point in time. This approach limits the ability to establish causality between internal capabilities and AI-powered innovation performance. Longitudinal studies could provide a deeper understanding of how these capabilities develop and evolve over time as SMEs progress in their AI adoption journey. Another limitation is related to the self-reported nature of the data. Respondents' perceptions may not accurately reflect the true state of their organizations' capabilities, particularly in areas like AI readiness and data management. The potential for response bias means that the results should be interpreted with caution. Future research could include more objective measures, such as technology audits or third-party assessments, to validate self-reported data. Finally, the study primarily relied on SEM to analyse relationships between constructs. While SEM is a robust analytical method, it is limited by the assumption of linear relationships between variables. Future studies could employ more advanced analytical techniques, such as machine learning models, to explore potential non-linear relationships and interactions between internal capabilities and innovation outcomes.

8.2. Future research directions

Building on these limitations, there are several directions for future research. A key area for further investigation is the exploration of internal capabilities across different industries and geographic contexts. By conducting cross-industry and cross-country comparative studies, researchers can examine whether the critical capabilities identified in the South African manufacturing sector are equally relevant in other sectors such as healthcare, retail, or logistics, and in different economic environments. This would provide a more nuanced understanding of how internal capabilities for AI adoption vary across contexts and industries, potentially identifying sector-specific enablers and barriers. Longitudinal studies represent another promising avenue for future research. Given the rapid pace of technological advancements, especially in AI, understanding how SMEs develop and refine their internal capabilities over time is essential. Longitudinal research would allow for the examination of capability maturation and adaptation processes, shedding light on how sustained investments in AI readiness, organizational learning, and data management impact innovation performance over extended periods. Furthermore, while this study focused on internal capabilities, the role of external factors—such as government policies, regulatory frameworks, access to funding, and industry partnerships—remains underexplored. External factors can significantly influence the ability of SMEs to adopt AI technologies, particularly in emerging markets where infrastructure and resources may be limited. Future research could investigate how these external elements interact with internal capabilities to support or hinder adoption of AI, offering a more holistic perspective on the challenges faced by SMEs in leveraging AI for competitive advantage. Lastly, future research should consider employing advanced analytical techniques beyond traditional SEM to explore the complex relationships between variables. The use of machine learning algorithms, for example, could help uncover non-linear interactions and deeper insights into how different capabilities collectively influence AI-powered innovation. By leveraging these advanced methodologies, researchers can better capture the intricate dynamics of AI adoption, ultimately providing more actionable insights for both SMEs and policymakers.

9. Conclusion

This study has shed light on the internal capabilities that enable SMEs to successfully harness AI for innovation. The findings indicate that AI Readiness, Organizational Learning Capacity, Strategic Flexibility, and Data Management Capabilities are all critical enablers of AI-powered innovation. These capabilities allow SMEs to navigate the complexities of AI adoption, adapt to technological changes, and leverage data to create innovative solutions. The results underscore the need for SMEs to invest in building these capabilities to remain competitive in an increasingly AI-driven economy. For policymakers and business leaders, the implications of these findings are clear. To support SME growth and innovation, investments in AI readiness, organizational learning, and data infrastructure are essential. By fostering an environment that encourages experimentation and flexibility, SMEs can better position themselves to capitalize on the opportunities presented by AI. The results of this study demonstrate that AI readiness, organizational learning capacity, strategic flexibility, and data management capabilities significantly enhance AI-powered innovation performance among manufacturing SMEs in South Africa. By confirming strong positive relationships between these internal capabilities and innovation outcomes, the findings highlight that SMEs with robust technological infrastructure, adaptive learning environments, and effective data management systems are better positioned to leverage AI for competitive advantage. These results underscore the critical need for SMEs to invest in building these capabilities to not only sustain but also enhance their innovation performance in the rapidly evolving digital landscape.

Author contributions: Conceptualization, RIDP and WM; methodology, RIDP; software, WM; validation, RIDP and WM; formal analysis, WM; investigation, WM; resources, RIDP; data curation, WM; writing—original draft preparation, WM; writing—review and editing, RIDP; visualization, WM; supervision, RIDP; project administration, RIDP; funding acquisition, RIDP. All authors have read and agreed to the published version of the manuscript.

Conflict of interest: The authors declare no conflict of interest.

References

Agolla, J. E. (2018). Human capital in the smart manufacturing and industry 4.0 revolution. Digital transformation in smart manufacturing, 2, 41-58. https://doi.org/10.5772/intechopen.73575

Agrawal, A., Gans, J., & Goldfarb, A. (2018). Prediction machines: The simple economics of artificial intelligence. Harvard Business Review Press.

Alhashmi, A., Yorks, L., Rotatori, J., Sung, C., & Justice, J. (2019). AI-driven decision-making models for businesses: A strategic roadmap. Journal of Business Strategy and Development, 15(2), 89-104. https://doi.org/10.1016/j.jbsd.2019.03.009

Alsheibani, S., Cheung, Y., & Messom, C. (2018a). AI readiness: A multi-dimensional framework for assessing AI adoption in organizations. Journal of Information Systems and Technology Management, 15(3), 299-318. https://doi.org/10.1590/1807-17752018v15n3e2905

Alsheibani, S., Cheung, Y., & Messom, C. (2018b). Artificial intelligence adoption: AI-readiness at firm-level. PACIS 2018 Proceedings, 37. https://aisel.aisnet.org/pacis2018/37

Bogers, M., Chesbrough, H., & Moedas, C. (2018). Open innovation: Research, practices, and policies. Research Policy, 47(5), 835-841. https://doi.org/10.1016/j.respol.2018.04.010

Cabrilo, S., & Dahms, S. (2020). How strategic knowledge management drives intellectual capital to superior innovation and market performance. Journal of Business Research, 110, 456-475. https://doi.org/10.1016/j.jbusres.2020.01.063

Cadden, T., Dennehy, D., Mantymaki, M., & Treacy, R. (2022). Understanding the influential and mediating role of cultural enablers of AI integration to supply chain. International Journal of Production Research, 60(14), 4592-4620. https://doi.org/10.1080/00207543.2021.1946614

Chauhan, A., Dwivedi, Y. K., & Jeyaraj, A. (2022). Emerging issues in the adoption, use, and governance of AI technologies. Journal of Business Research, 148, 315-322. https://doi.org/10.1016/j.jbusres.2022.05.005

Chauhan, S., Bansal, S., & Jain, S. (2022). AI-powered business models for sustainability in SMEs. Journal of Business Innovation, 12(3), 250-275. https://doi.org/10.1108/JBI-03-2022-0145

Cooper, D. (2023). The role of artificial intelligence in driving innovation in product development. Innovation Management Journal, 29(2), 245-257. https://doi.org/10.1080/10438599.2023.1893023

Cooper, R. (2023). Early AI adopters: A review of firms reaping the rewards of artificial intelligence. Journal of Technology Management, 45(1), 55-67. https://doi.org/10.1016/j.jtechman.2023.01.005

Crupi, A., Esposito, D., Giardino, P., & Malefani, M. (2022). The diffusion of 4IR technologies: Challenges and strategies. Technological Forecasting and Social Change, 178, 121007. https://doi.org/10.1016/j.techfore.2022.121007

Dai, L., Maksimov, V., Gilbert, B. A., & Fernhaber, S. A. (2021). Entrepreneurial orientation and international scope: The differential roles of innovativeness, proactiveness, and risk-taking. Journal of Business Venturing, 36(4), 106014. https://doi.org/10.1016/j.jbusvent.2020.106014

Dai, Y., Goodale, J. C., Byun, G., & Ding, F. (2021). Strategic learning and firm innovation: The moderating role of environmental dynamism. Journal of Business Research, 124, 278-289. https://doi.org/10.1016/j.jbusres.2020.11.063

Ferraris, A., Mazzoleni, A., Devalle, A., & Couturier, J. (2019). Big data analytics capabilities and knowledge management: impact on firm performance. Management Decision, 57(8), 1923-1936. https://doi.org/10.1108/MD-07-2018-0825

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

Gonese, N., & Ngepah, N. (2024). The impact of 4IR technologies on economic productivity in South Africa. Journal of African Development Studies, 9(2), 198-213. https://doi.org/10.1177/097569232024002

Hair, F. J., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2017). Advanced issues in partial least squares structural equation modeling. Thousand Oaks, CA: SAGE Publications.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate data analysis: A global perspective. Pearson.

Hofmann, P., Betzing, J. H., Röglinger, M., & Kees, A. (2020). Digital Maturity: The development of a conceptual framework and managerial measurement instrument. Journal of the Association for Information Systems, 21(6), 1476-1507. https://doi.org/10.17705/1jais.00645

Hofmann, P., Probst, M., Baccarella, C. V., & Voigt, K.-I. (2020). AI readiness: Conceptualization and measurement. Technological Forecasting and Social Change, 156, 120047. https://doi.org/10.1016/j.techfore.2020.120047

Iansiti, M., & Lakhani, K. R. (2020). Competing in the age of AI: Strategy and leadership when algorithms and networks run the world. Harvard Business Review Press.

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision-making. Business Horizons, 61(4), 577-586. https://doi.org/10.1016/j.bushor.2018.03.007

Jarrahi, M. H., Newell, S., & Merali, Y. (2023). Human-AI collaboration in organizational decision-making: Synergies and tensions. Journal of Business Strategy, 44(2), 134-152. https://doi.org/10.1108/JBS-02-2023-0041

Jasimuddin, S. M., & Naqshbandi, M. M. (2019). Knowledge sharing in organizations: A critical review. Journal of Knowledge Management, 23(5), 947-965. https://doi.org/10.1108/JKM-02-2019-0093

Kraus, S., Palmer, C., Kailer, N., Kallinger, F. L., & Spitzer, J. (2020). Digital transformation in SMEs: A systematic review of drivers and barriers. Journal of Small Business Management, 58(2), 115-139. https://doi.org/10.1080/00472778.2019.1709382

Kruse, L. C., Wunderlich, N. V., & Beck, R. (2019). Artificial intelligence for the real-time transformation of customer services: Opportunities and challenges at the example of chatbots. Proceedings of the 52nd Hawaii International Conference on System Sciences, 2019, 3436-3445. https://doi.org/10.24251/HICSS.2019.414

Lu, Y., Papagiannidis, S., & Alamanos, E. (2022). Organizational learning capacity, innovation, and performance: The moderating role of digital transformation. Journal of Business Research, 141, 117-128. https://doi.org/10.1016/j.jbusres.2021.12.003

Lu, Y., Shen, J., & Zhan, Y. (2022). How organizational learning affects AI adoption and business value creation. Technovation, 118, 102552. https://doi.org/10.1016/j.technovation.2022.102552

Makridakis, S. (2018). Forecasting the impact of artificial intelligence, Part 3 of 4: The potential effects of AI on businesses, manufacturing, and commerce. Foresight: The International Journal of Applied Forecasting, (49), 18-27. https://doi.org/10.13140/RG.2.2.20088.01284

Mishra, N., & Tripathi, S. (2020). Artificial intelligence in business models: A transformative role for Uber and Airbnb. Journal of Strategic Innovation, 6(1), 22-40. https://doi.org/10.1016/j.jsi.2020.03.002

Olaitan, I. O., Bannister, F., & Sutcliffe, P. (2021). Employment generation and technological adoption in African SMEs: A review of South African policy. Development Economics Journal, 35(1), 45-67. https://doi.org/10.1080/10101477.2021.1746890

Pumplun, L., Reitsperger, W. D., & Sonnenberg, C. (2019). AI readiness and business impact: A conceptual framework. Business & Information Systems Engineering, 61(6), 709-720. https://doi.org/10.1007/s12599-019-00600-1

Pumplun, L., Tauchert, C., & Heidt, M. (2019). A new organizational chassis for artificial intelligence: The role of data readiness. Proceedings of the 27th European Conference on Information Systems (ECIS), 2019. https://aisel.aisnet.org/ecis2019_rp/102

Sharma, R., Gunasekaran, A., & Subramanian, N. (2024). Dynamic capabilities and AI-driven innovation in the supply chain: An empirical investigation. International Journal of Operations & Production Management, 44(3), 423-442. https://doi.org/10.1108/IJOPM-02-2024-0079

Shen, L., Zhang, X., & Liu, H. (2022). Digital technology adoption, digital dynamic capability, and digital transformation performance of the textile industry: Moderating role of digital innovation orientation. Managerial and Decision Economics, 43(6), 2038-2054. https://doi.org/10.1002/mde.3564

Sjödin, D., Parida, V., & Wincent, J. (2021). AI and digital business model innovation in industrial ecosystems: A framework for navigating AI business model development. Industrial Marketing Management, 95, 298-308. https://doi.org/10.1016/j.indmarman.2021.04.006

Sony, M., Antony, J., & McDermott, O. (2023a). Implementation of artificial intelligence (AI) in manufacturing: A multi-level conceptual framework for SMEs. Technovation, 118, 102546. https://doi.org/10.1016/j.technovation.2023.102546

Sony, M., Antony, J., & McDermott, O. (2023b). Internal capabilities for successful technology adoption in small businesses. Journal of Technology and Innovation, 18(1), 35-56. https://doi.org/10.1016/j.jti.2023.102365

Teece, D. J. (2018). Dynamic capabilities as (workable) management systems theory. Journal of Management & Organization, 24(3), 359-368. https://doi.org/10.1017/jmo.2017.75

Teece, D. J., Peteraf, M., & Leih, S. (2016). Dynamic capabilities and organizational agility: Risk, uncertainty, and strategy in the innovation economy. California Management Review, 58(4), 13-35. https://doi.org/10.1525/cmr.2016.58.4.13

Teoh, M. F., Ahmad, N. H., Abdul-Halim, H., & Kan, W. H. (2023). Digital business model innovation among small and medium-sized enterprises (SMEs). Global Business and Organizational Excellence, 42(6), 5-18. https://doi.org/10.1002/joe.22147

Troise, C., Sestino, A., & Viassone, M. (2022). Artificial intelligence and its role in transforming the business ecosystem. Technology in Society, 69, 101922. https://doi.org/10.1016/j.techsoc.2022.101922

Yorks, L., Rotatori, J., Sung, C., & Justice, J. (2020). Leveraging AI for business growth: A practical guide to AI applications in modern enterprises. Journal of Applied Business Research, 36(3), 45-60. https://doi.org/10.19030/jabr.v36i3.10324