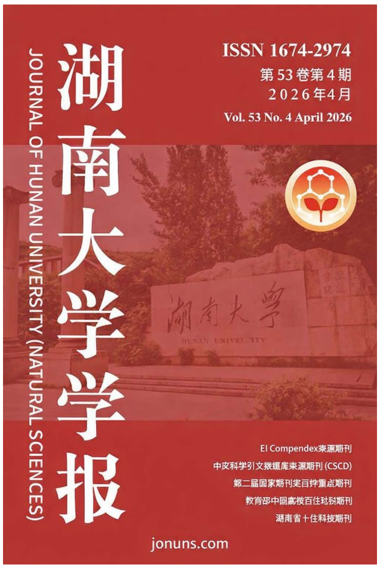

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AI Adoption, Innovation and Competitiveness in SMEs: Evidence from Creative Industries in Yogyakarta

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Abstract: This study examines the role of artificial intelligence (AI) adoption in enhancing innovation and competitiveness among small and medium-sized enterprises (SMEs) operating in the creative industries of the Special Region of Yogyakarta, Indonesia. Despite the growing strategic importance of AI for SMEs, empirical evidence from developing economies remains limited, particularly regarding how institutional and organizational factors jointly shape AI-driven competitiveness. To address this gap, this study proposes an integrative model that positions government support, organizational capacity, and inter-firm collaboration as antecedents of AI adoption. Data were collected from creative industry SMEs through a structured questionnaire. The measurement instrument captured organizational capacity, collaboration, government support, AI adoption, innovation, and competitiveness. Data analysis was conducted using Partial Least Squares–Structural Equation Modeling (PLS-SEM). The results indicate that both organizational capacity and collaboration play critical roles in facilitating AI adoption among creative SMEs. Government support emerges as a key enabling factor by strengthening internal capabilities and fostering collaborative networks. Furthermore, AI adoption is found to significantly stimulate product and process innovation, which in turn enhances SME competitiveness. Innovation functions as an essential mechanism through which AI adoption translates into superior competitive outcomes rather than acting as an isolated technological investment. The study concludes that AI adoption should be understood as a strategic capability embedded within a broader ecosystem of organizational readiness, collaboration, and policy support. For creative SMEs, effective AI utilization requires coordinated efforts across technological, organizational, and institutional dimensions to generate sustainable innovation and long-term competitive advantage.

Keywords: Artificial Intelligence Adoption; Small and Medium-Sized Enterprises (SMEs); Creative Industries; Innovation Performance; Firm Competitiveness; Developing Economies.

AI应用、创新与中小企业竞争力：来自日惹创意产业的证据

摘要：本研究考察了人工智能（AI）采用在提升印度尼西亚日惹特区创意产业中小企业（SMEs）创新能力与竞争力方面的作用。尽管人工智能对中小企业的战略重要性日益提升，但来自发展中经济体的实证证据仍然有限，尤其是在制度因素与组织因素如何共同塑造基于人工智能的竞争力方面。为弥补这一研究空白，本文构建了一个整合性模型，将政府支持、组织能力和企业间协作作为人工智能采用的前置因素。研究通过结构化问卷收集了创意产业中小企业的数据。测量工具涵盖了组织能力、协作、政府支持、人工智能采用、创新以及竞争力等变量。数据分析采用偏最小二乘结构方程模型（PLS-SEM）方法进行。研究结果表明，组织能力和企业间协作在促进创意产业中小企业采用人工智能方面发挥着关键作用。政府支持通过强化企业内部能力并促进协作网络的发展，成为重要的促进因素。此外，人工智能的采用显著推动了产品创新与过程创新，进而提升了中小企业的竞争力。创新在人工智能采用转化为更高竞争绩效的过程中发挥着关键中介机制的作用，而非作为孤立的技术投入存在。研究认为，人工智能的采用应被视为嵌入于组织准备度、协作关系及政策支持等更广泛生态系统中的一种战略能力。对于创意产业中小企业而言，实现人工智能的有效应用需要在技术、组织与制度层面进行协同努力，以实现可持续创新与长期竞争优势。

关键词：人工智能采用；中小企业（SMEs）；创意产业；创新绩效；企业竞争力；发展中经济体

1. Introduction

Small and medium-sized enterprises (SMEs) play a vital role in Indonesia’s economy, significantly supporting the country's gross domestic product and generating a large portion of employment opportunities. Empirical evidence consistently shows that SMEs dominate Indonesia’s business structure and play a critical role in sustaining economic resilience, particularly during periods of economic crisis and in the post-pandemic recovery phase. Despite their strategic importance, Indonesian SMEs are generally characterized by small-scale operations, labor-intensive production, and limited access to capital and advanced technologies. These structural constraints make them particularly vulnerable to global competitive pressures and rapid digital disruption [1,2].

In recent years, digital transformation has emerged as a strategic priority of the Indonesian government to enhance SME competitiveness, with AI increasingly positioned as a key enabling technology. Artificial Intelligence (AI) refers to algorithm-based systems capable of learning from data, generating predictions, and supporting autonomous decision-making processes [3]. International studies suggest that AI adoption can significantly improve SME performance through business process automation, customer data analytics, and enhanced managerial decision accuracy. These benefits are particularly relevant for SMEs operating in developing economies, where resource constraints necessitate efficiency-driven technological solutions [4,5].

Within the Indonesian context, AI adoption carries strategic implications for SMEs, as it offers a mechanism to overcome internal resource limitations. AI technologies enable SMEs to leverage digital transaction data, social media interactions, and e-commerce platforms to improve operational efficiency and customer service personalization. Prior studies on AI-driven analytics indicate that such technologies function not only as operational tools but also as strategic instruments that strengthen SMEs' dynamic capabilities in increasingly digitalized and competitive markets [1,6].

Beyond economic performance, the adoption of AI has also been increasingly associated with sustainability outcomes, an issue of growing importance in Indonesia amid escalating environmental and social pressures. The literature highlights that the combination of AI with synergistic digital technologies, including cloud computing and the Internet of Things (IoT), enables SMEs to optimize energy consumption, manage raw materials more efficiently, and reduce waste. Recent systematic reviews further confirm that AI-based technologies contribute positively to the sustainability performance of SMEs and their contribution to advancing the Sustainable Development Goals (SDGs), especially within the context of developing nations [2,7].

Nevertheless, despite its considerable potential, AI adoption among Indonesian SMEs remains constrained by several structural and contextual barriers. Challenges encompass low levels of digital literacy, a lack of technical skills, substantial implementation expenses, and apprehensions regarding data security and ethical implications of AI adoption [4,8]. Such challenges are particularly pronounced within the creative industry sector, where innovation capabilities are often suboptimal due to ineffective management of organizational knowledge assets, encompassing human, structural, and relational capital, as well as limited collaboration, weak ICT support, and insufficient integration with digital platforms. Previous studies in Central Java, for example, indicate that although sectors such as culinary, fashion, and crafts contribute significantly to creative economic value added, their innovation potential remains underexploited.

Moreover, the existing literature on AI adoption in SMEs is still predominantly shaped by cross-country studies or research conducted in developed economies. As a result, empirical understanding of how AI influences innovation and competitiveness among SMEs in Indonesia, particularly within the creative industry, remains limited [5]. This gap underscores the need for context-specific research that captures the institutional, technological, and socio-economic characteristics of Indonesian SMEs, thereby contributing both theoretically and practically to the SME and digital transformation literature.

Therefore, this study examines how AI adoption contributes to innovation and competitiveness among creative-industry SMEs in the Special Region of Yogyakarta, Indonesia. Rather than treating AI adoption as an isolated technological decision, the proposed model explains it as the outcome of interacting institutional, relational, and organizational conditions. Specifically, government support is modeled as an environmental enabler that strengthens collaboration and organizational capacity; these two factors then act as proximate determinants of AI adoption, which subsequently enhances innovation and competitiveness.

The contribution of this study does not lie merely in combining several antecedents of AI adoption. Instead, it advances prior TOE-based research in two specific ways. First, it extends the environmental dimension of TOE by specifying a capability-building role for government support, rather than treating environmental conditions only as background pressures or direct adoption triggers. Second, it introduces a capability-based explanation of AI adoption by showing how organizational capacity and inter-firm collaboration are converted into innovation and competitive outcomes through AI use. In this way, the study links the AI adoption literature to downstream performance mechanisms and provides evidence from creative SMEs in a developing regional ecosystem that remains underrepresented in existing research [9].

2. Literature Review

2.1. Government Support for SMEs

Government support for SMEs encompasses a range of public policy interventions designed to mitigate structural constraints that impede SME growth, survival, and competitiveness. These constraints typically include limited access to finance, regulatory barriers, and insufficient organizational capabilities [10]. Traditionally, government support has primarily taken the form of direct financial assistance, such as subsidized loans, credit guarantee schemes, and public funding programs aimed at reducing information asymmetry and collateral limitations commonly faced by SMEs in conventional financial markets. However, within the context of rapid digital transformation, the scope of government support has expanded beyond purely financial mechanisms toward technology-enabled and policies focused on promoting innovation that enable the integration of digital technologies, such as AI and fintech solutions [5].

In addition to financial assistance, government support plays a critical role in addressing non-financial barriers that constrain SME technology adoption. These barriers include limited digital literacy, inadequate technological capabilities, and low awareness of emerging digital solutions [10]. Public initiatives that promote digital skills training, technology diffusion, and institutional collaboration enable SMEs to leverage digital platforms, alternative lending models, and data-driven tools, thereby enhancing operational efficiency and organizational effectiveness [11]. In this regard, government intervention functions not only as a provider of financial resources but also as a key facilitator that strengthens inter-firm collaboration while significantly enhancing SMEs' internal technical capabilities and knowledge bases.

Furthermore, governments play a strategic role in fostering collaborative ecosystems by facilitating the development of industrial networks, business clusters, and incubation centers. These structures create enabling environments in which SMEs can collaborate, share knowledge, and access advanced resources and technologies that may otherwise be prohibitively costly if acquired individually [12]. Such collaborative platforms are particularly relevant for SMEs seeking to adopt AI, as they promote collective learning and reduce uncertainty associated with advanced technology implementation. Through these mechanisms, government support indirectly enhances collaborative intensity and innovation capacity among SMEs.

Governments also directly address the shortage of technical expertise and digital literacy through targeted educational interventions and technical assistance programs. One of the most impactful forms of support involves public investment in workforce training curricula aimed at equipping SME owners and employees with essential digital skills [13]. Government-sponsored training programs, workshops, and technical mentoring initiatives are therefore instrumental in enhancing the “digital hard skills” of entrepreneurs and employees, thereby increasing the capacity of SME personnel to understand, operate, and exploit AI technologies effectively [14].

Based on this theoretical reasoning, government support is expected to exert both direct and indirect effects on key organizational capabilities that underpin SME competitiveness in the digital era. Specifically, government interventions are theorized to strengthen collaborative relationships among SMEs while simultaneously enhancing their skill and knowledge capacity. Based on the above, the study puts forward the following hypotheses:

H1: Government support has a positive effect on collaboration among SMEs.

H2: Government support has a positive effect on the skill and knowledge capacity of SMEs.

2.2. Collaboration in SMEs

Collaborative business efforts and the integration of innovation are crucial in facilitating the dissemination of AI knowledge and Industry 5.0 technologies to SMEs, mainly through the establishment of shared infrastructure, expert mentoring, and the creation of collaborative ecosystems among SMEs. By offering supportive and resource-rich environments, business incubators and collaborative platforms enable SMEs to experiment, learn, and scale more effectively, thereby directly accelerating their capacity to develop and implement advanced technologies [12]. Such collaborative settings reduce uncertainty and learning costs, which are commonly associated with the adoption of complex digital technologies such as AI.

Collaboration between firms within the SME sector has been demonstrated to have a substantial and positive impact on the adoption of AI technologies. Collaboration not only serves as a defensive mechanism to mitigate internal resource constraints but also functions as a proactive strategic approach that accelerates innovation and technology integration. Through resource-sharing arrangements, SMEs are better able to overcome operational inefficiencies and enhance their collective technological readiness [15]. These collaborative interactions facilitate knowledge exchange, promote mutual learning, and strengthen SMEs’ absorptive capacity, all of which are critical for effective AI adoption.

Strategic alliances further enable SMEs to combine resources with external partners, allowing them to bypass the substantial internal investments of time, capital, and expertise typically required to develop AI capabilities independently. By leveraging partnerships with technology providers, research institutions, or other SMEs, firms can access broader pools of technical expertise and advanced technological resources, thereby transforming AI adoption from a high-risk, firm-specific endeavor into a more affordable and informed collective effort [13]. This collaborative approach not only reduces implementation costs but also fosters industry-level innovation and accelerates the diffusion of AI technologies across SMEs [15].

Despite the growing recognition of collaboration as a strategic enabler of digital transformation, empirical studies that explicitly examine the role of collaboration as a key driver of AI adoption in SMEs remain limited [16]. This gap in existing research underscores the necessity for additional empirical exploration into how collaborative relationships among SMEs influence their decisions and capabilities to adopt AI technologies. Therefore, this study aims to empirically examine the relationship between inter-organizational collaboration and the adoption of AI among SMEs. Based on prior studies, the following hypothesis is proposed:

H3: Collaboration among SMEs positively influences the adoption of AI.

2.3. Organizational Capacity in SMEs

AI has become a key catalyst in transforming operational processes and enhancing customer experiences in the dynamic creative industry. By leveraging AI-driven technologies, SMEs are progressively capable of offering more personalized customer interactions, thereby enhancing customer satisfaction and fostering long-term loyalty [17]. In the context of Indonesia’s creative industry, AI adoption further enables the development of more efficient project management processes as well as innovative and sustainable operational approaches, which ultimately contribute to improved project execution efficiency. These developments reflect the broader transformation toward smart industries, characterized by automation, data-driven decision-making, and process optimization facilitated by AI technologies embedded within industrial operations [18].

Despite its transformative potential, the implementation of AI in industrial and SME settings remains a complex and multifaceted endeavor. Prior studies indicate that numerous technical, organizational, and human-related challenges may constrain the capacity of AI to support sustainable business practices [11]. In particular, the integration of AI into existing organizational systems is often hindered by limitations in workforce skills and knowledge, which reduce the ability of SMEs to fully exploit AI-driven solutions. These constraints are especially salient in creative industry SMEs, where technological sophistication frequently outpaces the preparedness of human resources to adopt and manage advanced digital technologies effectively.

Human resource capacity therefore plays a central and multidimensional role in influencing AI adoption among SMEs. This capacity extends beyond technical competencies alone to encompass psychological readiness, adaptability to technological change, managerial support, and social dynamics within the organization. Empirical evidence consistently identifies employee capability and competence as among the most influential predictors of AI adoption. For instance, the availability of skilled human resources has been shown to be critical for SMEs seeking to utilize AI solutions effectively [19]. Moreover, recent research demonstrates that employee capability can emerge as the single most influential determinant of AI adoption above other external factors such as customer pressure or vendor support [20].

Conversely, a lack of skilled personnel and insufficient technical knowledge frequently constitute major barriers to AI adoption, leading to organizational unpreparedness and inhibiting the successful integration of innovation into existing systems [20]. SMEs with limited AI-related knowledge often struggle to align technological solutions with business needs, which undermines both adoption decisions and implementation outcomes. Conversely, employees possessing greater AI literacy are more likely to perceive AI technologies as beneficial, which in turn positively influences organizational willingness to adopt such innovations [21]. These results highlight the strategic value of enhancing skills and knowledge capabilities as a foundational enabler of AI adoption in SMEs, particularly within technology-intensive and creativity-driven sectors. In the context of creative SMEs, capacity is intentionally defined broadly to include not only AI-related technical knowledge but also the human learning and problem-solving capability required to translate AI tools into creative business applications. Based on this theoretical reasoning and empirical evidence, the following hypothesis is proposed:

H4: Skill and knowledge capacity of SMEs has a positive effect on AI adoption.

2.4. AI Adoption

Furthermore, this research aims to identify the dominant variables that effectively drive innovation and competitive advantage within the SME sector in the Special Region of Yogyakarta Province. One of the key drivers of innovation and competitiveness in SMEs frequently highlighted in prior studies is the implementation or adoption of AI technologies [5]. In the academic literature, AI adoption is defined as a multidimensional concept encompassing organizational capability, managerial willingness, and the processes through which AI technologies are integrated into firm operations to achieve strategic objectives. Previous studies conceptualize AI adoption not merely as the acquisition of software or digital tools, but rather as a gradual process that evolves from initiation and acceptance to routinization, where AI becomes embedded in everyday organizational workflows [22].

Within the SME context, AI adoption is commonly interpreted as the organization's capacity to employ emerging technologies, both internally, through technological infrastructure, and externally, through digital ecosystems, to transform business processes and improve efficiency [23]. This definition also includes the application of machine-driven systems that can produce predictions, suggestions, or decisions impacting both physical and digital environments. These systems are ultimately designed to improve organizational performance, lower operational expenses, and drive innovation in products and services.

Empirical evidence further demonstrates that AI adoption enables SMEs to develop more innovative and effective marketing strategies. During the ideation and creative phases, AI plays a crucial role in overcoming social barriers commonly encountered in traditional brainstorming sessions. According to Rowland and Grüning [24], interactions with AI can reduce the "fear of judgment" from colleagues, resulting in a greater quantity and diversity of ideas. These raw ideas serve as rich base material for innovation development. Importantly, this enhanced innovation capability does not represent a final outcome in itself; rather, it functions as a key mechanism that directly activates multiple levers of competitive advantage for SMEs in the marketplace. Simultaneously, AI-driven innovation capability strengthens SMEs' competitiveness in the digital era by improving organizational agility, personalization, and strategic decision-making.

Consistent with this view, previous research has established that the adoption of AI and machine learning has a significant impact on product innovation within SMEs [25]. The existing literature further suggests that AI integration not only improves operational efficiency but also acts as a primary catalyst for sustainable innovation across products, services, processes, and business models [19]. Moreover, the use of AI allows firms to accelerate product adaptation to evolving consumer needs, thereby enhancing overall business competitiveness. This dynamic is particularly evident among creative industry firms that actively utilize information and communication technologies (ICT), including AI. Accordingly, this research is expected to develop a model that can robustly explain the contribution of AI adoption to strengthening the competitiveness of creative SMEs.

Collectively, this body of evidence provides a strong foundation for formulating formal hypotheses regarding the positive relationships between AI adoption, enhanced innovation, and improved competitive advantage in SMEs. Based on the theoretical framework of technology adoption and the impact analysis discussed above, specific research hypotheses are proposed to articulate the anticipated effects of AI adoption on SMEs' innovation capacity and competitiveness. The main hypotheses are formally stated as follows:

H5: The adoption of AI by SMEs has a positive effect on their innovation.

H6: The adoption of AI by SMEs has a positive effect on their competitive advantage.

2.5. Innovation and Competitiveness in SMEs

Recent research by Osarenkhoe and Fjellström [26] highlights that innovation within SMEs is no longer conceptualized as a linear investment in research and development, but rather as an interactive, iterative, and cumulative process that emerges through continuous interaction between firms and their surrounding environments. In today's digital age, innovation within SMEs is increasingly reflected in the uptake of advanced technologies, including AI, the IoT, and big data analytics, which fundamentally reshape how firms design, produce, and deliver value [26]. Such digital advancements empower SMEs to adapt more efficiently to evolving market dynamics and to reconfigure their operational and strategic processes in dynamic competitive contexts.

Competitiveness in SMEs is commonly defined as the firm's ability to sustain market relevance, operational efficiency, and long-term growth amid intense competition from larger and more resource-rich firms [19]. This capability is highly contingent upon the firm's capacity to align and continuously adapt its internal resources and competencies with rapidly evolving external environments [26]. Contemporary strategic management literature often links SME competitiveness to the notion of sustainable competitive advantage (SCA), defined as a firm's capacity to attain and sustain superior performance over time by effectively utilizing and renewing its valuable organizational resources.

Building on this perspective, the present study assumes that innovation exerts a positive influence on SME competitiveness through a set of interconnected strategic mechanisms. Prior studies indicate that technological innovation, particularly through AI adoption and automation, directly enhances operational efficiency and productivity [19]. The implementation of these technologies allows SMEs to streamline internal processes, automate repetitive tasks, and reduce operational costs. Such cost efficiencies are especially critical for SMEs with limited financial resources, as they enable firms to reallocate scarce resources toward more strategic and value-adding activities [19].

By achieving higher levels of efficiency and productivity, SMEs are better positioned to "do more with less," allowing them to offer more competitive pricing or to improve profit margins. These outcomes represent key indicators of economic competitiveness and contribute directly to the strengthening of SMEs' competitive positions in the marketplace [20]. Consequently, innovation functions not only as a driver of operational improvement but also as a strategic lever through which SMEs can enhance and sustain their competitive advantage in increasingly digitalized and competitive environments. Drawing on prior studies, the following hypothesis is proposed:

H7: Innovation within SMEs positively affects their competitive advantage.

Although local government support, inter-organizational collaboration, and AI-related organizational capacity are theoretically connected, they capture different analytical domains in this study. Local government support refers to exogenous institutional assistance provided by public agencies, such as programs, mentoring, technical guidance, and facilitative interventions. Inter-organizational collaboration refers to exchange-oriented relationships through which SMEs access knowledge, resources, and problem-solving support from external partners. AI-related organizational capacity refers to the firm's internal stock of knowledge, skills, awareness, and learning readiness relevant to understanding and using AI. Accordingly, local government support is modeled as an environmental condition, collaboration as a relational mechanism, and capacity as an internal organizational resource. The three constructs are therefore related but not interchangeable.

3. Methodology

3.1. Research Design

This research utilizes a quantitative approach with the primary objective of testing a theoretical model that links antecedents of innovation and competitiveness among SMEs adopting AI technologies. The quantitative approach was selected because it provides a systematic, measurable, and objective analytical capability for examining the phenomenon under investigation. This approach enables researchers to statistically test the relationships between variables [27]. This study adopts a cross-sectional research design. This design aligns with the research objective of observing the conditions and relationships among variables at a particular moment, without any intervention or manipulation of the variables under observation. According to Neuman [27], a quantitative design with a cross-sectional approach is highly appropriate for studies aiming to identify relationships between independent and dependent variables within a relatively short time.

3.2. Procedure for Sampling and Data Collection

The units of analysis in this study are SMEs operating in three key regions: Yogyakarta City, Sleman Regency, and Bantul Regency. These locations were selected based on the rationale that they serve as key hubs for SME development in the Special Region of Yogyakarta Province and exhibit a strong dynamic in the adoption of digital technologies. In 2023, the government designated these regions as national creative industry hubs in Indonesia.

The final sample comprised 105 SMEs. Although modest in absolute terms, this sample size is adequate for the present analysis for three reasons. First, the structural model is relatively parsimonious, with a maximum of two predictors for any endogenous construct. Second, a power-based calculation ($f^2 = 0.15$; $\alpha = 0.05$; statistical power = 0.80) indicates a minimum required sample of 68 observations; therefore, the achieved sample size of 105 exceeds this threshold. Third, the achieved sample should be interpreted relative to the narrowly defined target population, as eligibility was restricted to creative SMEs that had operated for more than three years, possessed digital literacy, and had participated in local government capacity-building programs.

This study utilizes purposive sampling, a non-probability sampling method in which respondents are intentionally selected based on predetermined criteria aligned with the research objectives. The criteria applied in this study include: (1) having operated their business for more than three years; (2) possessing digital literacy skills; and (3) having participated in capacity-building training organized by the local government for small industry practitioners. Given the purposive sampling design and the specific focus on creative industry SMEs in Yogyakarta, this study is intended to provide context-specific insights rather than statistically generalizable conclusions for the broader SME population.

Data collection was carried out using a structured questionnaire, designed based on indicators of the research variables and informed by previous studies. The questionnaire was disseminated online through Google Forms to more efficiently reach SMEs actors and minimize geographical constraints. The questionnaire employed a self-report method, whereby respondents independently completed the provided questions. Because the study relies on purposive sampling and self-reported questionnaire data, several sources of bias should be acknowledged. The sampling criteria may have favored SMEs with relatively higher digital readiness, especially because participation required digital literacy and prior involvement in government-supported training. As a result, the sample may overrepresent firms that are more receptive to AI adoption than the broader SME population. In addition, self-reported measures may be affected by subjective evaluation, social desirability bias, and common method variance. Accordingly, the findings should be interpreted as associational and context-bound rather than as fully representative estimates of all SMEs.

3.3. Measures

All constructs were modeled as reflective latent variables. The indicators were informed by prior studies and adapted to the context of creative SMEs in Yogyakarta. Local government support was operationalized as respondents' perceived access to public programs, technical guidance, and facilitative support for AI-related business development. Inter-organizational collaboration was operationalized as the extent and quality of knowledge sharing, resource exchange, joint problem solving, and partnership effectiveness with external actors. AI-related organizational capacity was operationalized as the firm's internal stock of AI-relevant knowledge, skills, awareness of AI resources, and learning readiness. This operational distinction is important: capacity captures internal preparedness, collaboration captures relational embeddedness, and local government support captures institutional inputs originating outside the firm. AI adoption was operationalized as the extent to which AI is explored, implemented, routinized, and strategically developed in firm activities, whereas innovation and competitiveness were treated as downstream outcome constructs. All items were measured using a five-point Likert scale ranging from 1 = 'Strongly Disagree' to 5 = 'Strongly Agree'. The questionnaire items were written in Indonesian to ensure contextual comprehensibility for respondents (see Appendix A).

3.4. Sample Characteristics

As shown in Table 1, the findings indicate that the majority of respondent businesses were based in Yogyakarta, accounting for 50.5% of the total sample, and most were micro-enterprises employing fewer than 10 workers (90%). The distribution of establishment years indicated that the participating businesses were predominantly founded in 2013 (68%), reflecting a strong entrepreneurial growth dynamic in the three regions. In terms of business types, the food and beverage (39%) and fashion (30%) sectors emerged as the two most prominent categories, illustrating the rapidly developing creative economy characterizing these regions.

Table 1. Study participant profile (*n* = 105)

Sample Characteristics		Freq	(%)
Business location	Yogyakarta	53	50.5%
	Bantul	19	18.1%
	Sleman	33	31.4%
Year of establishment	1971–1977	1	1%
	1978–1984	0	0%
	1985–1991	4	4%
	1992–1998	6	6%
	1999–2005	9	9%
	2006–2012	13	12%
	2013–2019	39	37%
	> 2019	33	31%
Type of business	Agribusiness	2	2%
	Education	1	1%
	Fashion	32	30%
	Food and beverage	41	39%
	Handicrafts	13	12%
	Manufacture	9	9%
	Retailer	3	3%
	Service industry	4	4%
Number of Employees	0–10	95	90%
	11–21	4	4%
	22–32	1	1%
	33–43	1	1%
	44–54	2	2%
	55–65	1	1%
	66–76	0	0%
	> 76	1	1%

3.5. Data Analysis

The data were analyzed using SmartPLS 4 in two stages: assessment of the measurement model and assessment of the structural model. The measurement model was evaluated through indicator loadings, composite reliability, average variance extracted, and discriminant validity using the Fornell–Larcker criterion and cross-loadings. The structural model was assessed using path coefficients, bootstrapped t-statistics and p-values (5,000 resamples), effect size (f^2), and coefficients of determination (R^2).

4. Results

4.1. Evaluation of the Measurement Model

The measurement model was assessed to determine the reliability and validity of the latent constructs by examining both convergent and discriminant validity. Based on Table 2, the Composite Reliability (CR) values for all six measured constructs, namely AI Adoption (0.907), Capacity (0.947), Collaboration (0.941), Competitiveness (0.844), Innovation (0.921), and Government Support (0.897), are above the suggested minimum threshold of ≥ 0.70 and < 0.95. This demonstrates good internal reliability [9]. Following the guidelines of Hair et al. [9], the average variance extracted (AVE) values for all constructs surpass the recommended threshold of 0.5, confirming that each construct demonstrates satisfactory convergent validity. This is further supported by the outer loading values of the indicators, all of which exceed 0.7, as presented in the appendix. These high outer loadings indicate that the indicators effectively represent their corresponding latent constructs, in line with Hair et al. [9], who recommend a minimum outer loading of 0.7 for acceptable indicator reliability.

Table 2. Reliability and convergent validity

Construct	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
AI Adoption	0.907	0.711
Capacity	0.947	0.781
Collaboration	0.941	0.697
Competitiveness	0.844	0.730
Innovation	0.921	0.625
Gov. Support	0.897	0.745

Based on the two discriminant validity assessments presented in the appendix, the results indicate that the measurement model demonstrates satisfactory discriminant validity requirements established by the Fornell–Larcker criterion. Furthermore, the cross-loading analysis provides additional support for discriminant validity. Taken together, these results provide strong evidence that the constructs are empirically distinct. For the focal antecedent constructs, all constructs are clearly distinct. Although these constructs are theoretically related, each indicator loads highest on its intended construct, suggesting that the measures are associated but non-redundant.

4.2. Evaluation of the Structural Model

The evaluation of the structural model was conducted to examine the causal relationships among the latent constructs outlined in the conceptual framework. As illustrated in Table 3 and Figure 1, all proposed paths were found to be statistically significant, meeting the standard criteria of a *t*-statistic exceeding 1.96 and a p-value less than 0.05 at the 5% significance level [9]. The results reveal that AI adoption exerts a significant positive influence on Competitiveness ($\beta = 0.276$; $t = 2.290$; $p = 0.011$), indicating that the effective implementation of AI technologies enhances organizational competitive advantage. Moreover, AI adoption has a strong and highly significant effect on Innovation ($\beta = 0.826$; $t = 31.074$; $p = 0.000$), suggesting that AI functions as a key enabler of innovation within firms. This finding is reinforced by the significant path from Innovation to Competitiveness ($\beta = 0.566$; $t = 5.090$; $p = 0.000$).

Additionally, capacity significantly influences AI Adoption ($\beta = 0.454$; $t = 4.070$; $p = 0.000$), confirming that internal organizational capabilities, such as infrastructure, expertise, and readiness, serve as foundational antecedents to AI implementation. Collaboration also exhibits a significant yet moderate impact on AI Adoption (β = 0.259; t = 2.291; p = 0.011), indicating that inter-organizational collaboration facilitates knowledge exchange and technology diffusion, thereby promoting adoption. Furthermore, government support plays a vital role in fostering both Capacity (β = 0.737; t = 13.060; p = 0.000) and Collaboration (β = 0.519; t = 5.416; p = 0.000). The results emphasize the strategic role of public policy and institutional support in strengthening organizational readiness and fostering collaborative ecosystems.

Although all hypothesized relationships are statistically significant, their magnitudes are not uniform and therefore require differentiated interpretation. The path from AI adoption to innovation is by far the strongest in the model (β = 0.826), whereas the direct path from AI adoption to competitiveness is much smaller (β = 0.276). This pattern suggests that, in creative SMEs, AI functions primarily as an innovation-enabling mechanism rather than as an immediate source of competitive advantage. A similar difference appears in the antecedents of AI adoption: organizational capacity shows a stronger association with AI adoption (β = 0.454) than collaboration (β = 0.259), indicating that internal readiness remains more decisive than external relational support. Likewise, government support appears to contribute more strongly to capacity building (β = 0.737) than to collaboration (β = 0.519), implying that public intervention in this setting is more effective in strengthening internal preparedness than in generating sustained inter-firm coordination.

Table 3. Testing of hypotheses

Independent Variable	Dependent Variable	Coefficient β	Effect Size (f^2)	T-Statistic	p-values	Result
Gov. Support	Collaboration	0.519	0.369	5.416	0.000	H1 Accepted
Gov. Support	Capacity	0.737	1.186	13.060	0.000	H2 Accepted
Collaboration	AI Adoption	0.259	0.083	2.291	0.011	H3 Accepted
Capacity	AI Adoption	0.454	0.254	4.070	0.000	H4 Accepted
AI Adoption	Innovation	0.826	2.140	31.074	0.000	H5 Accepted
AI Adoption	Competitiveness	0.276	0.070	2.290	0.011	H6 Accepted
Innovation	Competitiveness	0.566	0.296	5.090	0.000	H7 Accepted

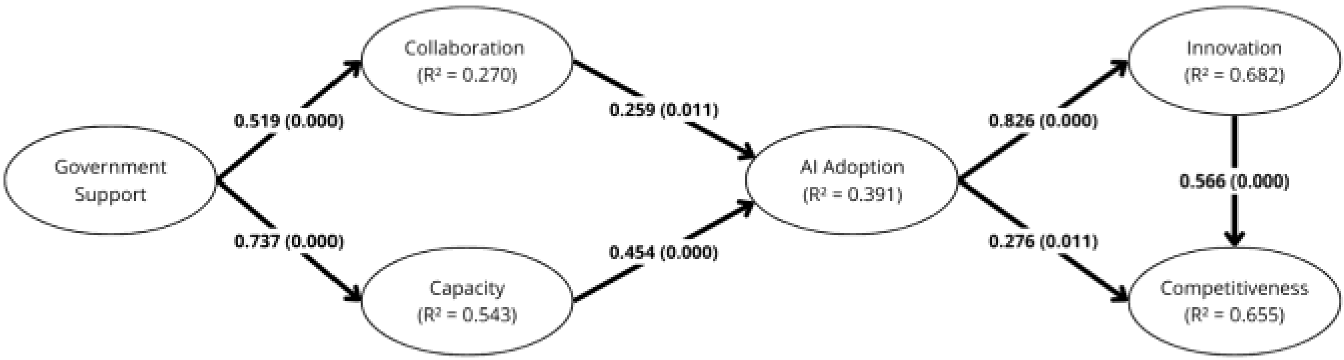

Figure 1. Structural model

Beyond statistical significance, effect sizes (f^2) were examined to assess the substantive contribution of each predictor to its endogenous construct. The results show that AI adoption has a very large effect on innovation (f^2 = 2.140) but only a small direct effect on competitiveness (f^2 = 0.070). Capacity exhibits a moderate effect on AI adoption (f^2 = 0.254), whereas collaboration shows only a small effect (f^2 = 0.083). Government support has a very large effect on capacity (f^2 = 1.186) and a strong effect on collaboration (f^2 = 0.369). Innovation also shows a moderate effect on competitiveness (f^2 = 0.296). Overall, these findings suggest that the model's strongest substantive relationships lie in the paths from government support to capacity and from AI adoption to innovation, whereas the direct effect of AI adoption on competitiveness is comparatively limited.

The model's explanatory strength is supported by the coefficient of determination (R^2) values obtained for the endogenous constructs: Collaboration (R^2 = 0.270), Capacity (R^2 = 0.543), AI Adoption (R^2 = 0.391), Innovation (R^2 = 0.682), and Competitiveness (R^2 = 0.655). Hair et al. (2011) categorized R^2 values into three general categories: values of 0.75 or greater as substantial, 0.50 or greater as moderate, and 0.25 or greater as weak. All R^2 values suggest that the model has moderate predictive relevance, particularly in explaining innovation and competitiveness outcomes. Notably, the high R^2 for Innovation and Competitiveness indicates that the model's antecedents effectively account for substantial variance in these constructs [9]. In summary, the structural model supports all hypothesized relationships, but the results should not be read as indicating uniform influence across paths. Instead, the coefficient pattern points to a layered mechanism in which government support is more strongly associated with capability formation than with collaboration, internal capacity is more influential than collaboration in shaping AI adoption, and competitiveness is driven more strongly by innovation than by AI adoption alone. This interpretation suggests that the value of AI for creative SMEs is realized mainly through capability development and innovation conversion rather than through technology uptake by itself.

5. Discussion

This study makes three theoretical contributions. First, it extends the Technology–Organization–Environment (TOE) framework by showing that the environmental context, captured here by government support, influences AI adoption indirectly through collaboration and organizational capacity. This moves beyond a conventional TOE reading in which environmental factors are treated mainly as external pressures or facilitating conditions surrounding adoption. Second, from a capability-based perspective, the findings suggest that AI adoption is better understood as a capability-building mechanism than as simple technology acquisition. In the present model, internal capacity and inter-organizational ties are translated into innovation and competitiveness through AI use. Third, the study clarifies the consequence chain by showing that innovation is the principal mechanism through which AI adoption strengthens competitiveness. The study therefore offers a process explanation of AI-enabled competitiveness that connects institutional support, organizational readiness, adoption, and downstream performance within a single framework.

Importantly, full hypothesis support does not imply that all relationships are equally strong or equally consequential. The model reveals clear asymmetries in effect magnitude. These asymmetries are theoretically informative because they indicate where the main leverage points are located in the AI adoption process and where complementary mechanisms are still required for business outcomes to materialize.

The effect pattern associated with government support deserves a more differentiated interpretation. Although government support significantly strengthens both collaboration and organizational capacity, the stronger path to capacity suggests that public intervention in this context is translated more readily into training, awareness, and internal readiness enhancement than into durable inter-firm cooperation. This is plausible because capacity building can be delivered directly through workshops, mentoring, and technical assistance, whereas collaboration depends on additional conditions such as partner fit, trust, reciprocity, and the perceived value of joint action. The result therefore indicates that government policy can accelerate AI preparedness, but it does not automatically produce dense collaborative ecosystems.

This finding is consistent with Lobel [28], who emphasizes that government support functions as a systemic factor in enhancing AI readiness through policies, governance mechanisms, and investments in human capital. Similarly, the UNCTAD 2025 report underscores that government-facilitated cross-sector collaboration accelerates knowledge exchange and reinforces national innovation infrastructures. By demonstrating these relationships, this study advances the Technology–Organization–Environment (TOE) framework [29] by empirically demonstrating that public policy directly contributes to strengthening organizational capabilities and fostering strategic alliances.

The difference between the effects of organizational capacity and collaboration on AI adoption is also analytically important. Although both are significant, organizational capacity exerts the stronger influence. This suggests that external collaboration is supportive rather than sufficient: firms may gain exposure to AI ideas and practices through networks, but actual adoption still depends more heavily on internal learning capability, awareness of AI applications, and the ability to embed new tools into daily routines [30,31]. In other words, collaboration can reduce uncertainty, but it cannot substitute for firm-level absorptive readiness. These results align with those of Kaushik and Agrawal [32], who identified technological readiness and internal expertise as strong predictors of digital innovation adoption.

The contrast between the two downstream effects of AI adoption is particularly revealing. AI adoption has a very strong relationship with innovation, but only a modest direct relationship with competitiveness. This implies that AI generates its most immediate value by expanding experimentation, improving product development, and supporting process redesign. Competitive gains, however, appear to require an additional translation stage. SMEs benefit competitively not simply because they adopt AI, but because they convert AI-enabled insights and efficiencies into marketable innovations.

The comparatively stronger path from innovation to competitiveness reinforces this interpretation. Innovation appears to be the principal route through which AI contributes to superior market positioning in this setting. Put differently, AI by itself is not yet a sufficient condition for competitiveness; its strategic value depends on whether firms are able to transform technological use into differentiated products, better processes, and commercially meaningful improvements. These findings provide compelling evidence that AI implementation serves as a key catalyst for enhancing organizational innovation and competitive performance [5].

For this reason, the findings are better interpreted as evidence of an innovation-mediated logic of AI value creation rather than a simple direct-effect model. The results therefore suggest that the main competitive payoff of AI in creative SMEs lies less in adoption per se than in the firm's ability to mobilize AI for innovation outcomes. Through AI, firms can improve process efficiency, accelerate decision-making, and develop new products and services with higher value-added potential [25]. This finding is consistent with prior literature emphasizing innovation as a strategic mediator between digital transformation and enhanced competitive performance [33].

The R^2 pattern supports the same interpretation. The model explains a substantial proportion of variance in innovation (R^2 = 0.682) and competitiveness (R^2 = 0.655), but a more moderate proportion in AI adoption (R^2 = 0.391). This indicates that the downstream logic of the model is stronger than the adoption-stage explanation. In substantive terms, once AI is in place, its links to innovation and competitiveness are relatively well captured by the model; by contrast, the decision and capacity to adopt AI are still influenced by additional factors not included here, such as implementation cost, infrastructure availability, data governance concerns, or owner risk orientation.

The value of the present model lies not simply in combining several predictors, but in specifying the sequence through which public support shapes collaboration and organizational capacity, which then influence AI adoption and its downstream effects on innovation and competitiveness. This sequencing offers a more explicit explanatory mechanism than studies that examine antecedents of AI adoption or firm performance outcomes in isolation. It also shows that, in the creative SME context, AI-related competitiveness is embedded in a regional ecosystem rather than determined by firm-level technological readiness alone [34].

5.1. Implications

The study contributes to theory in three ways: (1) by extending TOE through an indirect environmental pathway in which government support shapes adoption via collaboration and capacity; (2) by advancing a capability-based explanation in which AI adoption converts internal and relational resources into innovation outcomes; and (3) by positioning innovation as the mechanism through which AI adoption translates into competitiveness. Together, these contributions move the discussion from identifying correlates of adoption to explaining how adoption is transformed into competitive outcomes [35].

The findings also offer managerial and policy implications, particularly for creative SMEs and public agencies operating in regional ecosystems similar to Yogyakarta. The differences in path magnitudes also imply a practical sequencing: internal capability development should precede or accompany collaborative initiatives, and AI investment should be evaluated not only by adoption rates but by its conversion into innovation outputs. For SME owners and managers in the creative sector, the results suggest that investments in human capital and organizational learning are critical preconditions for realizing the benefits of AI. Firms should prioritize structured training in AI tools, encourage cross-functional teams to experiment with AI-enabled workflows, and establish mechanisms to capture and disseminate internal learning. Moreover, strategic collaborations with universities, technology providers, and peer SMEs can help reduce experimentation costs and risks while expanding access to specialized expertise. From a policy perspective, the evidence indicates that interventions are more effective when designed as integrated programs combining training, mentoring, and network facilitation rather than fragmented, one-off support schemes. Targeted support for creative industry clusters, such as subsidized AI training, shared digital infrastructure, and collaborative innovation platforms, can further amplify the positive feedback loop among capacity, collaboration, AI adoption, and competitiveness.

5.2. Limitations

Despite these contributions, several limitations point to directions for future research. First, the use of a cross-sectional research design limits the capacity to establish robust causal relationships concerning the evolving impact of AI adoption on innovation and competitiveness. Longitudinal studies would be valuable in capturing how AI usage evolves over time and how early capacity-building and collaboration initiatives translate into sustained performance gains.

Second, the study relies on self-reported measures. This design may introduce subjective evaluation, social desirability bias, and common method variance, particularly for innovation and competitiveness. Future research should combine perceptual measures with objective indicators and, where possible, collect responses from more than one informant per firm. Third, purposive sampling was used to ensure relevance to the research objective, but it may have systematically favored SMEs with higher digital awareness and prior exposure to government training. The sample should therefore not be interpreted as statistically representative of all SMEs. Future studies should employ formal sampling frames and probability-based selection procedures where feasible.

Fourth, the external validity of this study is limited because the sample consists exclusively of creative industry SMEs in the Special Region of Yogyakarta, a province with distinctive creative-economy dynamics and relatively active government support. Consequently, the observed relationships may not emerge with the same magnitude in SMEs operating in other Indonesian regions, in non-creative sectors, or in institutional environments with different levels of digital infrastructure, market maturity, and policy intervention. The findings should therefore be interpreted as context-specific rather than broadly representative of all SMEs. Comparative studies across regions and sectors are needed before broader generalizations can be made.

Finally, future studies could enhance the model by integrating additional factors, such as cost-related constraints, infrastructure readiness, ethical and regulatory concerns, or customer-driven pressures, to offer a more holistic understanding of the enablers and outcomes of AI adoption within SMEs.

6. Conclusion

This study provides context-specific evidence from creative industry SMEs in the Special Region of Yogyakarta that AI adoption is positively associated with innovation and competitiveness. The findings suggest that organizational capacity, inter-firm collaboration, and government support are important enabling conditions for AI use in this setting. However, because the study focuses on SMEs in a single region and predominantly within creative industries, these results should not be generalized uncritically to SMEs in other sectors, provinces, or national contexts. Accordingly, the practical implications of this study are most relevant to creative SMEs and policymakers operating in comparable regional ecosystems. Future research should extend this line of inquiry through longitudinal and comparative designs to assess whether the observed relationships remain stable across sectors and regions.

Declarations

Author Contributions

Conceptualization, I.M.S. and L.H.; methodology, I.M.S. and L.H.; software, I.M.S. and I.A.; validation, I.M.S., I.A. and A.; formal analysis, I.M.S. and A.; investigation, L.H. and A.; resources, I.M.S. and I.A.; data curation, L.H. and A.; writing original draft preparation, I.M.S.; writing review and editing, I.M.S.; visualization, I.A.; supervision, A.; project administration, I.A; funding acquisition, L.H.

Data Availability Statement

The data presented in this study are available on request from the corresponding author. The data are not publicly available due to ethical considerations.

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Conflicts of Interest

The authors declare no conflict of interest.

References

[1] DENICOLAI S., ZUCCHELLA A., and MAGNANI G. Internationalization, digitalization, and sustainability: Are SMEs ready? A survey on synergies and substituting effects among growth paths. *Technol Forecast Soc Change*, 2021, 166: 120650. https://doi.org/10.1016/j.techfore.2021.120650.

[2] MARTINS A., BRANCO M. C., MELO P. N., and MACHADO C. Sustainability in Small and Medium-Sized Enterprises: A Systematic Literature Review and Future Research Agenda. *Sustainability*, 2022, 14: 6493. https://doi.org/10.3390/su14116493.

[3] CHAUDHURI R., CHATTERJEE S., VRONTIS D., and CHAUDHURI S. Innovation in SMEs, AI Dynamism, and Sustainability: The Current Situation and Way Forward. *Sustainability*, 2022, 14: 12760. https://doi.org/10.3390/su141912760.

[4] CHATTERJEE S., RANA N. P., DWIVEDI Y. K., and BAABDULLAH A. M. Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. *Technol Forecast Soc Change*, 2021, 170: 120880. https://doi.org/10.1016/j.techfore.2021.120880.

[5] CHOTISARN N., and PHUTHONG T. A bibliometric analysis insights into the intellectual dynamics of artificial intelligence for the micro, small, and medium enterprises. *Cogent Business & Management*, 2025, 12. https://doi.org/10.1080/23311975.2025.2491684.

[6] BEHL A., GAUR J., PEREIRA V., YADAV R., and LAKER B. Role of big data analytics capabilities to improve sustainable competitive advantage of MSME service firms during COVID-19 – A multi-theoretical approach. *Journal of Business Research*, 2022, 148: 378–389. https://doi.org/10.1016/j.jbusres.2022.05.009.

[7] KANNAN S., and GAMBETTA N. Technology-driven Sustainability in Small and Medium-sized Enterprises: A Systematic Literature Review. *Journal of Small Business Strategy*, 2025, 35. https://doi.org/10.53703/001c.126636.

[8] GOVORI A., and SEJDIJA Q. Future prospects and challenges of integrating artificial intelligence

within the business practices of small and medium enterprises. *Journal of Governance and Regulation*, 2023, 12: 176–183. https://doi.org/10.22495/jgrv12i2art16.

[9] HAIR J. F., RISHER J. J., SARSTEDT M., and RINGLE C. M. When to use and how to report the results of PLS-SEM. *European Business Review*, 2019, 31. https://doi.org/10.1108/EBR-11-2018-0203.

[10] ABU N., DA SILVA F. P., and VIEIRA P. R. Government support for SMEs in the Fintech Era: Enhancing access to finance, survival, and performance. *Digital Business*, 2025, 5. https://doi.org/10.1016/j.digbus.2024.100099.

[11] MISRA S. K., SHARMA S. K., GUPTA S., and DAS S. A framework to overcome challenges to the adoption of artificial intelligence in Indian Government Organizations. *Technological Forecasting and Social Change,* 2023, 194. https://doi.org/10.1016/j.techfore.2023.122721.

[12] TAKAWIRA B., and POOE D. SME readiness for Industry 5.0: A systematic literature review. *Southern African Journal of Entrepreneurship and Small Business Management*, 2025, 17. https://doi.org/10.4102/sajesbm.v17i1.946.

[13] SCHWAEKE J., PETERS A., KANBACH D. K., KRAUS S., and JONES P. The new normal: The status quo of AI adoption in SMEs. *Journal of Small Business Management,* 2025, 63. https://doi.org/10.1080/00472778.2024.2379999.

[14] STRILETS V., FROLOV S., DATSENKO V., TYMOSHENKO O., and YATSKO M. State support for the digitalization of SMEs in European countries. *Problems and Perspectives in Management*, 2022, 20. https://doi.org/10.21511/ppm.20(4).2022.22.

[15] MAPHUMULO D. S., and NYIDE C. J. Exploring Smart Manufacturing Tools and Innovative Leadership Strategies in Small Manufacturing Enterprises. *Corporate and Business Strategy Review*, 2025, 6. https://doi.org/10.22495/cbsrv6i3siart5.

[16] ISLAM A., ISLAM M. A., DAL MAS F., FIJAŁKOWSKA J., RAHMAN M., and MASSARO M. Configuring AI-guided sustainable competitive advantage for SMEs through business model innovation: A systematic literature review approach. *Journal of Engineering and Technology Management,* 2025, 78. https://doi.org/10.1016/j.jengtecman.2025.101921.

[17] ALDOSERI A., AL-KHALIFA K. N., and HAMOUDA A. M. Re-Thinking Data Strategy and Integration for Artificial Intelligence: Concepts, Opportunities, and Challenges. *Applied Sciences (Switzerland)*, 2023, 13. https://doi.org/10.3390/app13127082.

[18] RANE N. Integrating Building Information Modelling (BIM) and Artificial Intelligence (AI) for Smart Construction Schedule, Cost, Quality, and Safety Management: Challenges and Opportunities. *SSRN Electronic Journal*, 2023. https://doi.org/10.2139/ssrn.4616055.

[19] YEN W. T. M., HONG T. L., and YEN Y. Y. A Proposed Framework for Assessing the Readiness of AI in Small and Medium Enterprises (SMEs) in Malaysia. *Journal of Ecohumanism*, 2024, 3. https://doi.org/10.62754/joe.v3i5.3893.

[20] SOOMRO R. B., AL-RAHMI W. M., DAHRI N. A., ALMUQREN L., AL-MOGREN A. S., and ALDAIJY A. A SEM–ANN analysis to examine impact of artificial intelligence technologies on sustainable performance of SMEs. *Scientific Reports,* 2025, 15. https://doi.org/10.1038/s41598-025-86464-3.

[21] SOVA R., TUDOR C., TARTAVULEA C. V., and DIEACONESCU R. I. Artificial Intelligence Tool Adoption in Higher Education: A Structural Equation Modeling Approach to Understanding Impact Factors among Economics Students. *Electronics (Switzerland),* 2024, 13. https://doi.org/10.3390/electronics13183632.

[22] WANG X., LIN X., and SHAO B. How does artificial intelligence create business agility? Evidence from chatbots. *International Journal of Information Management,* 2022, 66. https://doi.org/10.1016/j.ijinfomgt.2022.102535.

[23] RICHEY R. G., DAUGHERTY P. J., and ROATH A. S. Firm Technological Readiness and Complementarity: Capabilities Impacting Logistics Service Competency and Performance. *Journal of Business Logistics,* 2007, 28. https://doi.org/10.1002/j.2158-1592.2007.tb00237.x.

[24] ROWLAND N. J., and GRÜNING D. J. AI-assisted brainstorming for scenario thinking. *Futures*, 2025, 172. https://doi.org/10.1016/j.futures.2025.103644.

[25] STOJANOVSKA-STEFANOVA A., MITROVIĆ A., and SHOPOVA M. M. From Awareness to Action: Preparedness of SMEs for Artificial Intelligence Implementation in North Macedonia and Serbia. *International Journal of Cognitive Research in Science, Engineering and Education*, 2025, 13: 637–648. https://doi.org/10.23947/2334-8496-2025-13-3-637-648

[26] OSARENKHOE A., and FJELLSTRÖM D. A cluster's internationalization as a catalyst for its innovation system's access to global markets. *EuroMed Journal of Business*, 2024, 19. https://doi.org/10.1108/EMJB-11-2020-0127.

[27] NEUMAN W. L. *Social Research Methods: Qualitative and Quantitative Approaches. 7th ed.* Pearson, Harlow, 2014.

[28] LOBEL O. Technological readiness versus disruption: A framework for assessing distinct artificial intelligence policy strategies. *Emory Law Journal*, 2024, 74: 1055.

https://scholarlycommons.law.emory.edu/elj/vol74/iss5/1
[29] ARPACI I., YARDIMCI Y. C., OZKAN S., and TURETKEN O. Organizational adoption of information technologies: A literature review. *International Journal of eBusiness and eGovernment Studies,* 2012, 4: 37–50. https://izlik.org/JA35NC84HL
[30] BENHAYOUN L., AYALA N. F., and LE DAIN M. A. SMEs innovating in collaborative networks: how does absorptive capacity matter for innovation performance in times of good partnership quality? *Journal of Manufacturing Technology Management,* 2021, 32. https://doi.org/10.1108/JMTM-11-2020-0439.
[31] KASTELLI I., DIMAS P., STAMOPOULOS D., and TSAKANIKAS A. Linking Digital Capacity to Innovation Performance: the Mediating Role of Absorptive Capacity. *Journal of the Knowledge Economy,* 2024, 15. https://doi.org/10.1007/s13132-022-01092-w.
[32] KAUSHIK M. K., and AGRAWAL D. Influence of technology readiness in adoption of e-learning. *International Journal of Educational Management,* 2021, 35. https://doi.org/10.1108/IJEM-04-2020-0216.
[33] AYOKO O. B. Digital Transformation, Robotics, Artificial Intelligence, and Innovation. *Journal of Management and Organization,* 2021, 27. https://doi.org/10.1017/jmo.2021.64.
[34] KHAN A. N., MEHMOOD K., and SOOMRO M. A. Knowledge Management-Based Artificial Intelligence (AI) Adoption in Construction SMEs: The Moderating Role of Knowledge Integration. *IEEE Transactions on Engineering Management,* 2024, 71. https://doi.org/10.1109/TEM.2024.3403981.
[35] CHEN L., RAMLI K., HASTIADI F., and SURYANEGARA M. Accelerating digital transformation in Indonesia: Technology, market, and policy. *Economic Research Institute for ASEAN and East Asia (ERIA),* 2023. https://EconPapers.repec.org/RePEc:era:eriabk:2023-accelerating-digital-transformation-in-indonesia

参考文:

[1] DENICOLAI S., ZUCCHELLA A., and MAGNANI G. 国际化、数字化与可持续性：中小企业是否已做好准备？关于增长路径之间协同效应与替代效应的调查研究。Technol Forecast Soc Change, 2021, 166: 120650. https://doi.org/10.1016/j.techfore.2021.120650.
[2] MARTINS A., BRANCO M. C., MELO P. N., and MACHADO C. 中小企业中的可持续性：系统文献综述与未来研究议程。Sustainability, 2022, 14: 6493. https://doi.org/10.3390/su14116493.
[3] CHAUDHURI R., CHATTERJEE S., VRONTIS D., and CHAUDHURI S. 中小企业中的创新、人工智能动态性与可持续性：现状与未来发展方向。Sustainability, 2022, 14: 12760. https://doi.org/10.3390/su141912760.
[4] CHATTERJEE S., RANA N. P., DWIVEDI Y. K., and BAABDULLAH A. M. 基于整合TAM-TOE模型的制造与生产企业人工智能采纳机制研究。Technol Forecast Soc Change, 2021, 170: 120880. https://doi.org/10.1016/j.techfore.2021.120880.
[5] CHOTISARN N., and PHUTHONG T. 面向微型、小型与中型企业人工智能研究的知识结构与演化：一项文献计量分析。Cogent Business & Management, 2025, 12. https://doi.org/10.1080/23311975.2025.2491684.
[6] BEHL A., GAUR J., PEREIRA V., YADAV R., and LAKER B. 新冠疫情期间大数据分析能力在提升中小微服务企业可持续竞争优势中的作用——多理论视角分析。Journal of Business Research, 2022, 148: 378–389. https://doi.org/10.1016/j.jbusres.2022.05.009.
[7] KANNAN S., and GAMBETTA N. 技术驱动的中小企业可持续发展：系统文献综述。Journal of Small Business Strategy, 2025, 35. https://doi.org/10.53703/001c.126636.
[8] GOVORI A., and SEJDIJA Q. 将人工智能整合至中小企业商业实践中的未来前景与挑战。Journal of Governance and Regulation, 2023, 12: 176–183. https://doi.org/10.22495/jgrv12i2art16.
[9] HAIR J. F., RISHER J. J., SARSTEDT M., and RINGLE C. M. 偏最小二乘结构方程模型（PLS-SEM）的适用时机及结果报告方法。European Business Review, 2019, 31. https://doi.org/10.1108/EBR-11-2018-0203.
[10] ABU N., DA SILVA F. P., and VIEIRA P. R. 金融科技时代政府对中小企业的支持：提升融资可得性、生存能力与绩效。Digital Business, 2025, 5. https://doi.org/10.1016/j.digbus.2024.100099.
[11] MISRA S. K., SHARMA S. K., GUPTA S., and DAS S. 克服印度政府组织人工智能采纳障碍的框架研究。Technological Forecasting and Social Change, 2023, 194. https://doi.org/10.1016/j.techfore.2023.122721.
[12] TAKAWIRA B., and POOE D. 中小企业对工业5.0的准备度：系统文献综述。Southern African Journal of Entrepreneurship and Small Business Management, 2025, 17. https://doi.org/10.4102/sajesbm.v17i1.946.
[13] SCHWAEKE J., PETERS A., KANBACH D. K., KRAUS S., and JONES P. 新常态：中小企业人工智能采纳现状分析。Journal of Small Business Management, 2025, 63. https://doi.org/10.1080/00472778.2024.2379999.

[14] STRILETS V., FROLOV S., DATSENKO V., TYMOSHENKO O., and YATSKO M. 欧洲国家中小企业数字化发展的国家支持政策研究。Problems and Perspectives in Management, 2022, 20. https://doi.org/10.21511/ppm.20(4).2022.22.
[15] MAPHUMULO D. S., and NYIDE C. J. 小型制造企业中的智能制造工具与创新型领导战略探讨。Corporate and Business Strategy Review, 2025, 6. https://doi.org/10.22495/cbsrv6i3siart5.
[16] ISLAM A., ISLAM M. A., DAL MAS F., FIJAŁKOWSKA J., RAHMAN M., and MASSARO M. 通过商业模式创新构建人工智能引导的中小企业可持续竞争优势：系统文献综述。Journal of Engineering and Technology Management, 2025, 78. https://doi.org/10.1016/j.jengtecman.2025.101921.
[17] ALDOSERI A., AL-KHALIFA K. N., and HAMOUDA A. M. 重新思考人工智能的数据战略与整合：概念、机遇与挑战。Applied Sciences (Switzerland), 2023, 13. https://doi.org/10.3390/app13127082.
[18] RANE N. 建筑信息模型（BIM）与人工智能（AI）在智慧施工进度、成本、质量与安全管理中的整合：挑战与机遇。SSRN Electronic Journal, 2023. https://doi.org/10.2139/ssrn.4616055.
[19] YEN W. T. M., HONG T. L., and YEN Y. Y. 马来西亚中小企业人工智能准备度评估框架的构建。Journal of Ecohumanism, 2024, 3. https://doi.org/10.62754/joe.v3i5.3893.
[20] SOOMRO R. B., AL-RAHMI W. M., DAHRI N. A., ALMUQREN L., AL-MOGREN A. S., and ALDAIJY A. 基于SEM–ANN方法的人工智能技术对中小企业可持续绩效影响研究。Scientific Reports, 2025, 15. https://doi.org/10.1038/s41598-025-86464-3.
[21] SOVA R., TUDOR C., TARTAVULEA C. V., and DIEACONESCU R. I. 高等教育中人工智能工具采纳研究：基于结构方程模型的经济学学生影响因素分析。Electronics (Switzerland), 2024, 13. https://doi.org/10.3390/electronics13183632.
[22] WANG X., LIN X., and SHAO B. 人工智能如何塑造企业敏捷性？来自聊天机器人的实证证据。International Journal of Information Management, 2022, 66. https://doi.org/10.1016/j.ijinfomgt.2022.102535.
[23] RICHEY R. G., DAUGHERTY P. J., and ROATH A. S. 企业技术准备度与互补性：影响物流服务能力与绩效的关键能力研究。Journal of Business Logistics, 2007, 28. https://doi.org/10.1002/j.2158-1592.2007.tb00237.x.
[24] ROWLAND N. J., and GRÜNING D. J. 人工智能辅助的情景思维头脑风暴方法研究。Futures, 2025, 172. https://doi.org/10.1016/j.futures.2025.103644.
[25] STOJANOVSKA-STEFANOVA A., MITROVIĆ A., and SHOPOVA M. M. 从认知到行动：北马其顿与塞尔维亚中小企业实施人工智能的准备度研究。International Journal of Cognitive Research in Science, Engineering and Education, 2025, 13: 637–648. https://doi.org/10.23947/2334-8496-2025-13-3-637-648
[26] OSARENKHOE A., and FJELLSTRÖM D. 产业集群国际化作为其创新体系进入全球市场的催化剂。EuroMed Journal of Business, 2024, 19. https://doi.org/10.1108/EMJB-11-2020-0127.
[27] NEUMAN W. L. 社会研究方法：定性与定量研究路径。第7版。Pearson, Harlow, 2014.
[28] LOBEL O. 技术准备度与颠覆性冲击：评估不同人工智能政策战略的分析框架。Emory Law Journal, 2024, 74: 1055. https://scholarlycommons.law.emory.edu/elj/vol74/iss5/1
[29] ARPACI I., YARDIMCI Y. C., OZKAN S., and TURETKEN O. 组织层面信息技术采纳研究：文献综述。International Journal of eBusiness and eGovernment Studies, 2012, 4: 37–50. https://izlik.org/JA35NC84HL
[30] BENHAYOUN L., AYALA N. F., and LE DAIN M. A. 协作网络中中小企业的创新实践：在高质量伙伴关系背景下吸收能力对创新绩效的影响。Journal of Manufacturing Technology Management, 2021, 32. https://doi.org/10.1108/JMTM-11-2020-0439.
[31] KASTELLI I., DIMAS P., STAMOPOULOS D., and TSAKANIKAS A. 数字能力与创新绩效的关联：吸收能力的中介作用。Journal of the Knowledge Economy, 2024, 15. https://doi.org/10.1007/s13132-022-01092-w.
[32] KAUSHIK M. K., and AGRAWAL D. 技术准备度对电子学习采纳的影响。International Journal of Educational Management, 2021, 35. https://doi.org/10.1108/IJEM-04-2020-0216.
[33] AYOKO O. B. 数字化转型、机器人技术、人工智能与创新。Journal of Management and Organization, 2021, 27. https://doi.org/10.1017/jmo.2021.64.
[34] KHAN A. N., MEHMOOD K., and SOOMRO M. A. 基于知识管理的建筑业中小企业人工智能采纳研究：知识整合的调节作用。IEEE Transactions on Engineering Management, 2024, 71. https://doi.org/10.1109/TEM.2024.3403981.
[35] CHEN L., RAMLI K., HASTIADI F., and SURYANEGARA M. 加速印度尼西亚数字化转型：技术、市场与政策。Economic Research Institute for ASEAN and East Asia (ERIA), 2023. https://EconPapers.repec.org/RePEc:era:eriabk:2023-accelerating-digital-transformation-in-indonesia

Appendix A - Instrument used for measurement

Construct	Item	Factor loading	Mean	SD
AI Adoption	We regularly explore the potential of new AI applications to improve efficiency or create added value.	0.725	3.610	0.971
	The adoption of AI has reduced operational costs or the time required to complete certain tasks.	0.898	3.819	0.944
	We have conducted internal or external training for employees to ensure they can use the AI system effectively.	0.823	3.971	0.822
	We have a long-term strategy to continue to develop the use of AI in our business.	0.913	3.857	0.888
Capacity	We are aware of information resources (e.g.: journals, seminars, online communities) to deepen our knowledge of AI.	0.856	3.610	1.009
	We actively participate in training or skill enhancement programs related to digital technology and AI.	0.893	3.676	0.941
	There are strong creative and innovative skills within our team to develop unique products or services.	0.894	3.524	1.034
	We have a good understanding of the basic concepts and potential applications of Artificial Intelligence (AI) in the context of the creative industry.	0.862	3.543	0.916
	We are aware of various types of AI tools or platforms that can be used to increase efficiency and innovation.	0.911	3.543	0.916
Collaboration	We actively collaborate with external parties (e.g.: universities, technology startups, industry associations) in developing creative products or services.	0.823	3.905	0.951
	There is a clear mechanism for sharing information and resources between SMEs or with external parties in developing innovation.	0.856	4.010	0.867
	Our collaborations have increased access to new technologies and best practices in the creative industries.	0.869	3.971	0.899
	We feel that collaboration helps in solving complex problems that we cannot solve alone.	0.765	4.162	0.794
	There is adequate support from collaboration partners in the form of knowledge or resources for innovation projects.	0.834	3.990	0.787
	Collaboration has expanded the market network and potential customers for our products or services.	0.875	4.105	0.839
	We regularly evaluate the effectiveness of our collaborations for continuous improvement.	0.815	3.886	0.908
Competitiveness	Our products or services are of better quality than competitors in the market.	0.886	3.886	0.760
	We have effective marketing and branding strategies to attract and retain customers.	0.822	3.667	0.973
Innovation	We are actively developing new products or services that are not yet on the market.	0.808	3.705	0.965
	Our products or services have unique features or characteristics that differentiate them from competitors.	0.726	3.800	0.877
	We regularly conduct market research and development to identify innovation opportunities.	0.784	3.810	0.874
	Our product development process involves a creative approach and bold experimentation.	0.819	3.962	0.742
	We have successfully launched a number of innovative products or services in the last 3 years.	0.728	3.962	0.816
	Our product innovation has been recognized by customers or the industry (e.g. through awards, positive reviews).	0.840	3.867	0.794
	We have a system that supports new ideas from employees and facilitates their development into products.	0.823	3.867	0.782
Government Support	The Regional Government (PEMDA) provides programs or incentives that support the adoption of AI technology for SMEs in the creative sector.	0.783	3.590	1.039
	Our SME receives guidance and assistance from the local government, particularly through technical guidance and workshops.	0.915	3.552	0.966
	PDIN's (*Pusat Desain Industri Nasional*) role has contributed greatly to supporting business and the creation of innovative products in the SMEs where we operate.	0.887	3.324	1.019

Notes: All factor loadings are significant at $p < 0.001$.

Appendix B – Discriminant Validity: Fornell-Larcker Criterion

Construct	AI Adoption	Capacity	Collaboration	Competitiveness	Innovation	Gov. Support
AI Adoption	**0.843**					
Capacity	0.584	**0.883**				
Collaboration	0.486	0.500	**0.835**			
Competitiveness	0.744	0.648	0.451	**0.855**		
Innovation	0.826	0.491	0.482	0.794	**0.791**	
Gov. Support	0.601	0.737	0.519	0.631	0.523	**0.863**

Appendix C - Discriminant Validity: Cross Loadings

Indicators	AI Adoption	Capacity	Collaboration	Competitiveness	Innovation	Gov. Support
AIA1	**0.725**	0.632	0.479	0.706	0.575	0.613
AIA2	**0.898**	0.430	0.475	0.600	0.751	0.492
AIA3	**0.823**	0.296	0.238	0.506	0.704	0.368
AIA4	**0.913**	0.566	0.414	0.666	0.748	0.522
CAP1	0.472	**0.856**	0.398	0.557	0.390	0.594
CAP2	0.581	**0.893**	0.548	0.599	0.483	0.668
CAP3	0.488	**0.894**	0.489	0.574	0.419	0.678
CAP4	0.507	**0.862**	0.376	0.569	0.445	0.682
CAP5	0.524	**0.911**	0.387	0.558	0.427	0.625
COL1	0.414	0.417	**0.823**	0.360	0.379	0.425
COL 2	0.350	0.424	**0.856**	0.327	0.273	0.459
COL 3	0.384	0.430	**0.869**	0.357	0.373	0.492
COL 4	0.405	0.385	**0.765**	0.350	0.411	0.386
COL 5	0.400	0.452	**0.834**	0.391	0.417	0.375
COL 6	0.393	0.404	**0.875**	0.388	0.435	0.424
COL 7	0.483	0.409	**0.815**	0.451	0.515	0.458
COM1	0.660	0.422	0.331	**0.886**	0.759	0.407
COM6	0.610	0.719	0.455	**0.822**	0.585	0.706
INN1	0.677	0.394	0.407	0.576	**0.808**	0.460
INN2	0.600	0.304	0.331	0.530	**0.726**	0.323
INN3	0.748	0.485	0.440	0.661	**0.784**	0.480
INN4	0.665	0.343	0.364	0.662	**0.819**	0.432
INN5	0.552	0.383	0.378	0.584	**0.728**	0.396
INN6	0.677	0.421	0.350	0.659	**0.840**	0.393
INN7	0.633	0.376	0.394	0.707	**0.823**	0.399
GOVS1	0.473	0.522	0.443	0.393	0.343	**0.783**
GOVS2	0.507	0.701	0.473	0.601	0.477	**0.915**
GOVS3	0.575	0.671	0.431	0.621	0.522	**0.887**

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