ISSN: 3047-4108 P-ISSN: 3048-3751
Journal Economic Business Innovation -JEBI, Vol. 02, Issue.4, 2026, Page 519-537
DOI: https://doi.org/10.69725/jebi.v2i4.321

Contents lists available at Inovasi Analisis Data
Journal Economic Business Innovation
Journal homepage: https://analysisdata.co.id
ISSN: 3047-4108 P-ISSN 3048-3751

Digital Transformation and AI Implementation Effects on SME Financial Performance in Emerging Economies

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ARTICLE INFO

Article history:
Accepted 14 Nov, 2025
Revised 13 Dec, 2025
Publication 10 Jan, 2026

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Keywords:
Digitalised transformation; artificial intelligence; operational performance MSMEs, firm performance.

ABSTRACT

Purpose: This paper examines the impact of digital transformation and AI capabilities on MSME financial performance in an emerging economy via operational efficiency.
Method: A quantitative survey is used as a method of data collection for the study and PLS-SEM is used to test the mediation and moderation.
Findings: Results show that digital transformation capability, AI usage intensity, IT infrastructure preparedness and TTMS' (i.e., top management teams) digital competency drive operational efficiency, which in turn enhances financial performance. No direct financial implications from using AI or digital transformation capability are identified, highlighting that technological value is mainly achieved through operational efficiencies. On the other hand, IT infrastructure preparedness and digital management competence demonstrate both a direct and an indirect effect on performance. Environmental uncertainty has no direct effects on financial performance and does not moderate the relationships under study, indicating that digital and AI capabilities serve as basic rather than contingent drivers in this setting.
Novelty: This work adds by disambiguating the mediating role of digital value creation in MSME and by questioning the tacit boundary condition effect of environmental uncertainty in emerging economy context.
Implications: The findings emphasize therefore the necessity for integrating digital and AI strategy at heart of business process and developing managerial digital competencies to achieve durable performance improvements.

1. Introduction

This is particularly relevant in the current climate of widespread transition to digital and AI technologies, which is occurring in all types of organisations across all types of economies. Digital technologies have the potential to eliminate disadvantages faced by SMEs based on scale by enhancing the efficiency, responsiveness and informed decision-making capabilities of small and medium-sized enterprises. Current literature indicates that digital transformation capabilities, such as process digitalisation, system integration and data-driven decision-making, are to be a key element in enhancing firm performance, especially in resource-constrained settings (Amadasun & Mutezo, 2022; Dubey et al., 2023; Scholta et al., 2020; Vial, 2023). Concurrently, AI applications are progressively offering assistance with automation, analytics and predictive decision-making processes (Appel, 2024; Chen & Tajdini, 2025). This renders AI an essential concept in the operation of firms' activities and financial outcomes in volatile markets. These changes are of particular relevance to SMEs in emerging markets, where digitalisation is recognised as a strategic route to sustainable development.

Although the dissemination of digital technology and AI is expanding, MSMEs are actually still struggling with limitations in leveraging technological investment into operational performance. Previous studies have identified imbalanced states of digital readiness, insufficient IT infrastructure and intermediary capacity gaps as persistent obstacles to successful DT (Leso et al., 2024; Yadegaridehkordi et al., 2020). In addition, recent research indicates that merely having AI technology does not lead to performance benefits unless it is closely linked with organizational processes and bolstered by the right managerial capabilities (Appel, 2024; Chen & Tajdini, 2025). In developing economies, such concern is further exacerbated because of volatile demand, fierce competition, fast changing technology and ambiguity regarding regulation which raises the question of how MSME can take advantage of digital and AI capabilities amidst their environment (Dubey et al., 2020, 2023).

On a theoretical level, potential and few available studies refer primarily to the Resource-Based View (RBV) or technology adoption theories in capturing digitalization effects. But these views do little to explain how digital and AI capabilities are transformed into performance advantages through dynamic and processual mechanisms. The DCV is a more appropriate theory because it focuses on firms sensing opportunities, capturing digital value, and reconfiguring their operations to respond to environmental change (Scholta et al., 2020; Teece, 2010, 2019; Vial, 2023). However, empirical studies that combine DCV with firm-level operational antecedents such as operational efficiency or contextual factors such as environmental uncertainty are also scarce, particularly in the MSME and emerging economy context.

This study addresses several significant gaps in the literature. Firstly, the results of past research on the performance implications of digital transformation and AI adoption are somewhat inconclusive. While some studies indicate strong positive effects, others report weak or conditional relationships, with divergent complementary insights emerging. Secondly, to other theoretical nuances, little attention has been given to this association (Vial, 2019; Dubey et al., 2023; Appel et al., 2024). Secondly, there is little empirical evidence to suggest that operational efficiency is a mediating mechanism. The impact of business digital and AI capabilities on the financial performance of MSMEs is yet to be explored. Thirdly, whilst there is a general consensus that environmental uncertainty is a critical characteristic of EMs (Donaldson, 2001), there has been limited attention paid to its moderating effect on the effectiveness of digital and AI capabilities. Fourthly, the present paper addresses a research gap by considering more than one technological dimension. In the field, there has been little research on the influences of digital transformation capability, artificial intelligence utilisation intensity, IT infrastructure readiness and top management digital competence. Finally, as Leso et al. (2023) and Dubey et al. (2023) point out, there is a paucity of empirical studies on emerging economies, particularly in comparison to the much larger number of studies on developing countries. These countries are home to some of the world's largest populations of MSMEs, who are in urgent need of support.

The aim of the research is to examine the impact of digital transformation capability, the intensity of AI utilisation, the readiness of IT infrastructure and the digital competency of senior management on the financial performance of MSEs via operational efficiency in the presence of environmental uncertainty. This combination of approaches, including DCV, the Technology-Organization-Environment framework and contingency theory, provides a valuable theoretical foundation for understanding mechanisms and boundary conditions in digital value creation in the context of AI. Finally, the results provide valuable insights for MSME owners, managers and policymakers, offering practical guidance on developing effective digital and AI strategies that can lead to improved performance in volatile contexts.

ISSN: 3047-4108 P-ISSN: 3048-3751
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DOI: https://doi.org/10.69725/jebi.v2i4.321

Section 2 presents our study by literature review and theories construction, as well proposed research hypotheses. In Section 3 we present the research method, instruments and process -including the data collection. The empirical results and the interpretation are discussed in Section 4. Section 5 presents a summary of the main results, theoretical and managerial implications, limitations and future research.

2. Literature Review and Hypothesis Development

2.1 Digital transformation, artificial intelligence, and SME financial performance

DT capability allows organisations to transform their business processes, integrate digital technology, and leverage data-driven decision-making, thereby creating value for the organisation (Vial, 2019). From the DCV perspective, these capabilities enable the sensing, seizing and reconfiguring of behaviours that are necessary to ensure the continued financial performance of businesses, especially those SMEs which may not have abundant resources. Recent empirical findings indicate that digital transformation enhances revenue growth and profitability by increasing both agility and decision quality (Amadasun & Mutezo, 2022). Furthermore, increased AI usage has been shown to enhance the depth of analysis, automation and quality of managerial decisions by converting technological investment into financial benefit. Additionally, the technological infrastructure preparedness of IT systems for digitalisation facilitates scalable digital operations. Managing from the organisation's top level (e.g. CEO) enhances strategic alignment, governance, and efficient resource deployment in line with the viewpoints of RBVs and TOEs.

Hypothesis 1a: Digital transformation capability positively influences SME financial performance.
Hypothesis 1b: AI utilization intensity positively influences SME financial performance.
Hypothesis 1c: IT infrastructure readiness positively influences SME financial performance.
Hypothesis 1d: Top management digital competency positively influences SME financial performance.
Hypothesis 1e: The combined presence of digital transformation capability and AI utilization enhances SME financial performance beyond isolated digital initiatives.

2.2 Digital capabilities and operational efficiency in SMEs

Operational efficiency refers to an organisation's ability to carry out its back-end processes in a manner that reduces time, effort and cost while delivering optimal value. In terms of DCV and process-oriented view on digital transformation, the automation of routines, integration of workflows and facilitation of real-time coordination can result in enhanced efficiency (Dwivedi et al., 2022). The heavy use of AI contributes significantly to efficiency, seamlessly integrating predictive analytics and intelligent automation into operational processes. It is imperative for emerging-market SMEs to be IT infrastructure-ready in order to avoid limitations in efficiency gains, which can be caused by a lack of connectivity or system interoperability. Furthermore, it is vital for leaders to endorse and promote digital capability at the highest levels of an organisation (Dubey et al., 2020). This will ensure that the potential of technology can be successfully converted into operational routines. Such leadership endorsement can be achieved through training and governance that is consistent with TOE and UE theory.

Hypothesis 2a: Digital transformation capability is associated with a range of benefits, including enhanced operational efficiency.
Hypothesis 2b: AI usage has been shown to have a positive impact on operating performance.
Hypothesis 2c: IT Infrastructure Preparedness has a positive effect on operational efficiency.
Hypothesis 2d: The possession of digital skills by executives has been shown to have a positive impact on operational efficiency.
Hypothesis 2e: Compared with other SMEs, those with higher digital and AI capabilities have achieved greater operational efficiency.

2.3 Operational efficiency and financial performance of SMEs

Operational efficiency is an important pathway for companies to transform technological

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investments into economic value. Effective operations drive down costs, increase productivity, speed services and stabilize cash flow – all supporting financial performance. Formal studies exploring the operations and digital transformation realm agree, efficiency gains mediate the impact of technology use on firm performance, particularly in SMEs where cost leadership and flexibility are more important than sheer magnitude (Dubey et al., 2023). From the standpoint of value creation, operational efficiency allows SMEs to make better use of digital and AI capabilities to improve profitability and sustain revenue.

Hypothesis 3a: Efficiency has a positive impact on financial performance of SMEs.
Hypothesis 3b: Greater levels of operational efficiency enhance the revenue growth of SMEs.
Hypothesis 3c: Operating efficiency leads to better profitability and cost-to-revenue relationship.
Hypothesis 3d: Operational efficiency will positively influence financial stability of SMEs.
Hypothesis 3e: The more efficient the operations of an SME, the better does its overall financial performance.

2.4 Operational efficiency is the driving force behind value transformation.

Nevertheless, it should be noted that digital transformation capability, AI usage intensity, IT infrastructure readiness and top management skillset do not always guarantee financial returns. Instead, they create value by developing their own capabilities in a way that improves operational efficiency. As outlined in the DCV and RBV, OE is a value creation process that transforms digital and AI resources into performance results. Research conducted to date indicates a correlation between enhanced efficiency and the adoption of digital technologies, particularly among SMEs grappling with limitations in resources and capabilities. Therefore, it is anticipated that operational efficiency will provide a connection between the impact of digitally-driven and AI-enabled capabilities on financial performance.

Hypothesis 4a: Efficiency is a mediating variable that can be utilised to analyse the relationship between transformation capability and SME financial performance.
Hypothesis 4b: The impact of AI usage intensity on SME financial performance is mediated by operational efficiency.
Hypothesis 4c: Operational efficiency is a key factor in the association between IT infrastructure readiness and SME financial performance.
Hypothesis 4d: The direct impact of TMDs on SME financial performance is moderated by operational efficiency.
Hypothesis 4e: The positive effects of operational efficiency are amplified in SMEs where digital capabilities are more deeply embedded.

2.5 The natural environment as a contextual boundary condition

The ability of firms to harness digital and AI resources is determined by environmental uncertainty. This is reflected in demand fluctuations, competitive dynamism, technological volatility and regulatory modifications. From a contingency theory perspective, enhancing organisational performance entails aligning internal capabilities with environmental factors (Donaldson, 2001). In situations where uncertainty is high, SMEs must be able to swiftly identify changes in the external environment and adapt their operational processes accordingly. This underscores the crucial role that digital transformation capabilities and the extent to which artificial intelligence is utilised play in achieving operational efficiency (Teece, 2007; Vial, 2019). From an empirical perspective, environmental turbulence strengthens the links between digital and AI capabilities, making agility and swiftness even more important. At the same time, it limits the use of rigid and non-flexible structures (Dubey et al., 2023; Chen & Tajdini, 2024). Therefore, it is assumed that environmental uncertainty acts as the boundary condition for digital capabilities and operational efficiency among SMEs.

Hypothesis 5a: The impact of digital transformation capability on operational efficiency is moderated by environmental uncertainty, with the relationship being stronger in high-uncertainty environments.
Hypothesis 5b: In the context of AI application intensity and operational efficiency, environmental uncertainty has been shown to have a moderating

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effect. In other words, the relationship is stronger under higher environmental uncertainty.
Hypothesis 5c: The effect of IT infrastructure readiness on operational efficiency is moderated by environmental uncertainty.
Hypothesis 5d: The relationship between top management's digital competence and operational performance is moderated by environmental uncertainty.
Hypothesis 5e: In situations where the environment is characterised by a high degree of uncertainty, SMEs are able to achieve enhanced operational performance through the integration of digital and AI capabilities.

2.6 Conceptual research framework

This model integrates the Dynamic Capabilities View (DCV) (Red Box) as the main theory, explaining the mechanism of sensing-seizing-reconfiguring through the mediation of Operational Efficiency (OE). The TOE Framework (Blue Box) maps technological and organizational determinants, while RBV (Purple Box) highlights IT infrastructure and management competencies as strategic resources. Contingency Theory (Green Box) justifies the role of Environmental Uncertainty as a moderator. Hypotheses include direct effects on Financial Performance (H1a-H1d) and Operational Efficiency (H2a-H2d), OE impact on performance (H3), the mediating role of OE (H4a-H4d), and the moderating effect of the environment (H5a-H5d), forming a comprehensive X>M>Y framework in the context of uncertainty.

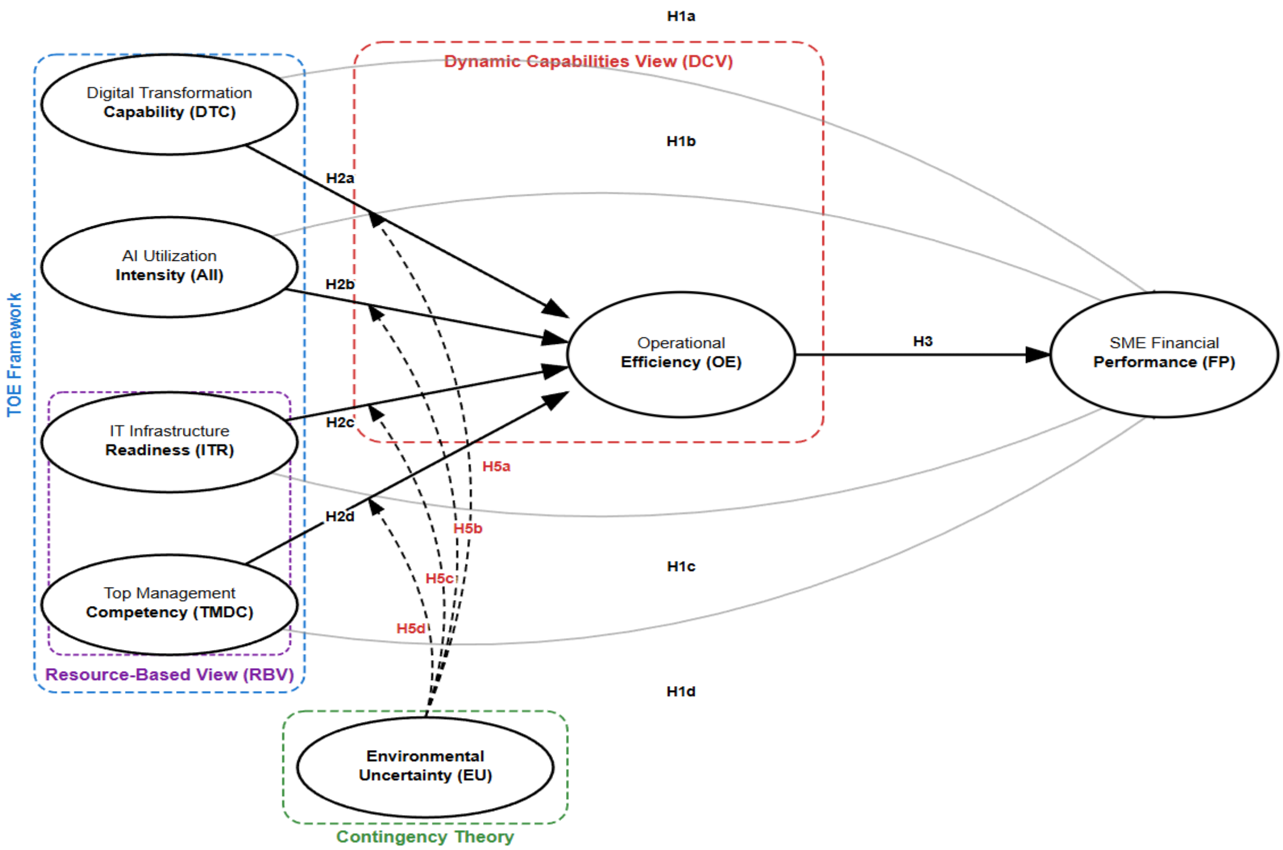

Figure 2. Conceptual Research Framework with Theoretical Mapping

Note:
H1a-H1d: Direct effects on Financial Performance.
H2a-H2d: Direct effects on Operational Efficiency.

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H3: Effect of Operational Efficiency on Financial Performance.
H4a-H4d: Mediation effects (OE mediates X > FP).
H5a-H5d: Moderation effects of Environmental Uncertainty.
Red Box: Dynamic Capabilities View (DCV); Blue Box: TOE Framework; Purple Box: Resource-Based View (RBV); Green Box: Contingency Theory.

3. Methods Innovation

3.1 Research design

The study uses a quantitative explanatory research design where we analyze the associations between digital transformation capability, AI usage intensity, IT infrastructure preparedness, top management digital competency efficiency and SME financial performance. The design is based on the Dynamic Capabilities View (Teece, 2007; Vial, 2019) as to how companies transform digital resources for performance results and complemented by TOE (Tornatzky & Fleischer, 1990) and Contingency Theory (Donaldson, 2001), in terms of rationalizing contextual effects. Cross-sectional survey Cross-section is used to capture managers' perceptions of digital and AI practices in MSMEs in emerging economies.

3.2 Data for research sample and population

The research sample is limited to Indonesia's MSME population, although open to every respondent at the firm level (owners, managers or supervisors). As documented in Appendix A, the sample eventually consists of 350 MSMEs from different sectors, firm's size and area which represent structural variety among Indonesia MSMEs. Google Forms was used to gather the data because it has wide geographic coverage and provides a cost-effective approach when seeking active digitally-engaged firms. This is in line with previous SME digitalization research which utilizes online surveys to capture perceptions of technology adoption and performance. The equal division of firm size, industry type, and respondent role further increases the generalizability and external validity of the sample.

3.3 Variable measurement and data instrument

All study variables were operationalized as multi-item reflective constructs based on the high-end literature and research. Six indicators scored on a 5-point Likert-type scale (1 = strongly disagree; 5 = strongly agree) were used to operationalize each construct. On the basis of this, we regard digital transformation capability, AI utilization intensity, IT infrastructure readiness and top management digital competency as independent variables, operational efficiency as mediate variable, environmental uncertainty is a moderate variable, SME financial performance is dependent variable. Detailed construct definitions, operationalisations and scale sources are presented in Appendix B to ensure content validity and replicability from previous empirical research.

3.4 Data analysis technique

The data were processed by means of Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS. 4, a key method recommended for complex research models including the mediation and moderation effects, predictive nature of research questions and non-normality in multivariate data – frequent attributes found in SMEs contexts. PLS-SEM is also suited to research focusing on theory development, and variance explanation rather than model fit optimisation (Hair et al., 2022). The analysis was conducted in two steps: a) test of the measurement model (indicator reliability, internal consistency reliability, convergent validity and discriminant validity), b) evaluation of the structural model (path coefficients, determination coefficient and mediation/moderation/predictive relevance). The significance of direct, indirect and moderation effects were undertested using bootstrapping with resampling which is a recommended method for robust inference in PLS-SEM (Hair et al., 2022; Henseler et al., 2015; Sarstedt et al., 2019).

4. Results of Innovation and Discussion

4.1 Measurement model assessment

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As illustrated in Table 1, the indicators demonstrate a high degree of reliability across the various constructs. All external loadings fall within the accepted range of 0.775–0.912, which is significantly higher than the commonly accepted cut-off point of 0.70. This indicates a robust association between each item and its underlying factor. The squared loadings (λ^2) are primarily concentrated between 0.60 and 0.83, suggesting a significant degree of explained variance at the indicator level. We can therefore conclude that collinearity is not a problem. All VIF values for indicators range between 1.819 and 4.153, below the conservative cut-off of 5.0. Overall, the measurement items demonstrate acceptable indicator quality and are worthy of reliability and validity testing.

As demonstrated in Table 2, the data demonstrates excellent internal consistency and convergent validity. The Cronbach's alpha values range from 0.896 to 0.951, and the composite reliability (CR) varies from 0.920 to 0.961. These values exceed the recommended cutoff of ≥0.70, indicating strong construct reliability in this model. Convergent validity is also supported, as all the Average Variance Equations (AVE) values exceed 0.50, ranging from 0.656 (EU) to 0.803 (FP). This indicates that each construct accounts for more than one half of the variance in its indicators. The AVE for FP (AVE = 0.803) and OE (AVE = 0.755) is the highest, which supports their high outer loading. It is generally satisfactory that the constructs demonstrate both reliability and convergent validity.

Discriminant validity has been demonstrated using the HTMT criterion (see Table 3). As demonstrated in the research by Leonard et al. (2017), the HTMT values for the core constructs are all below the moderate standard of 0.85 for "strict" thresholds and 0.90 for "liberal". This provides evidence that the constructs are empirically unique. The largest HTMT values are found between theoretically adjacent constructs, for example TMDC–DTC (0.756) and DTC–OE (0.742). However, these values do not exceed acceptable limits. It is evident that lower HTMT values between environmental uncertainty indicators suggest a distinct difference between the EU and its capability and outcome constructs (e.g., EU–TMDC = 0.187, EU–FP = 0.223). Overall, discriminant validity has been established.

Table 1. Indicator Reliability and Outer Loadings

Construct	Indicator	Outer loading	Indicator reliability (λ^2)	VIF
AII	AII1	0.795	0.632	1.994
	AII2	0.844	0.712	2.538
	AII3	0.801	0.642	2.117
	AII4	0.842	0.709	2.414
	AII5	0.775	0.601	1.819
	AII6	0.816	0.666	2.163
DTC	DTC1	0.827	0.684	2.296
	DTC2	0.877	0.769	2.957
	DTC3	0.862	0.743	2.743
	DTC4	0.814	0.663	2.165
	DTC5	0.858	0.736	2.679
	DTC6	0.825	0.681	2.286
EU	EU1	0.81	0.656	2.127
	EU2	0.836	0.699	2.376
	EU3	0.8	0.64	1.879
	EU4	0.796	0.634	1.983
	EU5	0.822	0.676	2.167
	EU6	0.795	0.632	2.131
FP	FP1	0.882	0.778	3.203
	FP2	0.912	0.832	4.153
	FP3	0.888	0.789	3.348

OPEN ACCESS
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Journal Economic Business Innovation -JEBI, Vol. 02, Issue.4, 2026, Page. 519-537
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Construct	Indicator	Outer loading	Indicator reliability (λ²)	VIF
	FP4	0.885	0.783	3.282
	FP5	0.904	0.817	3.835
	FP6	0.905	0.819	3.919
ITR	ITR1	0.81	0.656	2.185
	ITR2	0.831	0.691	2.264
	ITR3	0.833	0.694	2.356
	ITR4	0.837	0.701	2.377
	ITR5	0.847	0.717	2.458
	ITR6	0.805	0.648	2.076
OE	OE1	0.864	0.746	2.922
	OE2	0.888	0.789	3.352
	OE3	0.878	0.771	3.122
	OE4	0.856	0.733	2.713
	OE5	0.878	0.771	3.181
	OE6	0.85	0.723	2.62
TMDC	TMDC1	0.83	0.689	2.306
	TMDC2	0.849	0.721	2.464
	TMDC3	0.82	0.672	2.229
	TMDC4	0.829	0.687	2.268
	TMDC5	0.81	0.656	2.122
	TMDC6	0.807	0.651	2.193

Table 2. Internal Consistency Reliability and Convergent Validity

Construct	Cronbach's alpha	rho_A	(CR)	AVE
AII	0.897	0.897	0.921	0.66
DTC	0.919	0.92	0.937	0.713
EU	0.896	0.901	0.92	0.656
FP	0.951	0.951	0.961	0.803
ITR	0.908	0.909	0.929	0.684
OE	0.935	0.935	0.949	0.755
TMDC	0.906	0.907	0.927	0.679

Table 3. Discriminant Validity Assessment

	AII	DTC	EU	FP	ITR	OE	TMDC
AII	–						
DTC	0.707	–					
EU	0.279	0.233	–				
FP	0.598	0.621	0.223	–			
ITR	0.602	0.67	0.362	0.595	–		
OE	0.697	0.742	0.251	0.727	0.674	–	
TMDC	0.683	0.756	0.187	0.642	0.681	0.738	–

4.2 Structural model evaluation

As per Table 4, the issue of collinearity is not significant in the structural model. The VIF in the inner model ranges between 1.151 and 2.675, much lower than the threshold of 3.3 (conservative) and 5.0 (acceptable). For the FP equation, Dramatic VIFs are registered for DTC > FP (2.675) and OE > FP (2.653), while EU > FP (1.151) shows the lowest value. For the OE equation, VIF values low moderate with highest being DTC > OE (2.390). These findings indicate that the path coefficients of interest are not likely to be biased by multicollinearity.

Table 5 demonstrates high explanatory and predictive power of the model. 60.6% of the variance in OE is explained by predictors ($R^2 = 0.606$, adjusted $R^2 = 0.601$) and 52.9% of the variance in FP ($R^2 = 0.529$, adjusted $R^2 = 0.515$). Predictive relevance is established as both endogenous constructs have Q^2

values that are positive ($Q^2 > 0$), where OE (Q^2 = 0.452) and FP (Q^2 = 0.419) demonstrate strong predictive generalizability out-of-sample. In sum, the structural model exhibits substantial explanatory and predictive power with respect to a set of important MSME outcomes.

Table 4. (VIF Values)

Endogenous construct	Predictor path	VIF
FP	AII > FP	2.184
	DTC > FP	2.675
	EU > FP	1.151
	ITR > FP	2.067
	OE > FP	2.653
	TMDC > FP	2.504
	EU × DTC > FP	2.457
	EU × AII > FP	2.1
	EU × ITR > FP	1.973
	EU × TMDC > FP	2.351
OE	AII > OE	1.941
	DTC > OE	2.39
	ITR > OE	1.857
	TMDC > OE	2.31

Table 5. R^2 and Q^2

Endogenous construct	R^2	R^2 adjusted	Q^2 (cross-validated redundancy)
OE	0.606	0.601	0.452
FP	0.529	0.515	0.419

4.3 Direct effects hypothesis test

As shown in Table 6, there is a statistically significant positive relationship between all digital capability-related constructs (AI utilisation intensity, digital transformation capability, IT infrastructure readiness and top management digital competency) and operational efficiency, with $p < 0.001$. The corresponding beta coefficients are 0.262, 0.193, 0.267 and 0.202, respectively. The findings indicate that SMEs which leverage AI to a greater extent, possess stronger digital transformation capabilities, have sufficient IT infrastructure and task- and digitally capable top management, are more likely to streamline processes, reduce organisational inefficiencies and enhance productivity. In addition, it has been demonstrated that operational efficiency has a substantial and robust impact on financial performance ($\beta = 0.393$, $p < 0.001$), thereby validating its role as a conduit for enhancing performance. However, these direct effects do not reach statistical significance in terms of the firm's financial performance. This indicates that their influence on performance is primarily indirect. While they clearly lead to greater operational efficiency, they do not have a significant impact on immediate monetary outcomes. It is also important to note that IT infrastructure readiness and top management digital competency remain key factors in achieving strong financial performance. Their direct and structural contribution to revenue growth and profitability is undeniable. Finally, there is no evidence that financial performance is impacted by environmental uncertainty. This suggests that its impact may be more significant as a conditional or interactive than as a direct nature.

Please refer to Table 7 for details of the direct effects in the structural model. Effect sizes (f^2) are reported in order to provide a more accurate assessment of the practical relevance of each predictor, beyond statistical significance. As shown in the mid-point analysis, operations have a moderate impact on financial performance (F^2 = 0.123). This illustrates that operations are the core engine for achieving financial consequences in MSMEs. This demonstrates that maintaining high levels of cost efficiency, process speed and

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productivity leads to a significant improvement in financial performance. Research shows that digital transformation capability (f^2 = 0.073) and top management digital competency (f^2 = 0.068) have a moderate impact on operational efficiency. This suggests that these variables are indeed contributing significantly to the improvement of input values towards operations. In contrast, the intensity of AI use (f^2 = 0.059) and preparedness of IT infrastructure (f^2 = 0.051) exert small-to-medium effects on operational effectiveness, indicating supportive but non-central contributions. The direct impact of digital and AI-specific elements on financial performance is typically negligible to non-significant ($f^2 \leq$ 0.019), indicating that financial benefits primarily derive indirectly through operational efficiency rather than from direct or synergistic effects.

Table 6. Path Coefficients and Significance of Direct Effects

Hypothesis	Structural path	β (O)	STDEV	t-value	p-value
H1a	AII > OE	0.213	0.051	4.183	0.000
H1b	DTC > OE	0.262	0.06	4.362	0.000
H1c	ITR > OE	0.193	0.049	3.937	0.000
H1d	TMDC > OE	0.249	0.056	4.453	0.000
H2	OE > FP	0.393	0.063	6.223	0.000
H3a	AII > FP	0.099	0.057	1.725	0.085
H3b	DTC > FP	0.074	0.063	1.174	0.240
H3c	ITR > FP	0.115	0.055	2.075	0.038
H3d	TMDC > FP	0.15	0.063	2.385	0.017
H4	EU > FP	0.008	0.039	0.200	0.842

Table 7. Effect Size (f^2) of Direct Relationships

Structural path	f^2	Effect magnitude
AII > OE	0.059	Small–medium
DTC > OE	0.073	Medium
ITR > OE	0.051	Small
TMDC > OE	0.068	Medium
OE > FP	0.123	Medium
AII > FP	0.009	Negligible
DTC > FP	0.004	Negligible
ITR > FP	0.014	Small
TMDC > FP	0.019	Small
EU > FP	0.000	Negligible

4.4 Mediation analysis

The findings presented in Table 8 show that the indirect effects of all hypothesized pathways through operational efficiency are positive and statistically significant ($p < 0.01$), thereby reinforcing the mediating role of operational efficiency in the relationship between digital capabilities and financial performance. Specifically, AI usage intensity and digital transformation capabilities have a less than optimal impact on financial performance through operational efficiency. There is no significant direct impact on profit attractiveness, and full mediation is observed. Conversely, there is a significant indirect and direct impact on IT infrastructure readiness and top management digital competence. These findings indicate that partial mediation occurs. These results highlight the efficiency of digitalization and AI-related capabilities in terms of their ability to translate into tangible financial results for MSMEs.

As shown in Table 9, VAF estimates range from 39.5% to 58.2%. This indicates that most of the impact of digital capabilities on financial performance can be attributed to operational efficiency. Digital

ISSN: 3047-4108 P-ISSN: 3048-3751
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transformation capabilities have the highest VAF score, indicating full mediation; AI usage intensity also has a significantly mediated component, indicating a similar trend. It is recommended that partial mediation be considered for IT infrastructure readiness and top management digital expertise. VAF values below 50% indicate a partial mediation effect on these capabilities in relation to financial performance. To summarize, the mediation analysis results show that operational efficiency is an essential strategic driver and the main mechanism through which digital transformation (DT) and AI technology adoption influence the financial performance of SMEs.

Table 8. Indirect Effects and Mediation Results

Indirect Path	β (Indirect)	STDEV	t-value	p-value	Mediation type
AII > OE > FP	0.083	0.023	3.582	0.000	Full mediation
DTC > OE > FP	0.103	0.029	3.588	0.000	Full mediation
ITR > OE > FP	0.076	0.023	3.300	0.001	Partial mediation
TMDC > OE > FP	0.098	0.028	3.469	0.001	Partial mediation

Table 9. Variance Accounted For (VAF) of Mediation Effects

Relationship	Indirect effect	Total effect	VAF (%)	Mediation assessment
AII > FP	0.083	0.182	45.60%	Partial-to-full mediation
DTC > FP	0.103	0.177	58.20%	Full mediation
ITR > FP	0.076	0.19	40.00%	Partial mediation
TMDC > FP	0.098	0.248	39.50%	Partial mediation

4.5 Moderation analysis

As shown in Table 10, the moderation testing of environmental uncertainty on the relationships between digital capabilities and financial performance is demonstrated therein. It is evident from these findings that none of the interaction terms demonstrate statistical significance ($p > 0.10$). Despite the coefficients displaying an opposite direction (indicated by positive values for DTC, AIUI and ITIR, and negative values for TMDI), these effects were found to be weak and statistically insignificant. It is evident that the inherent characteristics of environmental uncertainty remain largely unaltered. Furthermore, the correlation between digital capability and financial performance within the selected MSME environment remains consistent. In contrast, digital and AI capabilities appear to offer performance benefits in a very similar way, regardless of environmental turbulence and uncertainty.

However, it should be noted that all interaction effects have effect sizes (f^2) below 0.02 (see Table 11), indicating a negligible relevance. Our research findings provide additional evidence that environmental uncertainty does not modify the direct and indirect effects of digital transformation capability, AI utilisation intensity, IT infrastructure readiness and top management digital competency on firm performance. In essence, this suggests that the economic value generated by the implementation of digital and AI capabilities in MSMEs is resilient across various levels of environmental uncertainty. This outcome indicates that uncertainty does not significantly influence outcomes, contradicting our initial theoretical expectations.

The measurement and structural model results of the PLS-SEM estimation are reported in figure 2. The first-order latent variables are all measured by reflective type indicators, and the outer loading values of items clearly ensure the indicator reliability. These R^2 values for both the operational efficiency and financial performance constructs are moderate to strong, showing the good explanatory power of the model. The structural model shows that digital capabilities and AI use are antecedents to operational efficiency, which in turn partly explains financial performance. In general, the present visualization represents a satisfying model that

ISSN: 3047-4108 P-ISSN: 3048-3751
Journal Economic Business Innovation -JEBI, Vol. 02, Issue.4, 2026, Page. 519-537
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satisfies the criteria proposed for PLS-SEM and it is appropriate to go on testing the hypotheses. Please refer to Figure 3 for the results of the structural model with moderation. It is clear that digital transformation capability, AI usage intensity, IT infrastructure readiness, and top management digital competency have a positive impact on operational efficiency. Operational efficiency has been shown to have a positive and significant impact on financial performance. It appears that multiple digital capabilities only have a weak direct impact on financial performance, with the effect instead being indirect. It is evident that the interaction terms with environmental uncertainty are not significant, indicating that there is no moderating effect.

Table 10. Moderating effects of environmental uncertainty

Hypothesis	Interaction Path	β (O)	STDEV	t-value	p-value
H5a	EU × DTC > FP	0.042	0.062	0.688	0.491
H5b	EU × AII > FP	0.031	0.056	0.546	0.585
H5c	EU × ITR > FP	0.056	0.052	1.084	0.278
H5d	EU × TMDC > FP	−0.041	0.058	0.702	0.483

Table 11. Effect Size (f^2) of interaction terms

Interaction Path	f^2	Effect magnitude
EU × DTC > FP	0.002	Negligible
EU × AII > FP	0.001	Negligible
EU × ITR > FP	0.003	Negligible
EU × TMDC > FP	0.002	Negligible

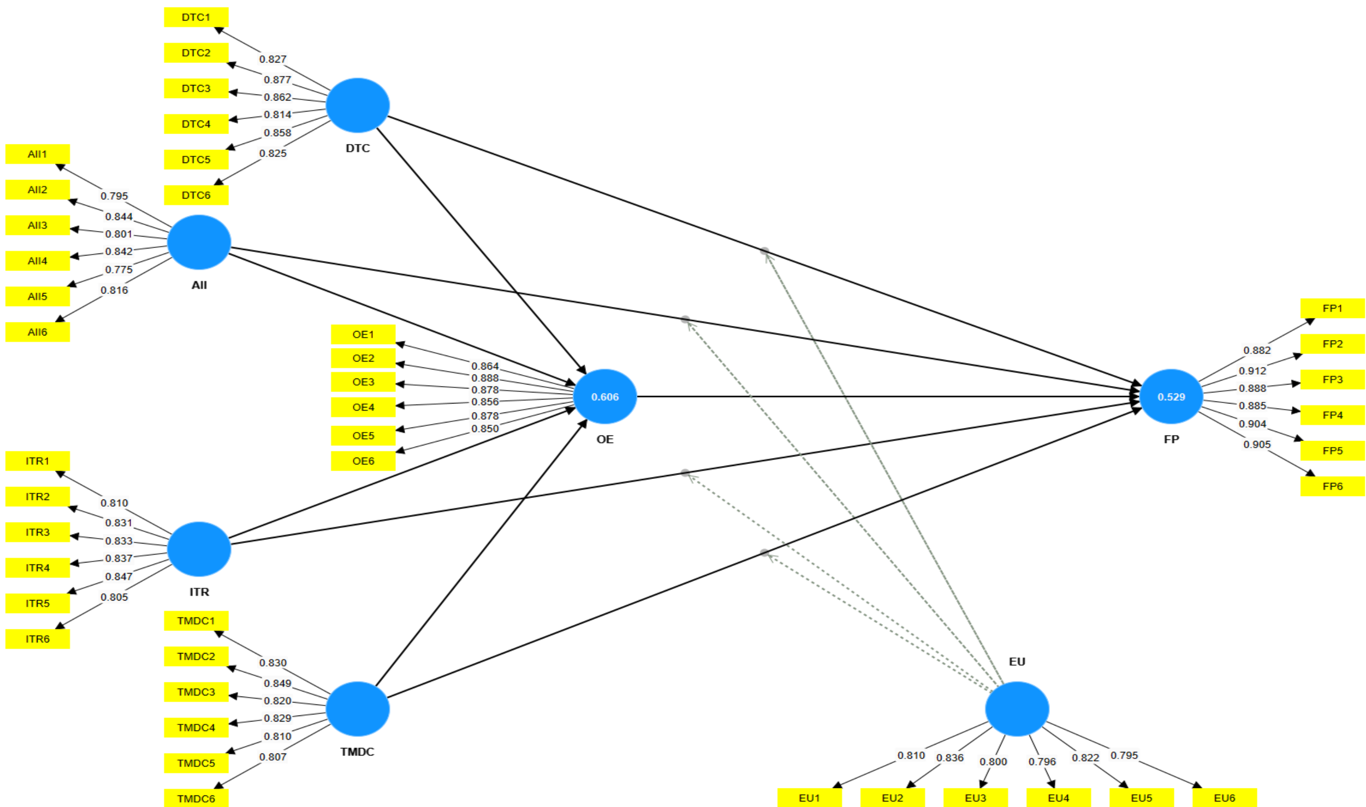

Figure 2. Outer Model Results (Measurement Model)

ISSN: 3047-4108 P-ISSN: 3048-3751
Journal Economic Business Innovation -JEBI, Vol. 02, Issue.4, 2026, Page. 519-537
DOI: https://doi.org/10.69725/jebi.v2i4.321

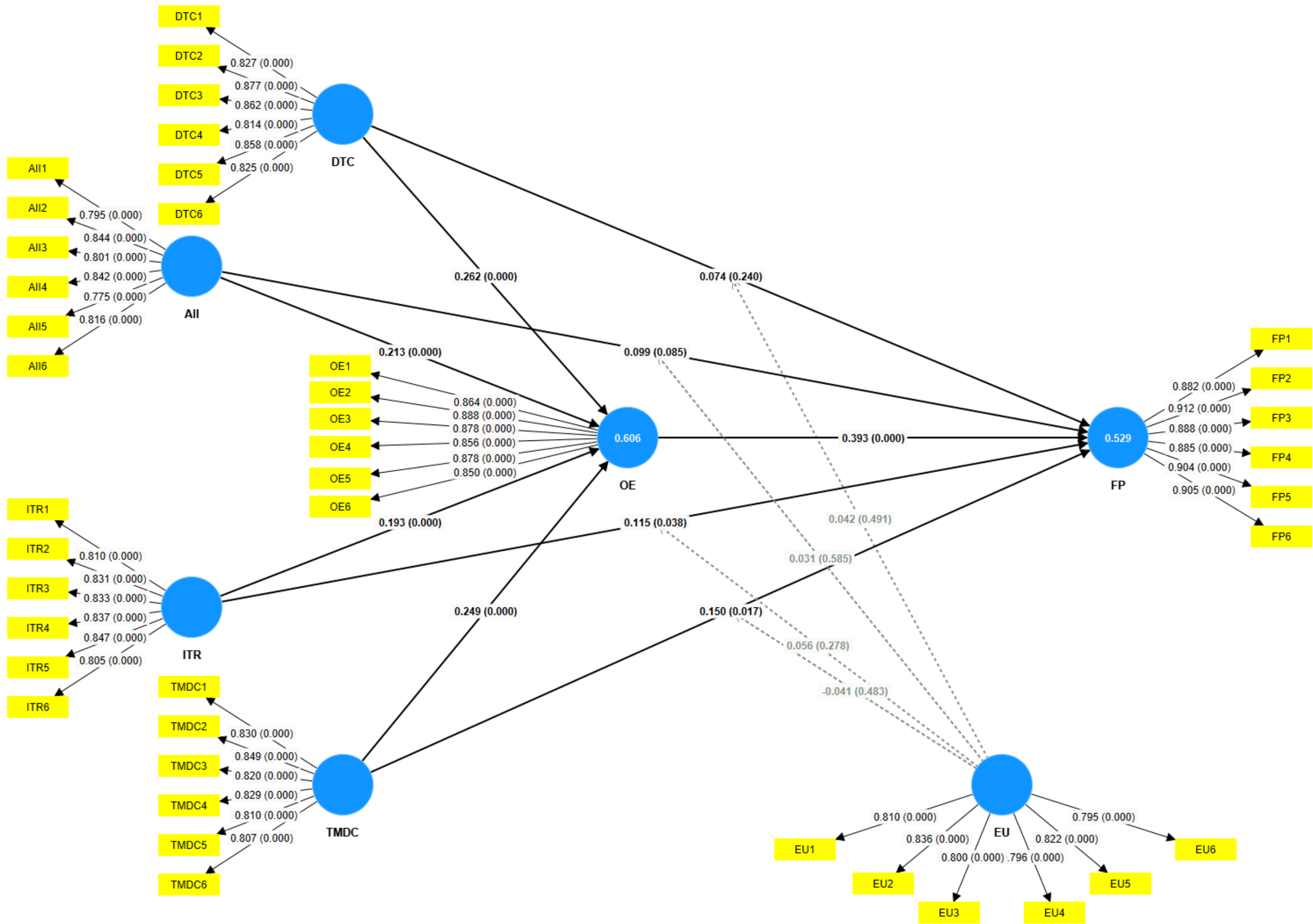

Figure 3. Inner Model Results (Structural Model with Moderation)

4.6 Model predictive assessment

Table 12 presents the predictions from PLS and PLSpredict using blindfolding-based Q² to evaluate the out-of-sample predictive ability of the model. The Q² values for both endogenous constructs are well above zero, demonstrating high predictive relevance. In particular, regarding operational efficiency (Q² = 0.452), high predictive relevance is identified, as digital transformation capability, AI usage intensity, IT infrastructure preparedness and top management digital competency jointly achieve excellent prediction of efficiency-related outcomes. Financial performance Financial performance (Q² = 0.419) also exhibits considerable predictive precision, being dominated by operational efficiency and selected digital capability variables as well. In general, these results support that the hypothesized PLS-SEM model is explanatory and has strong predictive power as well (reflecting a prediction-driven nature of PLS-SEM models in the SME research environment).

Hypothesis testing Table 13 presents a summary of hypothesis testing with the following details: standardised path coefficients and bootstrapped significance values. All digital capability-related variables (AI usage intensity, digitisation maturity level, IT base readiness and upper-level management's digital literacy) have statistically significant positive impacts on process efficiency ($\beta = 0.193–0.262$, $p < 0.001$), which concludes H1a-d. Operational efficiency is a significant predictor of financial performance ($\beta = 0.393$, $p < 0.001$), in accordance with H2. Conversely, there were no significant direct effects observed of intensity in AI

ISSN: 3047-4108 P-ISSN: 3048-3751
Journal Economic Business Innovation -JEBI, Vol. 02, Issue.4, 2026, Page. 519-537
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usage and IT infrastructure preparedness on financial performance. However, moderate yet significant direct effects were demonstrated by digital transformation capability and top management digital competence. It has been demonstrated that environmental turbulence does not have a direct impact on financial performance, nor does it moderate the relationships under investigation. All four mediation hypotheses (H6a–H6d) have been proven to be valid, which indicates that operational efficiency is a key factor in the relationship between digital and AI capabilities and financial performance for MSMEs.

Table 12. PLSpredict Results (Predictive Power Assessment)

Endogenous construct	Q² (Predictive relevance)	Predictive power
Operational Efficiency (OE)	0.452	Strong
Financial Performance (FP)	0.419	Strong

Table 13. Summary of Hypothesis Testing Results

Hypothesis	Structural Path	β (Std.)	t-value	p-value	Effect Type	Decision
H1a	AII > OE	0.213	4.183	0.000	Direct	Supported
H1b	DTC > OE	0.262	4.362	0.000	Direct	Supported
H1c	ITR > OE	0.193	3.937	0.000	Direct	Supported
H1d	TMDC > OE	0.249	4.453	0.000	Direct	Supported
H2	OE > FP	0.393	6.223	0.000	Direct	Supported
H3a	AII > FP	0.099	1.725	0.085	Direct	Not supported
H3b	DTC > FP	0.074	1.174	0.24	Direct	Not supported
H3c	ITR > FP	0.115	2.075	0.038	Direct	Supported
H3d	TMDC > FP	0.15	2.385	0.017	Direct	Supported
H4	EU > FP	0.008	0.2	0.842	Direct	Not supported
H5a	EU × DTC > FP	0.042	0.688	0.491	Moderation	Not supported
H5b	EU × AII > FP	0.031	0.546	0.585	Moderation	Not supported
H5c	EU × ITR > FP	0.056	1.084	0.278	Moderation	Not supported
H5d	EU × TMDC > FP	−0.041	0.702	0.483	Moderation	Not supported
H6a	AII > OE > FP	0.083	3.582	0.000	Indirect (Mediation)	Supported
H6b	DTC > OE > FP	0.103	3.588	0.000	Indirect (Mediation)	Supported
H6c	ITR > OE > FP	0.076	3.3	0.001	Indirect (Mediation)	Supported
H6d	TMDC > OE > FP	0.098	3.469	0.001	Indirect (Mediation)	Supported

4.7 Discussion

This research makes a significant contribution to the field of digital transformation and SME performance literature by providing evidence that digital and AI capabilities can improve financial assistance through enhanced operational efficiency. However, the study goes a step further by demonstrating that these technologies do not directly impact financial outcomes. According to the resource-based view (RBV), the ability to transform digitally, the intensity of AI use, the IT infrastructure preparedness and the digital competences of top management are strategic intangible resources that permit SMEs to reconfigure their processes and routines (Barney, 1991; Vial, 2019; Dubey et al., 2023). The results align with recent studies indicating that the value of digital technologies is enhanced when companies leverage them to create operational assets that contribute to efficiency (Teece, 2018; Leso et al., 2024; Rialti et al., 2023).

The predominant role of operational efficiency as a mediator aligns with dynamic capability theory. According to this theory, sensing, seizing and reconfiguring capabilities act as key intermediaries between digital investments and firm performance (Teece, 2007; Warner & Wäger, 2019; Appel et al., 2024). The extensive use of AI and advanced digital transformation capabilities have been shown to accelerate processes, reduce costs and enhance information utilisation efficiency, leading to tangible financial improvements. This finding is consistent with recent empirical research in emerging markets,

OPEN ACCESS
ISSN: 3047-4108 P-ISSN: 3048-3751
Journal Economic Business Innovation -JEBI, Vol. 02, Issue.4, 2026, Page. 519-537
DOI: https://doi.org/10.69725/jebi.v2i4.321

which indicates that SMEs often face challenges in scaling up and achieving financial benefits from digitisation without first streamlining their operational processes (Dubey et al., 2023; Gupta et al., 2024; Prashar et al., 2023).

Interestingly, direct impacts of AI intensity of use and digital transformation capability on financial performance are not statistically significant, indicating that employing technology by itself does not promise superior economic results. This finding contradicts techno-deterministic assumptions and is in favor of a process-oriented digital value creation perspective (Vial, 2019; Kraus et al., 2022; Troise et al., 2023). In contrast, IT infrastructures preparedness and top managements' digital competencies stillhas substantial direct links to financial performances that ensures foundational infrastructure is vital, as well governing strategic leadership in financial discipline, investment alignment and governance for SMEs digital initiatives (Zhu et al., 2023; Leso et al., 2024; Ahn & Kim, 2025).

Lack of mediating effects of environmental uncertainty indicates that in this setting, digital and AI capability are more generic resources as opposed to contingency-specific resource. Although contingency theory suggests that environmental turbulence should enhance the importance of flexible capabilities (Donaldson 2001; Sousa & Voss, 2008), recent SME research has suggested that in the context of an emerging economy persistent uncertainty could de-normalize turbulence diminishing its differential moderating effects (Kraus et al., 2022; Chen & Tajdini, 2024; Prashar et al., 2023). Digital tools may become essentials for SMEs, not just accommodations to an uncertain environment.

Theoretically, this research combines RBV perspective with dynamic capability theory and contingency view to make clear when and how digital capability and AI-based capability are relevant in firms' performance. It adds to literature by empirically verifying operational effectiveness as a core transmission mechanism and showing how leadership and infrastructure have both indirect and direct financial consequences. Practically, this suggests that SME managers ought to focus on process efficiency and capacity development rather than symbolic or experimental technology usage. Similarly, policy makers should foster SMEs to build infrastructure and learn managerial digital skills in order to have enduring value add creation through digital capabilities within the emerging markets (OECD, 2023; Bank Mondial, 2024; Appel et al., 2024).

5. Conclusion

The findings of this study offer a strong empirical indication that digital transformation capability, use intensity of AI, readiness of IT infrastructure and top management digital competency are important factors on the improvement in financial or monetary performance of MSMEs predominantly through operational efficiency. Combining resource-based view, dynamic capability theory and contingency perspectives, the results reveal that digital and AI investments do not per se imply superior financial performance unless they are realised efficiently embedded in operational processes. Operational value becomes the dominant mechanism through which digital capabilities create financial value, with IT infrastructure readiness and manager's digital competence also showing direct financial influence. The lack of strong moderating effect of environmental uncertainty implies that digital capabilities, in emerging economy environments are driver-cum-foundation-based rather than situation-specific. Theoretically, the study adds value by revealing the mediated character of digital value creation and empirically by highlighting process efficiency, leadership competence development, and readiness of infrastructure as strategic foci for MSMEs. Such findings carry important managerial and policy-making implications for those who wish to take advantage of digital transformation and AI for the sustainable performance of MSMEs under volatile and resource-scarce conditions.

CRediT Author Statement

Shela Fatimah: Conceptualization, Literature review, Methodology, Data curation, Formal analysis, Writing original draft, Visualization. **Diana**

ISSN: 3047-4108 P-ISSN: 3048-3751
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Puspitasari: Supervision, Validation, Writing review & editing, Methodological guidance, Academic supervision.

Declaration of Competing Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Acknowledgments

The authors wish to thank the Faculty of Economics and Business Dian Nuswantoro University for academic support and valuable feedback during study development. We also thank all survey respondents that participated voluntarily and provided feedback that made this work possible.

Funding

This work was not supported by any grant from funding agencies in the public, commercial or not-for-profit sectors: there are no grants involved.

Data Availability Statement

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request. The data is withheld from public due to containing sensitive information and ethical issues concerning the respondents.

Appendix/Appendices

Appendix A. Population and Sample Characteristics of MSMEs

Variable	Category / Description	Code	n	%
MSME Type	Micro (1–4 employees)	1	135	38.6
	Small (5–19 employees)	2	116	33.1
	Medium (20–99 employees)	3	99	28.3
Business Sector	Manufacturing / Production	1	71	20.3
	Trading / Retail	2	122	34.9
	Services / Consulting	3	65	18.6
	Food & Beverage (F&B)	4	54	15.4
	Creative / Technology	5	38	10.9
Respondent Position	Owner / Founder	1	175	50
	Manager	2	105	30
	Supervisor	3	70	20
Province (Location)	West Java (Jabar)	1	106	30.3
	Central Java (Jateng)	2	88	25.1
	East Java (Jatim)	3	66	18.9
	DKI Jakarta	4	52	14.9
	Other Provinces	5	38	10.9
Education Level	High School (SMA)	1	66	18.9
	Diploma (D3)	2	88	25.1
	Bachelor (S1)	3	162	46.3
	Master / Doctorate (S2/S3)	4	34	9.7
AI Experience Frequency	Very low	1	59	16.9
	Low	2	83	23.7
	Moderate	3	107	30.6
	High	4	63	18
	Very high	5	38	10.9
Continuous Variables	Min	Max	Mean	SD
Years in operation (years)	1	10	3.55	2.34
Monthly revenue (million IDR)	5	407.5	34.26	41.16
Respondent age (years)	25	55	39.79	6.28

ISSN: 3047-4108 P-ISSN: 3048-3751
Journal Economic Business Innovation -JEBI, Vol. 02, Issue. 4, 2026, Page. 519-537
DOI: https://doi.org/10.69725/jebi.v2i4.321

Appendix B. Variable Instrument

Variable (Abbrev.)	Code	Dimension	Indicator	Source
Digital Transformation Capability (DTC)	DTC1	Process digitalization	Our core business processes are digitally integrated end-to-end.	(Leso et al., 2024)
	DTC2	Cross-functional integration	Digital systems/applications are integrated across functions (operations, marketing, finance).	(Leso et al., 2024)
	DTC3	Data-driven decision-making	Operational decisions are largely supported by data analytics (dashboards/reports).	(Vial, 2023)
	DTC4	Automation	We use automation to reduce repetitive manual tasks.	(Bag et al., 2023)
	DTC5	Digital agility	We rapidly test and adopt new relevant digital technologies.	Li et al. (2023)
	DTC6	Digital decision support	We use digital decision-support tools (e.g., recommendations, predictions, alerts).	Dubey et al. (2023)
AI Utilization Intensity (AII)	AII1	Frequency	We use AI for business activities on a regular basis (daily/weekly).	(Chen & Tajdini, 2025)
	AII2	Breadth of use cases	AI is applied across multiple functions (marketing, operations, customer service).	(Chen & Tajdini, 2025)
	AII3	Depth / embeddedness	AI outputs are embedded in standard operating procedures.	(Mikalef et al., 2019; Mikalef & Gupta, 2021)
	AII4	Decision enhancement	AI helps us make decisions faster and more accurately.	Appel et al. (2024)
	AII5	Task automation	AI is used to automate routine tasks (content, responses, analytics).	(Mikalef et al., 2019; Mikalef & Gupta, 2021)
	AII6	Analytics intensity	AI is used for analytics (segmentation, demand forecasting, recommendations).	Appel et al. (2024)
IT Infrastructure Readiness (ITR)	ITR1	Hardware & devices	Our hardware (computers, mobile devices) adequately supports digital operations.	(L. Zhu et al., 2024; S. Zhu et al., 2026)
	ITR2	Network reliability	Internet and network connectivity are sufficiently reliable for operations.	(L. Zhu et al., 2024; S. Zhu et al., 2026)
	ITR3	Software & platforms	We possess essential digital platforms (POS, accounting, CRM, marketplaces).	(L. Zhu et al., 2024; S. Zhu et al., 2026)
	ITR4	Data management	Customer, sales, and operational data are well managed and accessible.	(L. Zhu et al., 2024; S. Zhu et al., 2026)
	ITR5	Cybersecurity basics	Basic cybersecurity practices (passwords, backups, access control) are implemented.	(L. Zhu et al., 2024; S. Zhu et al., 2026)
	ITR6	Interoperability	Our systems and applications can be easily integrated.	Li et al. (2023)
Top Management Digital Competency (TMDC)	TMDC1	Digital vision	Top management has a clear vision for digital and AI use.	(Al-Ayed, 2024; Albannai et al., 2025)
	TMDC2	Technology understanding	Top management understands the benefits and limitations of digital/AI technologies.	(Al-Ayed, 2024; Albannai et al., 2025)
	TMDC3	Championing	Top management actively champions digital innovation initiatives.	(Al-Ayed, 2024; Albannai et al., 2025)
	TMDC4	Resource allocation	Top management allocates adequate resources for digital and AI development.	(Al-Ayed, 2024; Albannai et al., 2025)
	TMDC5	Governance	Clear rules and targets (KPIs, SOPs) guide technology use.	Mikalef et al. (2023)
	TMDC6	Capability building	Top management supports digital and AI training for employees.	van Laar et al. (2024)
Operational Efficiency (OE)	OE1	Cost efficiency	Digital and AI initiatives reduce operational costs.	(Dubey et al., 2023)
	OE2	Speed	Work processes are faster (shorter lead times).	(Dubey et al., 2023)
	OE3	Error reduction	Process and administrative errors have decreased.	(Dubey et al., 2023)
	OE4	Productivity	Employee productivity has increased.	Mikalef et al. (2023)
	OE5	Resource utilization	Resources (materials, labor, time) are used more efficiently.	(Dubey et al., 2023)
	OE6	Flexibility	Processes are more flexible in responding to demand changes.	Appel et al. (2024)

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Journal Economic Business Innovation -JEBI, Vol. 02, Issue.4, 2026, Page. 519-537
DOI: https://doi.org/10.69725/jebi.v2i4.321

Variable (Abbrev.)	Code	Dimension	Indicator	Source
Environmental Uncertainty (EU)	EU1	Demand volatility	Customer demand changes rapidly and is difficult to predict.	(Miller et al., 2008)
	EU2	Competitive intensity	Competitive conditions change rapidly.	(Miller et al., 2008)
	EU3	Technological turbulence	Relevant digital technologies change rapidly.	(Mikalef et al., 2019; Papagiannidis et al., 2023)
	EU4	Regulatory uncertainty	Business-related regulations change frequently.	(Miller et al., 2008)
	EU5	Supply uncertainty	Availability of key inputs and services is unstable.	(Miller et al., 2008)
	EU6	Macro uncertainty	Economic conditions (inflation, costs, demand) are unstable.	(Miller et al., 2008)
Financial Performance (FP)	FP1	Sales growth	Our sales have increased relative to targets/competitors.	Wiklund & Shepherd (2005)
	FP2	Profitability	Our profit margins have improved.	Wiklund & Shepherd (2005)
	FP3	ROI	Returns from digital and AI investments are positive.	Mikalef et al. (2023)
	FP4	Cash flow	Cash flow has become more stable.	Wiklund & Shepherd (2005)
	FP5	Cost-to-revenue	The cost-to-revenue ratio has improved.	Dubey et al. (2023)
	FP6	Overall performance	Overall financial performance has improved.	Wiklund & Shepherd (2005)

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ISSN: 3047-4108 P-ISSN: 3048-3751
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