International Journal of Business Management and Economic Review

Vol. 7, No. 03; 2024

ISSN: 2581-4664

THE IMPACT OF ARTIFICIAL INTELLIGENCE (AI) ADOPTION ON THE PRODUCTIVITY OF SMALL AND MEDIUM ENTERPRISES (SMEs) INDUSTRIES IN INDONESIA: HIGH COST, LACK OF KNOWLEDGE, AND INADEQUATE INFRASTRUCTURE AS MEDIATION VARIABLES

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http://doi.org/10.35409/IJBMER.2024.3584

ABSTRACT

Small and Medium Enterprises (SMEs) constitute a huge portion of Indonesia's economy, yet their productivity lags developed nations. This study investigates the impact of Artificial Intelligence (AI) adoption on SME productivity, considering intervening variables. Using an explanatory quantitative approach, data from 200 SME workers in Indonesia were analyzed through Partial Least Square (PLS) analysis. Results indicate a significant positive relationship between AI adoption and high costs, as well as a reduction in the lack of knowledge. Moreover, high costs and knowledge deficits negatively affect productivity. However, AI adoption does not significantly influence inadequate infrastructure, which in turn does not significantly impact productivity. These findings underscore the potential of AI adoption in mitigating challenges within SMEs and enhancing productivity in Indonesia's economic landscape. Efforts to overcome these challenges and encourage AI adoption promise to increase the competitiveness of SMEs and contribute to national economic growth.

Keywords: Artificial Intelligence (AI), Productivity of Small and Medium Enterprises (SMEs), High Cost, Lack of Knowledge, Inadequate Infrastructure.

1. INTRODUCTION

Small and Medium Enterprises (SMEs) are the backbone of the Indonesian economy. This sector contributes around 61% of the total national Gross Domestic Product (GDP) and absorbs more than 97% of the workforce in Indonesia (Statistics Indonesia, 2022). However, SMEs in Indonesia still face challenges in terms of low productivity compared to developed countries.

Productivity is a fundamental concept that underpins the efficiency and effectiveness of businesses across various industries (Owalla et al., 2022). It represents the measure of output produced per unit of input, considering factors such as labor, capital, and other resources and achieving optimal results (Zalenyuk, 2023). In the context of small and medium enterprises (SMEs), productivity plays a pivotal role in determining their success and competitiveness in the market (Wong, 2009).

SMEs are often characterized by limited resources, including financial constraints, lack of skilled labor, and limited access to advanced technologies (Ong et al., 2020). These challenges can hinder their ability to achieve optimal productivity levels, affecting their profitability and growth prospects. Improving productivity is therefore a critical imperative for SMEs to enhance their competitiveness, reduce operational costs, and increase efficiency (Criscuolo et al., 2021). Beyond efficiency, productivity crucially shapes SMEs' overall performance and is notably impacted by technological advancements like Artificial Intelligence (AI). Integrating advanced technologies, such as AI, holds potential for bolstering productivity and operational efficiency in SMEs (Muhammad, 2021). One factor that can increase the productivity of SMEs is the adoption of Artificial Intelligence (AI) technology.

Integrating Artificial Intelligence (AI) technologies in SMEs can significantly impact their productivity levels. AI encompasses a range of technologies, including machine learning, natural language processing, and computer vision, that can automate and optimize various business processes (Ransbotham et al., 2019). For instance, AI-powered systems can streamline supply chain management, enhance customer service through chatbots, and provide data-driven insights for decision-making (Daugherty & Wilson, 2018). By leveraging AI technologies, SMEs can streamline their workflows, automate tasks, and gain valuable insights to make informed business decisions. The integration of AI into SMEs operations opens new avenues for growth and competitiveness in today's digital landscape (Badghish, 2024).

With the integration of AI, SMEs can strategically manage and reduce high operational costs. AI analyzes historical financial data to pinpoint growth opportunities and trends, facilitating informed decision-making. Despite initial setup costs, AI-driven efficiencies streamline operations, curbing expenses while enhancing productivity. This cost-effective approach positions SMEs for sustained growth and competitiveness in the market (Bandari, 2019).
Li et al., (2022) examines the interplay between AI capability and lack of knowledge within SMEs, mediated by knowledge sharing and moderated by organizational cohesion. Robust AI capabilities, coupled with effective communication and a collaborative atmosphere, facilitate knowledge dissemination, thereby stimulating lack of knowledge.

AI capability serves as a strategic tool for SMEs to address and mitigate the challenges posed by inadequate infrastructure. By streamlining operations and optimizing resource utilization, AI enhances operational efficiency, enabling SMEs to overcome infrastructure limitations and maintain competitiveness in the market landscape (Matchett, 2023). High operational costs can significantly impact productivity levels within SMEs, creating challenges in resource allocation and efficiency (Okumu & Buyinza, 2018). These cost constraints often limit investment in advanced technologies and process improvements, hindering productivity growth. Therefore, managing and reducing high costs through strategic planning and cost-effective solutions is crucial for enhancing productivity and maintaining competitiveness in the dynamic market environment.

The lack of knowledge directly impacts productivity in SMEs, highlighting the critical role of knowledge and skills in enhancing operational efficiency and fostering growth within small enterprises (Gamage et al., 2020). Turner & Endres (2017) highlighted that the lack of skills and knowledge significantly affects productivity in SMEs, creating hurdles for small business owners. To tackle these challenges and improve success rates, strategies like entrepreneurial education, knowledge sharing, and innovation practices have been recommended. Hassan et al., (2019) highlighted that inadequate infrastructure, especially electricity shortages, has a substantial negative impact on productivity within SMEs. While water and transport infrastructure contribute less, the overarching infrastructure deficiencies severely constrain the growth potential of SMEs, limiting overall economic development.

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Despite the significant contribution of Small and Medium Enterprises (SMEs) to the Indonesian economy, their productivity levels remain low compared to developed countries (Tambunan, 2019). This hinders their ability to achieve optimal efficiency, profitability, and growth prospects. While the adoption of Artificial Intelligence (AI) technologies has been recognized as a potential solution to enhance productivity in SMEs (Ransbotham et al., 2019), several challenges impede its effective implementation. These challenges include high implementation costs (Firmansyah & Fadlika, 2020), lack of technical knowledge and skilled labor (Hidayatullah et al., 2018), as well as inadequate digital infrastructure (Pradhan et al., 2021).

Consequently, there is a pressing need to investigate the impact of AI adoption on productivity in Indonesian SMEs and identify the mediating factors that influence this relationship. By addressing these challenges, SMEs can leverage the power of AI to streamline operations, optimize resource utilization, and gain a competitive edge in the market (Daugherty & Wilson, 2018). Furthermore, the adoption of AI by SMEs can contribute to the overall economic growth and competitiveness of the nation (Rajput & Soni, 2021), highlighting the significance of this research for both businesses and policymakers.

Despite the potential benefits, this research specifically examining the adoption of AI and its impact on the productivity of SMEs in Indonesia remains limited. This study needs to be conducted to understand the current state of AI adoption among Indonesian SMEs, assess its influence on productivity levels, and identify the key mediating factors that facilitate or hinder the successful implementation of AI technologies. By understanding the challenges and opportunities in integrating AI, effective strategies and policies can be formulated to promote AI adoption and enhance the productivity of SMEs in Indonesia.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 The Theory of Resource Based-View

Theory of Resource Based-View (RBV) is a prominent theoretical framework that offers insights into how firms can achieve sustainable competitive advantage by leveraging their valuable, rare, inimitable, and non-substitutable resources (Barney, 1991). This theory posits that firms can exploit their unique bundles of resources, encompassing both tangible and intangible assets, to formulate and implement strategies that create value for customers (Barney & Arikan, 2001). The RBV emphasizes the significance of internal resources and capabilities as the primary drivers of a firm's performance and success. According to Barney (2001), the RBV suggests that firms should identify, develop, and exploit their specific resources and capabilities to gain a competitive edge in the market. By efficiently utilizing their resources, firms can create value-adding strategies that are difficult for competitors to imitate or substitute, thereby achieving sustained competitive advantage. The RBV has been widely applied in various contexts, including strategic management, entrepreneurship, and innovation studies (Barney et al., 2011). It has also been extended and integrated with other theoretical perspectives, such as the dynamic capabilities view by Teece et al. (1997) and the knowledge-based view by Grant (1996).

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2.2 The Theory of Dynamic Capabilities

Theory of Dynamic Capabilities is an extension of the Resource Based-View (RBV) and was introduced by David Teece, Gary Pisano, and Amy Shuen in their seminal work "Dynamic Capabilities and Strategic Management" (1997). This theory suggests that in rapidly changing and highly competitive environments, firms must possess the ability to continuously reconfigure, renew, and adapt their resource base to create and sustain competitive advantage. Dynamic capabilities are defined as the "ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments" (Teece et al., 1997, p. 516). These capabilities are embedded in organizational processes, routines, and strategic decision-making, enabling firms to respond effectively to changing market conditions, technological advancements, and competitive pressures. Dynamic capabilities are particularly relevant in rapidly evolving industries, where firms must continuously adapt and innovate to maintain a competitive edge. They enable firms to create, modify, and extend their resource base, develop new products and services, and explore new markets (Eisenhardt & Martin, 2000; Helfat et al., 2007). The theory of dynamic capabilities has been widely applied in various contexts, including strategic management, innovation management, and entrepreneurship (Barreto, 2010; Teece, 2018). It has also been integrated with other theoretical perspectives, such as the knowledge-based view and organizational learning (Zollo & Winter, 2002; Zahra et al., 2006).

2.3 Artificial Intelligence (AI) Adoption

Artificial Intelligence (AI) refers to the emulation of human intelligence processes by machines, particularly computer systems. AI encompasses a wide array of technologies and techniques, including machine learning, natural language processing, computer vision, and robotics (Russell & Norvig, 2020). The rapid advancements in AI have led to its widespread adoption across various industries and domains, transforming the way businesses operate and individuals interact with technology. AI has the potential to enhance productivity, efficiency, and decision-making processes by automating tasks, analyzing large datasets, and providing insights and recommendations (Agrawal et al., 2018). However, the integration of AI also raises ethical concerns, such as privacy, bias, and the potential displacement of human workers (Floridi et al., 2018). As AI continues to evolve, it is crucial to address these challenges and ensure responsible development and deployment of AI systems. According to Brock & Wangenheim (2019), there are three key indicators of Artificial Intelligence (AI) adoption: access to quality data, availability of skilled personnel, and adequate infrastructure.

2.4 High Cost

High cost is a significant barrier that can impede the adoption, implementation, and utilization of various technologies, processes, or initiatives within organizations, particularly for small and medium enterprises (SMEs) with limited resources (Ghobakhloo & Tang, 2015). The high costs associated with acquiring, maintaining, and upgrading the necessary infrastructure, software, equipment, and skilled personnel can pose substantial financial burdens on businesses. Additionally, the costs of training employees, seeking expert consultations, and adapting organizational processes to accommodate new technologies or initiatives can further exacerbate the financial strain (Alshamaila et al., 2013). High costs can hinder competitiveness, profitability, and the ability to innovate, thereby posing significant challenges for businesses, especially SMEs, in their pursuit of growth and sustainability. According to Kovács (2020), there are three indicators of high cost such as eliminating waste, streamlining processes, and continuous.

2.5 Lack of Knowledge

Lack of knowledge refers to the absence or deficiency of essential skills, expertise, and understanding required to effectively implement, operate, or leverage specific technologies, processes, or initiatives within an organization (Chong & Olesen, 2017). This knowledge gap can manifest at various levels, including technical ability, operational proficiency, strategic planning, and decision-making. Lack of knowledge can stem from inadequate training, limited access to relevant resources or expertise, and insufficient investment in knowledge-building initiatives (Awa et al., 2015). It can pose significant challenges for businesses, particularly SMEs, as it hinders their ability to fully capitalize on the potential benefits offered by new technologies or strategic initiatives, thereby impacting their competitiveness and growth prospects. According to Edvardsson (2023), there are four indicators of lack of knowledge such as learning and development, strategic partnerships, leveraging external expertise, and fostering a culture of continuous improvement.

2.6 Inadequate Infrastructure

Inadequate infrastructure refers to the lack of sufficient and reliable physical and technological systems required to support the effective implementation and utilization of various technologies, processes, or initiatives within an organization (Kapurubandara & Lawson, 2006). This can include inadequacies in areas such as communication networks, power supply, data storage and processing capabilities, and other supporting facilities. Inadequate infrastructure can pose significant challenges for businesses, particularly in terms of data management, system reliability, and overall operational efficiency (Ghobakhloo & Tang, 2015). It can hinder the seamless integration of new technologies, disrupt workflows, and limit the ability to fully leverage the potential benefits offered by technological advancements or process improvements. According to Uhlenbrook et al., (2022), there are three indicators of inadequate infrastructure such as monitoring, planning, and management.

2.7 Productivity

Productivity refers to the efficient utilization of resources to produce outputs, measured by the ratio of outputs to inputs (Syverson, 2011). Productivity is a crucial determinant of a firm's competitiveness, profitability, and long-term survival (Syverson, 2011). In the context of SMEs, improving productivity is essential for enhancing profitability, competitiveness, and long-term sustainability (Criscuolo et al., 2021). Enhancing productivity in the SMEs industry hinges on several critical factors, including digital transformation through the adoption of technologies like cloud computing, big data analytics, and AI (OECD, 2021). According to Gambin et al., (2009), there are three indicators of productivity such as technological advancements, employee skills, and operational efficiency that can influence productivity levels.

2.8 Hypothesis Development

Adopting AI in SMEs entails significant initial and ongoing costs, but its long-term benefits include cost reduction and improved operational efficiency through task automation, process optimization, and enhanced decision-making (Agrawal et al., 2018; Brynjolfsson & McAfee, 2014). AI enabled predictive maintenance can preempt equipment failures, cutting downtime and costs, while AI driven supply chain and inventory management can trim waste and streamline operations for SMEs (Duan et al., 2019). As SMEs integrate AI into their operations, the initial high costs may be offset by the long-term benefits of increased efficiency and cost savings.

H1: Artificial Intelligence (AI) Adoption has a positive and significant effect on High Cost

AI integration in SMEs can alleviate knowledge gaps by serving as repositories of insights and decision support, leveraging vast data processing capabilities (Chui et al., 2018; Agrawal et al., 2018). Experience with AI systems in SMEs can facilitate skill development among employees, aided by AI-based training tools, thus diminishing knowledge deficits (Davenport & Ronanki, 2018). SMEs can enhance workforce knowledge by embracing AI and exploiting its capacity to augment knowledge, progressively narrowing the knowledge gap.

H2: Artificial Intelligence (AI) Adoption has a positive and significant effect on Lack of Knowledge

Integration of AI systems in SMEs can alleviate infrastructure constraints over time, utilizing AI-powered cloud computing and virtualization to provide scalable computing resources and minimize hardware investments (Duan et al., 2019; Ghobakhloo & Tang, 2015). AI-driven optimization and predictive maintenance techniques can enhance efficiency and prolong infrastructure lifespan in SMEs by identifying bottlenecks and addressing potential issues proactively (Agrawal et al., 2018). By leveraging these AI capabilities, SMEs can gradually overcome infrastructure inadequacies and enhance their technological capabilities without significant upfront investments.

H3: Artificial Intelligence (AI) Adoption has a positive and significant effect on Inadequate Infrastructure

The substantial costs of adopting and maintaining technologies and skilled personnel can strain SMEs' budgets, hindering productivity across industries (Alshamaila et al., 2013). High costs associated with technology adoption may prevent SMEs from fully capitalizing on productivity-enhancing measures, potentially limiting investments in employee training and operational efficiency improvements, irrespective of industry (Ghobakhloo & Tang, 2015).

H4: High Cost has a positive and significant effect on Productivity

SMEs face productivity challenges due to a lack of expertise and resources, hindering effective implementation of productivity-enhancing technologies and processes across industries (Chong & Olesen, 2017). Insufficient knowledge within SMEs across industries may impede the full utilization of productivity measures, leading to inefficiencies in implementation, decision-making, and resource allocation, constraining productivity gains (Awa et al., 2015).

H5: Lack of Knowledge has a positive and significant effect on Productivity

SMEs face challenges in productivity due to insufficient infrastructure, hindering the effective implementation of productivity-enhancing technologies across industries (Kapurubandara & Lawson, 2006). Without reliable infrastructure, SMEs may encounter workflow disruptions and data management inefficiencies, limiting the integration and benefits of productivity-enhancing technologies across industries (Ghobakhloo & Tang, 2015).

H6: Inadequate Infrastructure has a positive and significant effect on Productivity

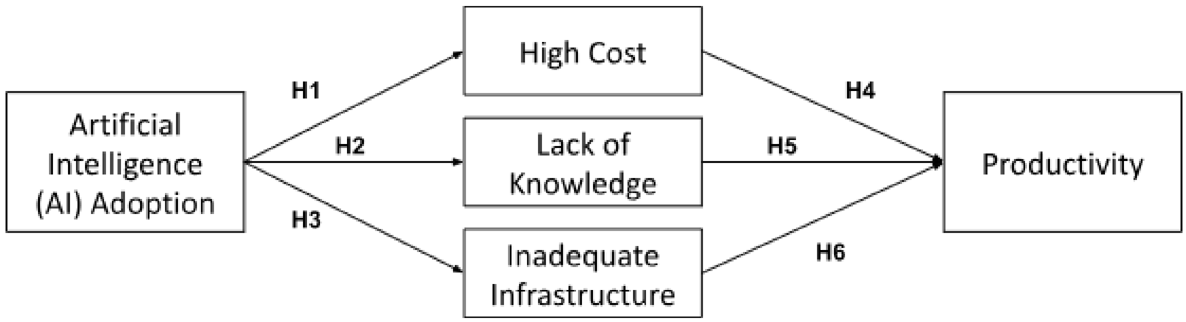

Figure 1. Conceptual Framework

3. METHODS

This study employs an explanatory research design (Sekaran et al., 2016) with a quantitative methodology, aiming to elucidate the influence between variables by introducing interventions in each statement item. Cross-sectional data were gathered from primary sources through the simultaneous distribution of questionnaires to respondents. The target population comprises workers in Small and Medium Enterprises (SMEs) operating in Indonesia. As the precise population size is unknown, the research adopted a non-probability sampling technique to determine the research sample, specifically utilizing the convenience sampling method for samples of an unknown population size and calculating the sample-to-item ratio (multivariate rule of thumb).

The determination of the sample size adheres to the 10-times rule (Hair et al., 2021). The author established a sample size of 10 x 16 = 160. Each variable statement will be measured using a five-point Likert scale, ranging from Strongly Disagree (1) to Strongly Agree (5). The analysis method employed is the Partial Least Square (PLS) analysis program. Data collection for this research involves questionnaires developed and distributed to 200 respondents through an online platform. The data analysis technique to be utilized involves preliminary considerations, measurement model assessment (robustness checks CTA-PLS), structural model assessment (robustness checks for nonlinearity, endogeneity, heterogeneity), and conducting a hypothesis test to determine the significance of variables X, M1, M2, M3 and Y (Hair et al., 2019).

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4. RESULT AND DISCUSSION

4.1 Profile of the Respondents

The profile of respondents shows (57.5%) female and (42.5%) male, which shows that the number of women is greater than men. Additionally, the main age ranges are 30 to 40 years for (50%) and 20 to 30 years for (38%). Most respondents (70%) live outside JABODETABEK (Table 2. Respondent Profile, appendix).

4.2 Reliability and Validity

The validity and reliability of this study were evaluated through two testing phases. Cronbach's alpha and Composite Reliability (CR) with a threshold of 0.7, as well as Average Variance Extracted (AVE) greater than 0.5, as suggested by Fornell and Larcker (1981) and Hair et al. (2013), were applied to each item. This approach may strengthen the data from the convergent validity test findings. The discriminant validity utilized the Discriminant Validity Heterotrait-Monotrait Ratio (HTMT), which also recommends that the square root of each AVE construct should have a higher value than the correlation with the latent construct. The processed data results demonstrate that all items surpass the recommended value, indicating that no items need to be eliminated. Furthermore, all the outer models exhibit higher values than the cross-loadings, confirming discriminant validity (Table 3. Mean, SD, Internal Consistencies, and Item Loadings, and Table 4. Discriminant Validity using Heterotrait-Monotrait Ratio Matrix (HTMT), appendix).

4.3 Structural Model

This test uses a structural equation modeling test (PLS-SEM) to establish connections between each variable and form hypotheses. Partial Least Squares Structural Equation Modeling (PLS-SEM) is a variance-based structured equation technique. It enables the calculation and identification of the primary structures and structural theories used as models during testing (Hair et al., 2021). The R2 value represents the coefficient of determination for the endogenous construct (Sekaran and Bougie, 2016), and the R2 result for productivity is 0.682 or 68.2%, which falls within the moderate construct range (Sarstedt et al., 2017). A latent construct is considered relevant if Q2 has predictive significance, and its observed value lies between zero and one, with values closer to one indicating a better model (Shmueli et al., 2016). Additionally, all endogenous latent variables demonstrate predictive capabilities (Table 5. Collinearity Statistics (VIF), and Table 6. R2 and Q2, appendix).

Figure 2 illustrates the coefficients between the variables and their levels of significance using PLS-SEM bootstrapping to obtain the standard error for hypothesis testing. In testing the hypotheses, it is necessary to repeatedly take random samples with the original sample in the bootstrapping process to produce 5000 samples. Consequently, all tested hypotheses were supported, except for hypothesis 3 (H3) and hypothesis 6 (H6), which were not supported (Table 7. Bootstrapping, appendix).

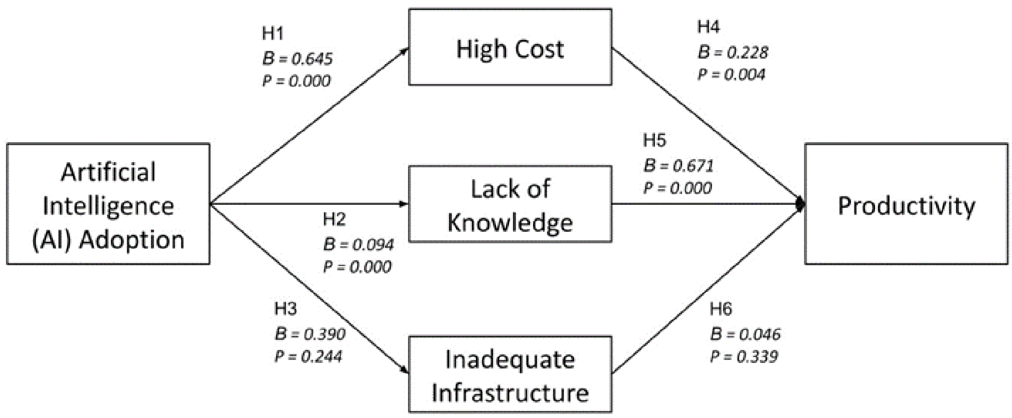

Figure 2. Structural Model

4.4 Bootstrapping

The results of the hypothesis in Table 7 show that; AI Adoption → High Cost (ß = 0.645, t = 15.275, *p* = 0.000), AI Adoption → Lack of Knowledge (ß = 0.094, t = 1.166, p = 0.000), AI Adoption → Inadequate Infrastructure (ß = 0.390, t = 5.643, p = 0.244), High Cost → Productivity (ß = 0.228, t = 2.907, p = 0.004), Lack of Knowledge → Productivity (ß = 0.671, t = 9.364, p = 0.000), Inadequate Infrastructure → Productivity (ß = 0.046, t = 0.956, p = 0.339). (Table 7. Bootstrapping, appendix).

This study supports a substantial and positive relationship between AI adoption and high cost (H1), indicating that AI adoption has the potential to reduce costs, thereby providing a significant impact on high costs. A McKinsey study revealed that the implementation of AI-driven automation can generate annual savings of about $2 trillion across different sectors worldwide (Manyika et al., 2017). This assertion finds reinforcement in research conducted by Davenport & Ronanki (2018) for the Harvard Business Review, which suggests that AI can automate various business processes, leading to cost savings and increased operational efficiency. Substantial and positive results were also obtained in this study on the relationship between AI adoption and lack of knowledge (H2), indicating that AI adoption has the potential to reduce lack of knowledge, thereby providing a significant impact on lack of knowledge. The research aligns with the findings by Ransbotham et al., (2019) in the MIT Sloan Management Review, highlighting AI's role in enhancing organizational learning and bridging knowledge gaps. As noted by (Dery et al., 2018), AI-powered tools like chatbots offer on demand support, addressing knowledge deficiencies and boosting productivity.

In contrast, the relationship between AI adoption and inadequate infrastructure (H3) is rejected. This study found new findings that AI adoption does not have a positive and significant effect in reducing inadequate infrastructure. Chen et al., (2020) identified that although AI adoption has many benefits, including increased efficiency and increased decision-making capacity, its impact on infrastructure deficiencies is still small. Adopting AI does not automatically solve problems caused by inadequate infrastructure. This requires reliable physical and digital infrastructure, technological accessibility, and skilled human resources. Therefore, although AI offers innovative solutions, unpreparedness to adopt AI, especially in the context of inadequate infrastructure, remains a significant barrier to AI adoption (Wang et al., 2022). The relationship between high costs and productivity (H4) shows a positive and significant relationship, indicating that the high costs of adopting and maintaining technologies such as AI can strain SMEs budgets, hindering productivity (Zwick, 2023), as also explained by (Sánchez & Martínez, 2024) in their book on digital transformation.

A positive and substantial relationship is also seen in the relationship between lack of knowledge and productivity (H5), indicating that lack of knowledge can be a significant obstacle to SME productivity, especially if not supported by effective knowledge management efforts (Johnson et al., 2021). According to Smith et al., (2023) in their book also highlight the importance of appropriate knowledge acquisition and utilization in increasing productivity and emphasize that lack of knowledge can be a major obstacle in achieving desired results. This study found no evidence of a positive and significant effect between inadequate infrastructure and productivity (H6), indicating that infrastructure factors have no impact on an increase or decrease in productivity. Previous research has found that while infrastructure plays a role, other factors like human resource management and business strategy exert a more substantial influence on productivity (Li et al., 2022).

5. CONCLUSION

These research findings highlight the critical role of AI adoption in enhancing SMEs productivity, underscoring the challenges posed by high costs, lack of knowledge, and inadequate infrastructure. These findings can be understood through the Resource-Based View (RBV) theory and the Theory of Dynamic Capabilities. From an RBV perspective, the positive impact of AI adoption on productivity aligns with the notion that valuable, rare, and inimitable resources, such as AI capabilities, can provide a competitive advantage to SMEs. However, the challenges of high costs, knowledge gaps, and infrastructure deficiencies represent potential barriers to acquiring and effectively utilizing these valuable resources. The Theory of Dynamic Capabilities complements this view by emphasizing the importance of SMEs' ability to reconfigure their resources and capabilities to adapt to changing environments, such as the rapid technological advancements brought about by AI. The findings suggest that SMEs must develop dynamic capabilities to leverage AI effectively, address knowledge gaps, and overcome infrastructure constraints to achieve sustained productivity gains and maintain a competitive edge in the market.

This research extends existing literature by elucidating the mechanisms through which AI adoption influences productivity in SMEs. The findings highlight the importance of leveraging internal resources and dynamic capabilities to effectively integrate AI technologies, thereby enhancing productivity. Practically, the study provides valuable insights for SME owners, managers, and policymakers in Indonesia. It highlights the potential of AI adoption to reduce high costs and knowledge gaps, thereby enhancing productivity and competitiveness. SMEs should consider investing in AI technologies and capabilities to streamline operations, automate processes, and augment organizational knowledge.

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While this study offers valuable insights into the relationship between AI adoption and SME productivity, several limitations warrant consideration. The cross-sectional nature of the data restricts the ability to establish causal relationships and observe long-term effects. Future research employing longitudinal designs would better capture the dynamic nature of AI integration and its impact over time. Moreover, the study's focus on Indonesia may limit the generalizability of findings to other contexts. To address this, future research could extend to diverse regions, facilitating broader insights into the productivity implications of AI adoption in SMEs. Additionally, future research could explore the moderating or mediating effects of organizational factors, such as leadership, culture, and change management practices, on the relationship between AI adoption and productivity in SMEs. Furthermore, the study could be expanded to investigate the impact of specific AI technologies (e.g., machine learning, natural language processing, computer vision) on various aspects of SME operations, such as marketing, supply chain management, and customer service. This granular analysis could inform targeted AI adoption strategies and yield more nuanced insights into the productivity implications of different AI applications.

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ISSN: 2581-4664

APPENDIX

Table 1. Measurement of Variable

Variable	Indicator	Statement
Artificial Intelligence (AI) (Brock & von Wangenheim, 2019)	Access to quality data	Saya percaya bahwa akses terhadap data berkualitas merupakan hal penting untuk operasional perusahaan.
	Skilled personnel	Saya percaya bahwa keberadaan sumber daya manusia yang terampil dalam bidang teknologi merupakan hal penting untuk kemajuan perusahaan.
	Adequate infrastructure	Saya percaya bahwa infrastruktur yang memadai merupakan hal penting untuk mendukung perkembangan perusahaan.
High Cost (Kovács, 2020)	Eliminating waste	Saya percaya bahwa mengurangi pemborosan merupakan hal penting untuk mengendalikan biaya di perusahaan.
	Streamlining processes	Saya percaya bahwa menyederhanakan proses operasional merupakan hal penting untuk membantu mengurangi biaya tambahan.
	Continuous	Saya percaya bahwa menjaga proses operasional tetap berkelanjutan merupakan hal penting untuk menghindari biaya tambahan.
Lack of Knowledge (Edvardsson, 2023)	Learning and development	Saya percaya bahwa program pembelajaran dan pengembangan merupakan hal penting untuk meningkatkan pengetahuan di tempat kerja.
	Strategic partnerships	Saya percaya bahwa membangun kemitraan strategis merupakan hal penting untuk membantu meningkatkan pengetahuan dan keahlian di perusahaan.
	Leveraging external expertise	Saya percaya bahwa memanfaatkan keahlian eksternal merupakan hal penting untuk menjadi strategi efektif dalam mengatasi kekurangan pengetahuan di perusahaan.
	Fostering a culture of continuous improvement	Saya percaya bahwa menciptakan budaya perbaikan terus-menerus di tempat kerja merupakan hal penting untuk membantu mengatasi kekurangan pengetahuan.
Inadequate Infrastructure (Uhlenbrook et al., 2022)	Monitoring	Saya percaya bahwa monitoring yang efektif merupakan hal penting untuk menjaga infrastruktur agar tetap berjalan lancar di tempat kerja.
	Planning	Saya percaya bahwa perencanaan yang matang terkait infrastruktur merupakan hal penting untuk membantu menghindari masalah di masa mendatang.
	Management	Saya percaya bahwa manajemen yang efektif terhadap infrastruktur merupakan hal penting untuk memastikan kinerja perusahaan yang optimal.
Productivity (Gambin et al., 2009)	Technological advancements	Saya percaya bahwa kemajuan teknologi merupakan hal penting untuk meningkatkan tingkat produktivitas di tempat kerja.
	Employee skills	Saya percaya bahwa keterampilan karyawan merupakan hal penting untuk tingkat produktivitas perusahaan.
	Operational efficiency that can influence productivity levels.	Saya percaya bahwa efisiensi operasional merupakan hal penting untuk mencapai tingkat produktivitas yang tinggi di perusahaan.

Table 2. Profile of Respondents

Characteristic	Category	Number (%)
Jenis Kelamin	Laki-Laki	85 (42.5)
	Perempuan	115 (57.5)
Usia	20 - 30 Tahun	76 (38)
	30 - 40 Tahun	100 (50)
	40 - 50 Tahun	14 (7)
	Diatas 50 Tahun	10 (5)
Domisili	JABODETABEK	60 (30)
	Diluar JABODETABEK	140 (70)

Table 3. Mean, SD, Internal Consistencies, and Item Loadings

Construct	Mean	SD	Item	Loading	Cornbach's Alpha	Composite Reliability	(AVE)
Artificial Intelligence (AI) Adoption	0.879	0.022	AI-1	0.881	0.849	0.849	0.768
	0.881	0.019	AI-2	0.867			
	0.867	0.023	AI-3	0.844			
High Cost	0.843	0.030	HC-1	0.910	0.839	0.840	0.758
	0.910	0.014	HC-2	0.855			
	0.855	0.028	HC-3	0.767			
Lack of Knowledge	0.733	0.185	LK-1	0.879	0.891	0.951	0.744
	0.856	0.139	LK-2	0.918			
	0.858	0.129	LK-3	0.778			
	0.835	0.158	LK-4	0.898			
Inadequate Infrastructure	0.766	0.040	II-1	0.899	0.816	0.821	0.735
	0.879	0.019	II-2	0.869			
	0.918	0.017	II-3	0.892			
Productivity	0.892	0.017	P-1	0.886	0.871	0.872	0.794
	0.885	0.027	P-2	0.895			
	0.895	0.018	P-3	0.880			

Table 4. Discriminant Validity using Heterotrait-Monotrait Ratio Matrix (HTMT)

	Al Adoption	High Cost	Inadequate Infrastucture	Lack of Knowledge	Productivity
Al Adoption					
High Cost	0.761				
Inadequate Infrastucture	0.473	0.661			
Lack of Knowledge	0.109	0.114	0.130		
Productivity	0.438	0.700	0.423	0.161	

Table 5. Collinearity Statistics (VIF)

	Al Adoption	High Cost	Inadequate Infrastucture	Lack of Knowledge	Productivity
Al Adoption		1.000	1.000	1.000	
High Cost					1.424
Inadequate Infrastucture					1.434
Lack of Knowledge					1.020
Productivity					

Table 6. R^2 and Q^2

Construct	R^2	Adjust R^2	p-Value	Q^2
High Cost	0.416	0.413	0.000	0.404
Lack of Knowledge	0.009	0.005	0.001	0.189
Inadequate Infrastucture	0.152	0.148	0.000	0.139
Productivity	0.682	0.678	0.000	0.128

Table 7. Bootstrapping

Hypothesis	Relationship	β-Value	T-Statistics	p-Value	Remarked
H1	AI Adoption → High Cost	0.645	15.275	0. 000	Suported
H2	AI Adoption → Lack of Knowledge	0.094	1.166	0. 000	Suported
H3	AI Adoption → Inadequate Infrastructure	0.390	5.643	0.244	Rejected
H4	High Cost → Productivity	0.228	2.907	0.004	Suported
H5	Lack of Knowledge → Productivity	0.671	9.364	0.000	Suported
H6	Inadequate Infrastructure → Productivity	0.046	0.956	0.339	Rejected