AI Adoption, Digital Innovation Capability, and Sustainable Performance: Operational Efficiency as a Strategic Mediator in the Food and Beverage Sector

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ABSTRACT

The COVID-19 pandemic has accelerated the urgency of digital transformation for SMEs; however, AI adoption alone is insufficient without digital innovation capabilities and adequate ecosystem support. This study aims to examine the influence of AI adoption and digital innovation capabilities on the sustainable performance of Food and Beverage SMEs in Yogyakarta, with operational efficiency as a mediator and digital ecosystem support as a moderator. A quantitative approach with a cross-sectional survey design was employed, involving 305 F&B SMEs in the Special Region of Yogyakarta selected via purposive sampling. Data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). AI adoption and digital innovation capabilities have a positive and significant effect on both operational efficiency and sustainable performance, both directly and indirectly through the mediation of operational efficiency. However, digital ecosystem support was not found to significantly moderate the effect of AI adoption or digital innovation capabilities on sustainable performance. Operational efficiency acts as a central mediating mechanism that translates digital technology and capabilities into economic, social, and environmental performance outcomes. The lack of significant moderation by digital ecosystem support reveals infrastructure gaps between districts, low digital literacy, ineffective policies, and collaboration that remains transactional in DIY. F&B SMEs are advised to begin adopting AI in operational features such as predictive analytics for demand forecasting, integrating AI with existing digital systems, and actively participating in training and partnerships with universities and local technology providers to strengthen business competitiveness and sustainability.

KEYWORDS: AI adoption, Digital innovation capabilities, Operational efficiency, Digital ecosystem support, Sustainable performance

INTRODUCTION

Food and Beverage (F&B) SMEs are a vital pillar of the creative economy and a major employer in the Special Region of Yogyakarta, making a significant contribution to the Regional Gross Domestic Product (BPS DIY, 2023; Susilo, 2017). The COVID-19 pandemic exposed the vulnerabilities of manual business models whilst accelerating the urgency of digital transformation to build business resilience (Obschonka & Audretsch, 2020; Mikalef et al., 2022; Wamba et al., 2021). In a competitive landscape driven by shifts in consumer behaviour, the adoption of AI has become a strategic necessity, ranging from chatbots and predictive analytics to supply chain automation (Huang & Rust, 2021; Soomro et al., 2025; Zhao, 2025). However, simply possessing the technology is not enough without the digital innovation capabilities to adaptively integrate and utilise digital resources (Marzi, 2025; Rosalin, 2025; Youssef, 2025). On-the-ground realities show that F&B SMEs in Yogyakarta are still grappling with operational inefficiencies, raw material wastage, inaccurate stock management, and slow production processes that erode profitability (Sahoo, 2025; Beena, 2025; Pandi, 2025). These issues are exacerbated by disparities in access to supporting digital ecosystems (infrastructure, affordable platforms, training, government policies) as well as variations in AI adoption readiness across districts (Khemakhem, 2025; Rozak et al., 2024; Rana et al., 2024). Consequently, the potential of digital transformation to achieve sustainable performance (economic, social, environmental) is often not fully realised (Utami , & Purnomo, 2023; Zhao, 2025; Mrad et al., 2025). To examine this complexity, this study integrates the Resource-Based View (RBV), Dynamic Capabilities Theory, and the Technology–Organisation–Environment (TOE) framework. RBV views the adoption of AI and digital innovation capabilities as VRIN resources that form the foundation of sustainable competitive advantage (Barney, 1991; Abdou, 2025; Bhatti et al., 2025). The Dynamic Capabilities Theory emphasises an organisation's ability to reconfigure resources in response to change, which in the digital realm manifests as digital innovation capabilities (sensing, seizing, transforming) (Teece, 2007; Marzi, 2025; Hafeez et al., 2025; Ahmad et al., 2025). The TOE framework asserts that the effectiveness of technology adoption is also determined by external environmental conditions such as government policy and infrastructure (Li et al., 2025; Khemakhem, 2025). The integration of these three perspectives explains the mechanism by which AI adoption and digital innovation capabilities influence sustainable performance through the mediation of operational efficiency, as well as the moderation of digital ecosystem support (Tandilino, 2025; Mutanda, 2025).

Previous research has provided an important empirical foundation but still leaves crucial gaps. A number of studies have documented a positive relationship between AI adoption and business performance, both in the context of large companies and corporate innovation (Ma, 2025; Saiyed, 2025; Zhao, 2025). A recent study by Soomro et al. (2025), using a SEM-ANN approach across 305 SMEs in various sectors, also confirmed that AI adoption significantly enhances the economic, social, and environmental performance of SMEs. Research in the SME sector is beginning to emerge, such as the exploration of the impact of digital transformation on the sustainable performance of youth-owned SMEs (Muhammad et al., 2025), the role of disruptive and frugal technologies in African SMEs (Jha, 2022; Mutanda, 2025), and the influence of digital innovation capabilities on the performance of Indonesian SMEs (Fitri et al., 2025). However, the mechanisms through which these influences operate still require substantial further investigation. This study proposes **operational efficiency as a key mediator**, based on the logic that the adoption of AI and digital innovation capabilities will first optimise operational processes, as demonstrated in studies on energy-efficient task scheduling in cloud computing (Beena, 2025) and IIoT solutions for cost reduction (Pandi, 2025), which subsequently lead to improved sustainable performance (Rawat et al., 2025; Mrad et al., 2025; Wamba et al., 2021). Findings by Li et al. (2025) through a systematic literature review of international SMEs also confirm that organisational capabilities act as a key mediator that translates technology adoption into performance advantages.

However, these studies have not specifically tested this mediation model in the context of F&B SMEs in Yogyakarta, which possess distinctive socio-cultural characteristics and operational challenges. The strength of the relationships between variables is also likely to be conditioned by contextual factors. Therefore, this study introduces digital ecosystem support (government policies, infrastructure, technology platforms, digital collaboration) as a moderating variable predicted to strengthen the influence of digital capabilities on efficiency and performance (Rozak et al., 2024; Tandilino, 2025; Rana et al., 2024). Khemakhem's (2025) study on the challenges of AI adoption in Africa, as well as Hafeez et al. (2025) on the role of digital ecosystem intermediaries, reinforce the argument that the local ecosystem context is a critical determinant of digitalisation success. Furthermore, there is a scarcity of research that formally tests digital ecosystem support as a moderator within a comprehensive model integrating AI adoption, digital innovation capabilities, operational efficiency, and sustainable performance simultaneously among local Indonesian F&B SMEs (Li et al., 2025; Bhatti et al., 2025; Fitri et al., 2025). This gap constitutes the primary research gap. The novelty of this study lies in testing an integrative model that links the five variables within a single analytical framework applied to F&B SMEs in Yogyakarta (Li et al., 2025; Youssef, 2025). This model not only examines direct relationships but also indirect pathways via the mediation of operational efficiency and boundary conditions through the moderation of digital ecosystem support, thereby providing a more comprehensive understanding of the mechanisms of digital transformation towards sustainability (Rawat et al., 2025; Tandilino, 2025; Khemakhem, 2025).

LITERATURE REVIEW

The Impact of Artificial Intelligence Adoption and Digital Innovation Capabilities on Operational Efficiency

The adoption of Artificial Intelligence (AI) has been shown to drive improvements in operational efficiency through the automation of repetitive tasks, the minimisation of human error, and the use of predictive analytics to optimise processes such as inventory management and production scheduling. These effects directly reduce operational costs (by up to 30%) and save working time (>20 hours/month) whilst increasing productivity (Huang & Rust, 2021; Wamba et al., 2021; Ma, 2025; Zhao, 2025; Saiyed, 2025; Soomro et al., 2025; Agbaakin, 2025; Kgomo & Lavhengwa, 2025). Similarly, digital innovation capabilities encompassing sensing, seizing, and transforming have a positive impact on operational efficiency by enabling organisations to adaptively redesign processes, eliminate bottlenecks, and optimise resource utilisation through the integration of digital technology into workflows (Teece, 2007; Marzi, 2025; Hafeez et al., 2025; Ahmad et al., 2025; Youssef, 2025). Empirical studies confirm that digital business model innovation and big data analytics capabilities significantly improve operational efficiency in SMEs (Zhang & Wang, 2026; Bhatti et al., 2025; Muhammad et al., 2025; Fitri et al., 2025). Based on this synthesis, the first and second hypotheses proposed are:

H1: The adoption of artificial intelligence has a positive and significant effect on operational efficiency.

H2: Digital innovation capabilities have a positive and significant effect on operational efficiency.

The Impact of Operational Efficiency on Sustainable Performance

Operational efficiency serves as a crucial bridge between technological capabilities and sustainable performance, as it reduces costs, increases productivity, minimises waste, and optimises workflows, thereby positively impacting the economy (profitability), society (well-being), and the environment (reduction of waste/emissions) (Utami & Purnomo, 2023; Mrad et al., 2025). Empirical studies support this: Rawat et al. (2025) demonstrate that operational efficiency contributes significantly to the sustainable performance of SMEs through resource optimisation and waste reduction; Mrad et al. (2025) confirm that internal process efficiency is a key determinant of the success of digital transformation within a digital-circular synergy framework. Research in Uganda (Bindeeba et al., 2025) also suggests that operational efficiency mediates the relationship between the integration of digital business processes and economic and environmental performance. Wamba et al. (2021) add that organisations capable of converting efficiency into sustainable performance possess robust data governance and analytical capabilities, whilst Zhao (2025) identifies operational efficiency as an enabler of sustainable performance through green supply chains and the circular economy. Based on this synthesis, the third hypothesis is proposed:

H3: Operational efficiency has a positive and significant effect on sustainable performance.

The Influence of Artificial Intelligence Adoption and Digital Innovation Capabilities on Sustainable Performance

The adoption of Artificial Intelligence (AI) directly drives sustainable performance through three key mechanisms: (1) intelligent resource management, (2) data-driven strategic decision making, and (3) environmentally friendly product and process innovation. Through predictive analytics and machine learning, AI is capable of identifying energy consumption patterns, predicting market demand , and optimising supply chains, thereby simultaneously enhancing economic (profitability), social (well-being), and environmental (reduction of emissions/waste) dimensions (Zhao, 2025; Ma, 2025; Soomro et al., 2025; Saiyed, 2025). Empirical evidence from various contexts (manufacturing, SMEs, the service sector) confirms that AI strengthens the circular economy, green supply chains, and labour efficiency, which in turn impacts the achievement of sustainability indicators (Zhao, 2025; Ma, 2025; Soomro et al., 2025; He & Yang, 2025; Alsadoun & Alateeg, 2026). Similarly, digital innovation capabilities—reflecting the ability to develop, integrate, and reconfigure digital technologies into business processes—enable organisations to respond to sustainability demands through the creation of digital products, processes, and business models that are socially valuable and environmentally friendly. This aligns with the Twin Transition concept, which unites digital transformation and sustainable innovation, thereby simultaneously accommodating economic, social, and environmental dimensions (Youssef, 2025; Marzi, 2025; Mrad et al., 2025). Digital capabilities such as big data analytics, platforms, and digital networks have been shown to drive green supply chain innovation, the financial performance of SMEs, and green innovation practices among SMEs in Indonesia and Ghana (Fitri et al., 2025; Bhatti et al., 2025; Bindeeba et al., 2025; Abdou, 2025). Based on this synthesis, the fourth and fifth hypotheses are:

H4: The adoption of artificial intelligence has a positive and significant effect on sustainable performance.

H5: Digital innovation capability has a positive and significant effect on sustainable performance.

The Mediating Role of Operational Efficiency

Operational efficiency acts as a mediating mechanism that explains how the adoption of AI and digital innovation capabilities translate into sustainable performance. This mediation logic is based on the premise that AI and digital technologies first improve internal efficiency through automation, process optimisation, and the reduction of waste, which subsequently creates slack resources and organisational capacity to invest in long-term sustainability initiatives (Rawat et al., 2025; Mrad et al., 2025). Without prior efficiency improvements, the impact on sustainability tends to be suboptimal as resources are absorbed by internal inefficiencies (Li et al., 2025; Wamba et al., 2021). Empirical studies support this: Rawat et al. (2025) and Mrad et al. (2025) found that operational efficiency mediates the relationship between technological capabilities/digital transformation and sustainable performance. Research by Bindeeba et al. (2025) confirms partial mediation between digital business process integration and economic and environmental performance. Soomro et al. (2025) emphasise AI as an enabler of both short-term operational gains and long-term sustainability objectives. He & Yang (2025) confirm the mediating role of operational capabilities, whilst Li et al. (2025) identify organisational capabilities as a key mediator of the relationship between digital technology adoption and performance. Based on this empirical synthesis, the following mediation hypotheses are proposed:

H6: Operational efficiency mediates the effect of artificial intelligence adoption on sustainable performance.

H7: Operational efficiency mediates the effect of digital innovation capabilities on sustainable performance.

7. The Moderating Role of Digital Ecosystem Support

The relationship between AI adoption, digital innovation capabilities, and sustainable performance is shaped by contextual factors, particularly the support of the digital ecosystem, namely government policies, digital infrastructure, affordable access to technology, training, and multi-stakeholder collaboration (Rozak et al., 2024; Tandilino, 2025; Khemakhem, 2025). The Technology–Organisation–Environment (TOE) framework emphasises that the effectiveness of technology adoption is influenced by external environmental conditions (Li et al., 2025; Khemakhem, 2025). A robust digital ecosystem provides access to cloud computing, digital literacy training, fiscal incentives, and collaborative networks that accelerate technological adaptation (Rana et al., 2024; Mutanda, 2025), whilst a weak ecosystem hinders the potential benefits of AI (Khemakhem, 2025). Empirical studies support this moderation: Li et al. (2025) found that government policies and competitive pressures moderate the relationship between digital adoption and SME performance; Tandilino et al. (2025) demonstrated that digital financial inclusion mediates the relationship between financial literacy and government support on performance; Rozak et al. (2024) found that government support programmes strengthen the resilience of Indonesian SMEs; Mutanda (2025) demonstrates that a conducive digital environment enhances the effectiveness of digital transformation; a study in Ahmed et al. (2025) confirms that perceptions of government support moderate the relationship between e-business and SME performance; Hafeez et al. (2025) add that innovation intermediaries within the digital ecosystem strengthen SME transformation. Based on this synthesis, a moderation hypothesis is proposed:

H8: Digital ecosystem support strengthens the influence of artificial intelligence adoption on sustainable performance.

H9: Digital ecosystem support strengthens the influence of digital innovation capabilities on sustainable performance.

METHOD

This study employs a quantitative approach using a cross-sectional survey design to test the causal relationships between the hypothesised variables (Creswell & Creswell, 2018). The study population consists of all MSME actors in the Food and Beverage sector in the Special Region of Yogyakarta, with a sample of 305 respondents selected via purposive sampling based on the following inclusion criteria: (1) having used at least one digital device in daily operations, (2) the owner/manager has attended government-organised training on the use of AI, and (3) the business has been operating for at least three years (Etikan et al., 2016; Sugiyono, 2019). These criteria were established to ensure respondents possessed a basic understanding of digitalisation and AI, as well as sufficient operational experience to assess the impact of technology adoption on performance (Islami & Kholidah, 2025). The sample size of 305 respondents met the minimum requirement for Structural Equation Modelling (SEM) analysis based on the rule of 5–10 times the number of indicators, thereby providing adequate statistical power (Hair et al., 2014; Kock & Hadaya, 2018). Data collection was conducted both online and offline via the distribution of a Google Forms-based questionnaire during the AI training sessions, to maximise the response rate and ensure respondents were in a relevant context (Soomro et al., 2025). The following are the indicators measured in this study:

Table 1. Measurement of variables

Variable	Indicator
Artificial Intelligence (AI) Adoption The level of utilisation of artificial intelligence technology to support data analysis, decision-making, automation, and organisational system integration. Zhao (2025); Ma (2025)	AI-enabled decision-making The ability of AI systems to assist management in making data-driven decisions quickly and accurately.
	AI-based data analytics The use of AI to process and analyse big data to generate valuable insights.
	AI-driven automation The use of AI to automate both routine and complex work processes.
	AI system integration The level of integration between AI systems and an organisation's information systems and digital processes.
Digital Innovation Capabilities An organisation's ability to develop and utilise digital technologies to generate innovations in products, processes and business models. Marzi et al. (2025)	Digital product innovation A company's ability to create or improve products based on digital technology.
	Digital process innovation The use of digital technology to improve and update operational processes.
	Digital business model innovation An organisation's ability to create or adapt digital-based business models.
	Digital flexibility The ability of digital systems to adapt to changes in the environment and business needs.
	Digital experimentation capability An organisation's ability to experiment with new digital technologies.
Operational efficiency An organisation's ability to minimise costs, time and resources to produce optimal output. Rawat et al. (2025)	Cost efficiency A company's ability to reduce operational costs without compromising the quality of its output.
	Time efficiency A company's ability to complete operational processes in a shorter time.
	Resource utilisation efficiency A company's ability to utilise resources optimally.

	Process productivity The level of productivity of work processes in generating output.
Sustainable performance An organisation's achievements reflecting a balance of economic, environmental and social performance in the long term. Mrad et al. (2025)	Sustainable financial performance A company's ability to achieve stable and sustainable financial performance.
	Environmental performance A company's ability to minimise negative impacts on the environment.
	Social performance A company's ability to fulfil its social responsibilities towards stakeholders.
	Long-term value creation A company's ability to create long-term value for the organisation and its stakeholders.
	Stakeholder-oriented sustainability The company's focus on creating sustainability for all stakeholders.
Digital ecosystem support The level of external environmental support that enables an organisation to adopt and utilise digital technology and AI effectively and sustainably. Rana et al. (2024); Tandilino et al. (2025)	Availability of digital infrastructure The level of adequacy of information and communication technology infrastructure (internet, networks, digital systems) that supports an organisation's digital transformation.
	Regulatory and policy support The extent to which regulations, government policies, and institutional rules favour the adoption of digital technologies and AI.
	Access to digital platforms The ease with which an organisation can access digital platforms, cloud-based systems, and digital technology ecosystems.
	Digital collaboration among stakeholders The level of digital collaboration between organisations and business partners, technology providers, and other stakeholders.
	Maturity of the digital ecosystem The level of readiness and development of the digital ecosystem as a whole in supporting innovation and sustainability.

All indicators were measured using a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Data processing was carried out using SmartPLS, which is suitable for variance-based SEM models (PLS-SEM), as it is capable of estimating complex models with many indicators, handling non-normally distributed data, and testing direct, mediating, and moderating relationships simultaneously (Hair et al., 2014). Data analysis techniques included evaluation of the measurement model (outer model) via tests of discriminant validity and convergent composite reliability, as well as evaluation of the structural model (, inner model) via testing of path coefficients, significance values (t-statistic and p-value) to address all research hypotheses (Hair et al., 2014; Sarstedt et al., 2021).

RESULTS

Respondent Characteristics and Profile

Respondent characteristics based on gender, age, education, company age, and monthly turnover are shown in Table 1.

Table 1. Research Respondent Profile

Respondent Profile		Frequency	Percentage (%)
Gender	Male	137	44.9
	Female	168	55.1
Age	< 25 years	72	23.6
	> 45 years	39	12.8
	25–35 years	106	34.8
	36–45 years	88	28.9
Highest Level of Education	Diploma (D3)	61	20.0
	Postgraduate (S2/S3)	8	2.6
	Bachelor's Degree (S1)	135	44.3
	Secondary School/Vocational School	101	33.1
Number of Employees	> 30 people	16	5.2
	1–5 people	142	46.6
	16–30 people	53	17.4
	6–15 people	94	30.8
Company Age	< 1 year	34	11.1
	> 6 years	62	20.3
	1–3 years	120	39.3
	4–6 years	89	29.2
Monthly Turnover	< 10 million	125	41.0
	> 100 million	20	6.6
	10–50 million	125	41.0
	51–100 million	35	11.5
	Total	305	100.0

Source: Processed Primary Data, 2026

Based on Table 1, it can be described that the largest groups of respondents, in order, are female (55.1%), aged under 25–35 years (34.7%), holding a bachelor's degree (44.3%), companies with 1–5 employees (46.6%), companies aged 1–3 years (39.3%) and monthly turnover below 50 million rupiah (82.0%).

Quality Criteria

Discriminant Validity

The test of discriminant validity using the Fornell-Larcker criteria showed that the square root of the Average Variance Extracted (AVE) for each construct (shown on the diagonal) was greater than the correlation values between constructs (off-diagonal). The results of the discriminant validity can be seen in Table 2:

Table 2. Discriminant validity

Construct	AIA	DES	DIC	OE	SP
AIA	**0.981**				
DES	0.021	**0.973**			

DIC	-0.016	0.191	**0.974**		
OE	0.162	0.083	0.157	**0.974**	
SP	0.207	0.292	0.223	0.195	**0.946**

All research variables have a higher value of the $\sqrt{AVE}$ than the correlation between variables, so they can be considered valid.

Convergent Composite Reliability

Convergent validity refers to the validity of the items comprising a latent construct with its reflective indicators. Convergent validity is assessed using two measures: the Average Variance Extracted (AVE) and the composite reliability (CR) of the reflective latent construct. Convergent validity is established when the AVE is greater than 0.5 and the composite reliability is above 0.7. The composite reliability results are shown in Table 3:

Table 3. Composite Reliability

No	Construct	AVE Value	Composite Reliability	Notes
1	AIA	0.963	0.991	Reliable
2	DES	0.946	0.989	Reliable
3	DIC	0.949	0.989	Reliable
4	OE	0.948	0.986	Reliable
5	SP	0.895	0.977	Reliable

Table 3 shows that all research variables have a CR value > 0.7 and an AVE value above 0.5. This means that there is no possibility of measurement error in the outer model. Therefore, these variables can be used to predict structural functions in the inner model effectively.

Path Analysis

The path coefficient test aims to examine the relationships between variables in accordance with the hypotheses. Significance is determined via a bootstrapping procedure using the criteria of a t-statistic > 1.96 or a p-value < 0.05. The results of the analysis are presented in Figure 1 and Table 4:

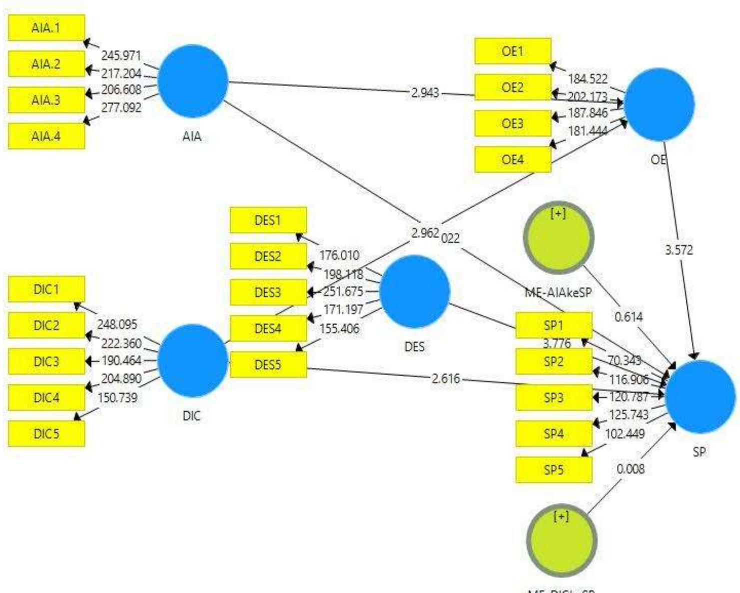

Figure 1. Structural Model (Inner Model) of Latent Variables

Table 4. Results of the Inner Model Test

H	Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T-Statistics (|O/STDEV|)	P-values
1	AIA → OE	0.165	0.164	0.056	2.943	**0.003**
2	DIC → OE	0.159	0.162	0.054	2.962	**0.003**
3	OE → SP	0.190	0.186	0.053	3.572	**0.000**
4	AIA → SP	0.153	0.156	0.051	3.022	**0.003**
5	DIC → SP	0.159	0.161	0.061	2.616	**0.009**
6	AIA → OE → SP	0.031	0.031	0.014	2.250	**0.025**
7	DIC → OE → SP	0.030	0.030	0.013	2.302	**0.022**
8	MOD AIA → SP	0.031	0.031	0.050	0.614	0.539
9	MOD DIC → SP	0.000	0.000	0.049	0.008	0.993

Based on Table 4 of the hypothesis testing results, it was found that the adoption of artificial intelligence and digital innovation capabilities each have a positive and significant effect on operational efficiency and on sustainable performance, both directly and through operational efficiency. Operational efficiency was also found to have a significant effect on sustainable performance. Furthermore, operational efficiency mediates the influence of AI adoption and digital innovation capabilities on sustainable performance. Additionally, digital ecosystem support was not found to strengthen the influence of AI adoption or digital innovation capabilities on sustainable performance.

DISCUSSION

The ability of AI systems to support data-driven decision-making, for example, enables SME owners to project demand more accurately, thereby reducing excess stock of raw materials that is prone to wastage (Sahoo, 2025; Beena, 2025). Meanwhile, process automation via AI reduces reliance on manual labour for repetitive tasks, accelerates workflows, and minimises the potential for human error (Soomro et al., 2025). Integrating AI with existing digital systems such as point-of-sale or inventory management applications enhances data synergy and enables organisations to utilise resources more optimally. These findings confirm that AI is not merely a technical tool, but a strategic asset that meets the VRIN criteria (valuable, rare, inimitable, non-substitutable) as outlined in the Resource-Based View (Barney, 1991; Abdou, 2025). When implemented within the context of F&B SMEs, these four indicators collectively generate measurable efficiencies in terms of costs, time, resource utilisation, and process productivity (Rawat et al., 2025), in line with Agbaakin’s (2025) study, which reported a reduction in operational costs of up to 30% and savings of over 20 working hours per month for SMEs using AI.

Digital innovation capabilities act as a driving force for efficiency through more dynamic mechanisms. The ability to create or update digital-based products, for example, opens up opportunities for rapid menu diversification in line with market trends without having to proportionally increase operational burdens. Digital process innovation enables SMEs to redesign workflows so that bottlenecks previously hindering productivity can be eliminated (Fitri et al., 2025). Digital flexibility and experimentation capabilities provide business owners with the scope to adaptively trial new technologies without disrupting core operations, allowing the organisation to continuously learn and adapt to changes in the environment. Within the Dynamic Capabilities framework, the sensing, seizing, and transforming capacities embodied in these indicators— —enable SMEs to continuously reconfigure their resources to achieve greater efficiency (Teece, 2007; Hafeez et al., 2025). This aligns with the study by Bhatti et al. (2025), which found that big data analytics capabilities and digital innovation significantly enhance the operational performance of manufacturing SMEs. AI as a technology and digital innovation capabilities as organisational competencies both play an active role in creating more efficient and productive operations, whilst simultaneously building a solid foundation for achieving greater objectives.

This research also demonstrates that the adoption of AI and digital innovation capabilities does not merely stop at efficiency, but directly drives the sustainable performance of SMEs. Sustainable performance variables show a significant increase in line with the intensity of AI utilisation. AI-enabled decision-making and AI-based data analytics play a crucial role here. AI's ability to process big data and provide strategic recommendations helps business operators not only pursue short-term profits but also design environmentally friendly business practices, for example through precise forecasting of raw material requirements, thereby drastically reducing food waste (Zhao, 2025; Soomro et al., 2025). On the social front, AI also supports better service personalisation, which in turn enhances the satisfaction and well-being of both employees and consumers (Huang & Rust, 2021).

Digital innovation capabilities make a similar contribution through different channels. The ability to create digital business models enables MSMEs to respond to the preferences of consumers who are increasingly environmentally and socially conscious, whilst creating long-term value that is not purely financial. Digital product innovations, such as eco-friendly packaging promoted via digital platforms or online ordering systems that reduce paper usage, are concrete examples of how this works. Digital flexibility and experimentation allow SMEs to continually adapt business practices to sustainability demands without losing competitiveness. This interconnection between digital innovation capabilities and sustainable performance reinforces the argument for the Twin Transition, a dual transformation in which digitalisation and sustainability mutually reinforce one another and are inseparable (Youssef, 2025; Mrad et al., 2025). These findings are also consistent with Le's (2026) study on Vietnamese manufacturing SMEs, which showed that green AI capabilities enhance resource flexibility and coordination, which in turn drives circular economy practices and sustainable performance. In the Indonesian context, these results are consistent with Fitri et al. (2025) and Bhatti et al. (2025), who confirmed that digital innovation and big data analytics make a significant contribution to financial performance and green innovation.

The Central Role of Operational Efficiency as a Mediator

The most important finding of this study is the confirmation of the mediating role of operational efficiency. Neither the impact of AI adoption nor that of digital innovation capabilities on sustainable performance occurs in a vacuum, but is channelled through improved operational efficiency first. Operational efficiency indicators are the tangible manifestation of this transmission mechanism. When AI automates processes and digital innovation capabilities redesign workflows, the first outcomes are cost savings, accelerated production times, more optimal resource utilisation, and increased productivity. The accumulation of these efficiencies creates what is known as 'slack resources' financial, time, and labour resources that can then be allocated to investments in sustainability initiatives such as employee training, the procurement of environmentally friendly raw materials, or improved waste management (Utami & Purnomo, 2023; Rawat et al., 2025). Without sufficient efficiency, SMEs which generally operate on slim margins—will struggle to justify investments in sustainability, as all their resources are already absorbed in maintaining basic operations.

The significance of this mediation explains why some SMEs fail to achieve sustainability despite having adopted digital technology. If AI adoption is merely implemented as an administrative add-on without being deeply integrated into operational processes—and thus fails to yield meaningful efficiency—its impact on sustainability will also be minimal. Therefore, operational efficiency is not merely an intermediate outcome, but a prerequisite that enables the conversion of technological capabilities into long-term value. These findings align with the study by Bindeeba et al. (2025), which confirms the mediating role of operational efficiency between the integration of digital business processes and economic and environmental performance among SMEs in Uganda, as well as the study by Soomro et al. (2025), which positions AI adoption as an enabler linking short-term operational gains with long-term sustainability goals. Within the theoretical framework, these results reinforce the integration between RBV and Dynamic Capabilities: strategic resources (AI and innovation capabilities) create competitive advantage through internal processes (efficiency), which are then directed towards achieving sustainable goals (Mrad et al., 2025).

Digital Ecosystem Support: Insignificant Moderation

Digital ecosystem support fails to significantly moderate the influence of AI adoption or digital innovation capabilities on sustainable performance because each of its constituent indicators still leaves fundamental issues unresolved. Rana et al., (2024) reveal that the availability of digital infrastructure in DIY is highly uneven across districts, as is common in developing countries (Khemakhem, 2025), so that high variations in perception weaken the moderating effect in aggregate. Regulatory and policy support has been formally established, but without a coordinating body responsive to local needs, such policies tend to be ceremonial and fail to provide direct incentives that alleviate the costs of AI adoption for micro-enterprises (Tandilino et al., 2025). Access to digital platforms is technically available, but low digital literacy means that platforms function more as administrative tools than as strategic instruments that strengthen the impact of AI on sustainability (Rana et al., 2024). Digital collaboration among stakeholders remains limited to short-term transactional interactions, failing to form the intensive co-creation partnerships between MSMEs, technology providers, and research institutions required to strengthen digital transformation (Hafeez et al., 2025; Tandilino et al., 2025). Meanwhile, the overall maturity of the digital ecosystem remains below the threshold required for external support to function as a catalyst; a weak ecosystem actually hinders the potential benefits of AI (Khemakhem, 2025). This is compounded by the early stage of adoption, where internal determinants such as owner commitment and human resource capacity remain dominant. Ecosystem support currently serves only as a hygiene factor; it has not yet become a significant lever capable of driving the strengthening of relationships towards sustainability.

CONCLUSION AND MANAGERIAL IMPLICATIONS

This study confirms that the adoption of artificial intelligence (AI) and digital innovation capabilities significantly drives operational efficiency and the sustainable performance of F&B SMEs in Yogyakarta, through both direct and indirect channels. Operational efficiency has been shown to be a central mediating mechanism that translates technology and digital capabilities into balanced achievements across economic, social and environmental dimensions. These findings underscore that AI and digital innovation are not merely technical tools, but strategic assets which, through cost savings, time acceleration, resource optimisation, and productivity improvements, can create fiscal space and organisational capacity for SMEs to invest in long- -term sustainability initiatives. Conversely, digital ecosystem support failed to significantly moderate this relationship. Although the direction of the coefficient is positive, this lack of significance is a critical finding that reveals the contextual reality: infrastructure gaps between districts, ineffective policy coordination, low digital literacy, and collaboration that remains transactional mean that the digital ecosystem in DIY currently functions merely as a hygiene factor, not yet as a strengthening catalyst. The novelty of this research lies in the testing of an integrative model that simultaneously links AI adoption, digital innovation capabilities, operational efficiency, sustainable performance, and digital ecosystem support within a single framework—an approach that has not previously been applied to F&B SMEs in Yogyakarta.

To ensure that digital transformation does not stop at mere technology ownership, F&B SMEs and stakeholders need to implement strategic measures that have been empirically proven to drive operational efficiency and sustainable performance. The following recommendations can be implemented:

1. Begin adopting AI by utilising the features most relevant to operations, such as predictive analytics for demand forecasting and raw material inventory management. This implementation can directly minimise production waste and reduce operational costs (Soomro et al., 2025; Sahoo, 2025).
2. Seamlessly integrate AI applications with existing digital systems, for example by linking stock forecasting tools with point-of-sale and sales recording applications so that daily transaction data automatically forms the basis for raw material purchasing decisions. Such integration yields tangible time and cost efficiencies in routine operations (Rawat et al., 2025; Bindeeba et al., 2025).
3. Actively and continuously participating in technical training programmes and mentoring sessions organised by local government agencies and universities, whilst building direct partnerships with local technology providers and campus-based research laboratories in the Yogyakarta region. This collaborative engagement will transform the use of digital technology from a mere administrative formality into a strategic instrument that strengthens competitiveness and long-term business sustainability (Hafeez et al., 2025).

LIMITATIONS

This study has a number of limitations that need to be noted. Firstly, the sample of Food and Beverage SMEs in Yogyakarta remains highly heterogeneous, encompassing cafes, eateries, and street food vendors without stratification by sub-sector; consequently, differences in operational characteristics and patterns of technology adoption across business types have not been captured in detail. Secondly, the variation in respondents' educational levels with a third having a high school or vocational school background poses challenges in understanding questionnaire items laden with technical terms such as 'AI-enabled decision-making' and 'digital experimentation capability', which may affect the accuracy of responses. Thirdly, the construct of AI adoption was measured without distinguishing the type, level of sophistication, or intensity of use of the AI technology implemented by each MSME, ranging from simple rule-based AI to machine learning; consequently, the measurement results do not yet fully and precisely represent the impact of each level of implementation.

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REFERENCE

Abdou, A. H. (2025). Smarter technologies, innovation, and managerial capabilities driving hotel sustainability: The integration of resource-based view and dynamic capabilities perspective. *Tourism and Hospitality*, 6(5). https://doi.org/10.3390/tourhosp6050252

Agbaakin, O. (2025). Leveraging artificial intelligence as a strategic growth catalyst for small and medium-sized enterprises. *arXiv preprint*. https://ar5iv.labs.arxiv.org/html/2509.14532

Ahmad, M., Wu, Q., & Khattak, M. S. (2025). Linking green intellectual capital to sustainability and sustainable business model innovation in manufacturing SMEs: The role of green dynamic capability. *Discover Sustainability*, 6, 955. https://doi.org/10.1007/s43621-025-01916-0

Ahmed, M., Al-Riyami, S. N., Husain, W. R. B. W., Juhdi, N. B., Al-Shuwaikh, F., & Haji, A. (2025). Examining the moderating effect of perceived government support on e-business adoption among Omani SMEs. *International Journal of Information Management Data Insights*, *5*(2), 100378. https://doi.org/10.1016/j.jjimei.2025.100378

Alsadoun, A. A., & Alateeg, S. (2026). Impact of Artificial Intelligence on Sustainable Performance: The Mediating Roles of Supportive Leadership and Organizational Change. *Sustainability*, *18*(5), 2435. https://doi.org/10.3390/su18052435

Barney, J. B. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99–120. https://doi.org/10.1177/014920639101700108

Beena, B. M. (2025). A green cloud-based framework for energy-efficient task scheduling using carbon intensity data for heterogeneous cloud servers. *IEEE Access*, 13, 73916–73938. https://doi.org/10.1109/ACCESS.2025.3562882

Bhatti, S., Ahmed, A., Ferraris, A., Hussain, W. M. H. W., & Wamba, S. F. (2025). Big data analytics capabilities and MSME innovation and performance: A double mediation model of digital platform and network capabilities. *Annals of Operations Research*, 350(2), 729–752. https://doi.org/10.1007/s10479-025-06580-9

Bindeeba, D. S., Atuhaire, S., Bakashaba, R., & Tukamushaba, E. K. (2025). Digital business process integration and sustainability among smes: the mediating role of operational efficiency and the moderating role of credit access. *Journal of Sustainable Business*, *10*(1), 11. https://doi.org/10.1186/s40991-025-00121-6

BPS DIY. (2023). *Profil industri mikro dan kecil Daerah Istimewa Yogyakarta 2023*. Badan Pusat Statistik Provinsi D.I. Yogyakarta.

Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE Publications.

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics*, 5(1), 1–4. https://doi.org/10.11648/j.ajtas.20160501.11

Fitri, Habbe, A. H., Pontoh, G. T., & Afdal. (2025). The impact of accounting information systems, knowledge management, digital platforms, and digital innovation on the performance of SMEs. *Journal of Governance & Regulation*, 14(4), 200–211. https://doi.org/10.22495/jgrv14i4art19

Hafeez, S., Shahzad, K., & De Silva, M. (2025). Enhancing digital transformation in SMEs: The dynamic capabilities of innovation intermediaries within ecosystems. *Technovation*, 143, 103287. https://doi.org/10.1016/j.technovation.2025.103287

Hair, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European Business Review*, 26(2), 106–121. https://doi.org/10.1108/EBR-10-2013-0128

He, M., & Yang, S. (2025). From generative AI adoption to sustainable performance: Operations capability mediation and environmental dynamism. *IEEE Access*, *13*, 209640–209657. https://doi.org/10.1109/ACCESS.2025.3531421

Huang, M. H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science*, 49(1), 30–50. https://doi.org/10.1007/s11747-020-00749-9

Islami, N. W., & Kholidah, F. N. (2025). Pengaruh literasi digital, pengalaman usaha, dan akses permodalan terhadap kinerja UMKM. *Jurnal Manajemen dan Bisnis*, 12(1), 45–58. https://doi.org/10.24843/jmb.2025.v12.i01.p05

Jha, R. S. (2022). Relevance of disruptive technologies led knowledge management system and practices for MSME. *Lecture Notes in Networks and Systems*, 321, 139–147. https://doi.org/10.1007/978-981-16-5987-4_15

Khemakhem, R. (2025). Artificial intelligence adoption in sustainability reporting: Opportunities and challenges for African small-medium enterprises. *Journal of African Business*. https://doi.org/10.1080/15228916.2025.2609006

Kgomo, A. A., & Lavhengwa, T. J. (2025). Artificial intelligence adoption for small, medium and micro-sized enterprises in developing countries: A scoping review. *Journal of Information Systems Engineering and Management*, 10(1). https://jisem-journal.com/index.php/journal/article/view/12982

Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Information Systems Journal*, 28(1), 227–261. https://doi.org/10.1111/isj.12131

Le, T. L. (2026). Green AI, strategic flexibility, and open innovation: advancing circular economy and sustainable performance in SMEs. *Journal of Manufacturing Technology Management*, 1-19. https://doi.org/10.1108/JMTM-09-2025-0925

Li, Y., Sulaiman, N., Guo, F., & Lu, S. (2025). The impact of the digital economy on SMEs: A systematic literature review based on organisational and environmental moderators. *International Journal of Business Process Integration and Management*, 12(4), 379–391. https://doi.org/10.1504/IJBPIM.2025.151631

Ma, Y. (2025). Artificial intelligence, data elements, digital economy, and corporate innovation performance. *International Review of Economics and Finance*, 103. https://doi.org/10.1016/j.iref.2025.104560

Marzi, G. (2025). Corrigendum to "Artificial intelligence and the reconfiguration of NPD teams: Adaptability and skill differentiation in sustainable product innovation." *Technovation*, 147. https://doi.org/10.1016/j.technovation.2025.103317

Mikalef, P., Conboy, K., Lundström, J. E., & Popovič, A. (2022). Thinking responsibly about responsible AI and 'the dark side' of AI. *European Journal of Information Systems*, 31(3), 257–268. https://doi.org/10.1080/0960085X.2022.2026621

Mrad, M. (2025). Digital–circular synergies in sustainable supply chain management: An integrative framework for SME performance enhancement. *Sustainability*, 17(23). https://doi.org/10.3390/su172310616

Muhammad, A. S., Adalier, A., & Adeshola, I. (2025). Digital transformation in youth owned MSMEs: A mixed method exploration on the impact of contemporary social commerce on sustainable performance. *Information Development*. https://doi.org/10.1177/02666669251329908

Mutanda, B. (2025). Disruptive digital technologies and the performance of micro, small and medium-size enterprises. Dalam *Disruptive frugal digital innovation in Africa* (pp. 135–154). Emerald. https://doi.org/10.1108/978-1-83549-568-120251008

Obschonka, M., & Audretsch, D. B. (2020). Artificial intelligence and big data in entrepreneurship: A new era has begun. *Small Business Economics*, 55(3), 529–539. https://doi.org/10.1007/s11187-019-00202-4

Pandi, V. S. (2025). Innovative Industrial Internet of Things (IIoT) solutions for cutting costs, maximizing efficiency, and optimizing energy usage. *2025 International Conference on Engineering Innovations and Technologies (ICOEIT)*, 1229–1234. https://doi.org/10.1109/ICoEIT63558.2025.11211717

Rana, N. P., Chatterjee, S., Dwivedi, Y. K., & Akter, S. (2024). Understanding dark side of artificial intelligence (AI) integrated business analytics: Assessing firm's operational inefficiency and competitiveness. *European Journal of Information Systems*, 33(3), 341–363. https://doi.org/10.1080/0960085X.2023.2232400

Rawat, S., Kumar, S., & Sharma, R. (2025). Operational efficiency and sustainable performance nexus in MSMEs: Mediating role of green innovation. *Journal of Cleaner Production*, 450, 141987. https://doi.org/10.1016/j.jclepro.2025.141987

Rosalin, S. (2025). Mapping the intellectual core of technology adoption in digital startups: A bibliometric analysis via bibliographic coupling and co-word networks. *International Journal of Environment Engineering and Education*, 7(3), 168–181. https://doi.org/10.55151/ijeedu.v7i3.355

Rozak, A., Priyono, A., & Hidayat, R. (2024). Digital ecosystem and MSME resilience: The role of government support programs in Indonesia. *Journal of Indonesian Digital Economy*, 2(1), 15–32.

Sahoo, P. (2025). SPC based critical parameters monitoring of vendor supplied parts by auto OEM for quality control. *SAE Technical Papers*. https://doi.org/10.4271/2025-01-8334

Saiyed, S. (2025). Harnessing artificial intelligence to strengthen green innovation capacity in pursuit of sustainable development goals: Evidence from Taiwan's manufacturing sector. *Equilibrium: Quarterly Journal of Economics and Economic Policy*, 20(3), 877–904. https://doi.org/10.24136/eq.3748

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial least squares structural equation modeling. Dalam C. Homburg, M. Klarmann, & A. Vomberg (Eds.), *Handbook of market research* (pp. 1–47). Springer. https://doi.org/10.1007/978-3-319-57413-4_15

Soomro, R. B., Al-rahmi, W. M., Dahri, N. A., Almuqren, L., Al-Mogren, A. S., & Aldaijy, A. (2025). A SEM–ANN analysis to examine impact of artificial intelligence technologies on sustainable performance of SMEs. *Scientific Reports*, 15, 5438. https://doi.org/10.1038/s41598-025-86464-3

Sugiyono. (2019). *Metode penelitian kuantitatif, kualitatif, dan R&D*. Alfabeta.

Susilo, Y. S. (2017, Desember 22). Pariwisata dan UMKM, mesin pertumbuhan Yogyakarta. *Berita Satu*. https://www.beritasatu.com/ekonomi/469899/pariwisata-dan-umkm-mesin-pertumbuhan-yogyakarta. Diakses 25 March 2025

Tandilino, C. (2025). Digital financial inclusion as a mediator of digital financial literacy and government support in MSME performance. *International Journal of Financial Studies*, 13(4). https://doi.org/10.3390/ijfs13040199

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28(13), 1319–1350. https://doi.org/10.1002/smj.640

Utami, I. W., & Purnomo, M. R. A. (2023). Sustainable performance of MSMEs in Indonesia: Integrating economic resilience and social-environmental responsibility. *Journal of Sustainable Development and Management*, 8(2), 145–160.

Wamba, S. F., Bawack, R. E., Guthrie, C., Queiroz, M. M., & Carillo, K. D. A. (2021). Are we preparing for a good AI society? A bibliometric review and research agenda. *Technological Forecasting and Social Change*, 164, 120482. https://doi.org/10.1016/j.techfore.2020.120482

Youssef, A. B. (2025). Twin transition: Digital transformation pathways for sustainable innovation. *Sustainability*, 17(21). https://doi.org/10.3390/su17219491

Zhao, J. (2025). From CSR to sustainable performance: The pathways of green supply chain management, circular economy capability, and AI adoption in China. *Corporate Social Responsibility and Environmental Management*. https://doi.org/10.1002/csr.70323

Zhang, W., & Wang, X. (2026). How does digital business model innovation enhance firms' operational efficiency? *Finance Research Letters*, 99. https://doi.org/10.1016/j.frl.2026.105437