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Integrated Adaptive Digital Systems and SME's Business Competitiveness: The Role of Analytics and Decision-Making Capability

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ABSTRACT

Purpose – This study examines how integrated adaptive digital systems, digital data analytics capability, and technology-based decision-making capability relate to Indonesian MSME competitiveness, and whether digital literacy and organizational adaptive capability condition the system- and analytics-based relationships.

Design/methodology/approach – A cross-sectional survey of 340 MSME respondents from five Indonesian provinces measured six reflective constructs on five-point Likert scales. PLS-SEM in SmartPLS 4 assessed measurement quality, three direct paths, and four moderation effects.

Finding/Results – Integrated adaptive digital systems showed the largest direct association with competitiveness ($\beta = 0.620$, $p < .001$), followed by analytics capability ($\beta = 0.354$, $p < .001$) and technology-based decision-making capability ($\beta = 0.148$, $p = .002$). Digital literacy moderated the analytics relationship ($\beta = 0.092$, $p = .016$), as did organizational adaptive capability ($\beta = 0.282$, $p < .001$); neither moderated the systems path. The Fornell–Larcker matrix indicated inadequate X2–Y1 discriminant validity, so the analytics coefficient requires cautious interpretation.

Originality/Value – By separating infrastructure, analytics, decision use, digital literacy, and organizational adaptability, the study identifies capability-specific complementarity: human and organizational capabilities are more consequential for extracting value from analytics than for the integrated-systems path in this sample.

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1. Introduction

Digital transformation has moved beyond the digitization of isolated tasks toward the reconfiguration of processes, information flows, decision structures, and value creation. This distinction is important because the possession of digital tools does not, by itself, produce organizational transformation; performance gains depend on how digital resources become embedded in routines, integrated across activities, and combined with complementary managerial capabilities (Vial, 2019; Verhoef et al., 2021). For small and medium-sized enterprises (SMEs), this transition is especially consequential because limited financial slack, smaller specialist workforces, and owner-centered decision structures can constrain the absorption and scaling of new technologies (Eller et al., 2020; Kraus et al., 2022).

Evidence from SMEs increasingly links digitalization with operational efficiency, market access, customer value, innovation, and entrepreneurial performance, yet the magnitude of these gains varies substantially across firms. Differences in digital maturity, business-model adaptation, technological integration, managerial readiness, and capability configuration help explain why apparently similar technology investments yield different outcomes (Garzoni et al., 2020; Matarazzo et al., 2021; Kim & Jin, 2024). Recent configurational research similarly shows that digital capability and organizational performance are shaped by combinations of technological and organizational conditions rather than by a single digital input (Karadağ et al., 2026).

The Indonesian MSME context provides a useful setting for examining this capability problem because firms differ markedly in sector, scale, age, and digital maturity. National statistics continue to show the economic centrality and heterogeneity of micro and small enterprises (Badan Pusat Statistik [BPS], 2025), while recent Indonesian studies associate digital transformation, digital literacy, supply-chain competence, and business intelligence with MSME performance and competitive advantage (Wediawati et al., 2025; Firdaussiah et al., 2026; Hakim et al., 2026; Solikhah & Maulana, 2026). Institutional conditions also matter: evidence from South Sulawesi indicates that government support can shape how digital marketing and digital literacy translate into business performance (Haryadi, 2026).

A persistent gap is therefore not whether digitalization matters, but which capabilities matter at different points in the digital value-creation process. Prior studies often employ broad constructs such as digital transformation, digital capability, or digital readiness. Such aggregation can obscure theoretically meaningful differences between (a) the integration and adaptability of digital systems, (b) the capacity to analyze data and generate actionable insight, and (c) the capacity to use digital intelligence in managerial decisions. Analytics research makes this distinction explicit by separating access to data and technology from the organizational capability to convert data into information, insight, and action (Gupta & George, 2016; Akter et al., 2016; Wamba et al., 2017).

This study addresses that gap by examining three focal capabilities—integrated adaptive digital systems, digital data analytics capability, and technology-based decision-making capability—and two complementary moderators, digital literacy and organizational adaptive capability. Drawing on the Resource-Based View (RBV) and dynamic capabilities theory, the study asks whether the competitive value associated with digital resources depends on human and organizational capabilities that enable firms to interpret information and reconfigure responses (Barney, 1991; Teece, 2007; Warner & Wäger, 2019). The contribution is capability-specific: rather than treating digital transformation as a unitary predictor, the model separates infrastructure, analytics, and decision use and tests whether digital literacy and organizational adaptability condition the system- and analytics-based paths to competitiveness.

2. Literature Review & Hypothesis Development

2.1. Theoretical foundation: resources, dynamic capabilities, and digital value creation

RBV explains competitive differences by emphasizing valuable firm resources and the organizational conditions under which those resources can support advantage (Barney, 1991). In digital settings, however, technology ownership alone rarely satisfies the conditions for sustained advantage because software, platforms, and cloud services can be widely accessible. What becomes strategically important is the way firms integrate technology with routines, knowledge, decision processes, and complementary skills. This logic is consistent with studies showing that business value from analytics and digitalization depends on alignment between technology, strategy, human capital, and organizational processes (Akter et al., 2016; Kraus et al., 2022).

Dynamic capabilities theory extends this argument by explaining how firms sense changes, seize opportunities, and reconfigure resources under conditions of uncertainty (Teece, 2007). Digital transformation can therefore be understood as an ongoing capability-building process rather than as a discrete technology purchase. Research on strategic renewal, SME digital transformation, and resource-adaptive capability emphasizes that digital value emerges when firms can reorganize knowledge, processes, and relationships as environments change (Warner & Wäger, 2019; Yamamoto et al., 2026; Yao et al., 2026). Combining RBV and dynamic-capabilities logic supports a model in which digital infrastructure provides a resource foundation, while analytics, decision-making, literacy, and adaptability shape how that foundation is exploited.

2.2. Integrated adaptive digital systems and MSME competitiveness

Integrated adaptive digital systems refer to the digital architecture through which applications, information flows, and operational processes are connected and can be adjusted to changing business requirements. The construct is deliberately system-level: adaptability here describes the flexibility of the technological architecture, not the broader organizational ability to reconfigure strategies and resources. Integrated systems can reduce information fragmentation, coordinate transactions across functions, and provide more timely operational visibility. SME research indicates that progression from isolated digital tools toward integrated digital processes is associated with deeper transformation and stronger organizational outcomes (Garzoni et al., 2020; Lu & Shaharudin, 2024).

For resource-constrained MSMEs, the competitive relevance of integrated systems lies in their ability to reduce duplication, connect customer and operational information, and support faster responses without requiring the scale of large-firm information infrastructures. Indonesian evidence also associates digital transformation and resource integration with competitive advantage, although the mechanisms vary across firms and sectors (Firdaussiah et al., 2026; Hakim et al., 2026). On this basis, the first hypothesis predicts a positive association rather than a causal effect.

H1: Integrated Adaptive Digital Systems (X1) are positively associated with MSME Competitiveness (Y1).

2.3. Digital data analytics capability and MSME competitiveness

Digital data analytics capability is the organizational capacity to collect, process, analyze, and convert data into actionable insight. It is not equivalent to owning analytical software. Gupta and George (2016) conceptualize analytics capability as a bundle of data, technology, managerial, and human elements, while Akter et al. (2016) show that performance gains depend on strategic alignment. Wamba et al. (2017) similarly connect analytics and firm performance through dynamic capabilities, underscoring the organizational processes required to move from data availability to business action.

For MSMEs, analytics can improve demand sensing, customer understanding, inventory decisions, pricing, and resource allocation, but the scale and sophistication of these practices are likely to vary with digital maturity. Recent SME research links data-driven culture and analytics to transformation outcomes, while conference evidence specifically highlights the role of big-data analytics in SME decision-making and performance (Ciasullo et al., 2026; Khabaziyan & Ahuja, 2026). Accordingly, stronger analytics capability is expected to be associated with stronger competitiveness.

H2: Digital Data Analytics Capability (X2) is positively associated with MSME Competitiveness (Y1).

2.4. Technology-based decision-making capability and MSME competitiveness

Technology-based decision-making capability captures the use of digital intelligence, analytical outputs, and decision-support tools in strategic and operational choices. Whereas analytics capability concerns the production and interpretation of insight, decision-making capability concerns the incorporation of that insight into managerial action. This distinction is important in MSMEs, where owner-manager intuition often remains central and formal decision-support routines may be less developed than in large firms. Data-driven organizational cultures nevertheless show that decision quality can improve when digital insight becomes embedded in routines and managerial processes (Ciasullo et al., 2026).

Empirical work in emerging economies further suggests that digital capabilities, institutional support, and decision processes jointly shape business outcomes. Indonesian evidence indicates that digital skills and institutional support can strengthen the conditions under which digital initiatives translate into performance, while SME analytics research emphasizes the role of dynamic decision-making in turning data into action (Haryadi, 2026; Khabaziyan & Ahuja, 2026). The model therefore treats technology-based decision-making as a direct capability rather than inferring an untested mediation mechanism.

H3: Technology-Based Decision-Making Capability (X3) is positively associated with MSME Competitiveness (Y1).

2.5. Moderating role of digital literacy

Digital literacy refers to the ability to use digital technologies, evaluate digital information, and apply digital outputs appropriately. In MSMEs, this capability can reside in owners, managers, and employees and therefore functions as a human-capital complement to technological resources. Indonesian evidence links digital literacy with MSME performance, resilience, and adaptability, although the magnitude of the relationship varies across contexts (Wediawati et al., 2025; Ningsih et al., 2026).

The moderating logic is capability-specific. Digital literacy may help firms use integrated systems more effectively by reducing user errors and improving information access, but it should be especially important for analytics because analytical outputs require interpretation and contextual judgment. Thus, the study tests whether digital literacy strengthens both the systems–competitiveness and analytics–competitiveness relationships, while allowing the empirical results to reveal whether the two moderation effects differ.

H4a: Digital Literacy (Z1) positively moderates the relationship between Integrated Adaptive Digital Systems (X1) and MSME Competitiveness (Y1).

H4b: Digital Literacy (Z1) positively moderates the relationship between Digital Data Analytics Capability (X2) and MSME Competitiveness (Y1).

2.6. Moderating role of organizational adaptive capability

Organizational adaptive capability denotes the capacity to sense environmental change, adjust strategies, and reconfigure resources. Unlike system adaptability in X1, which concerns the flexibility of digital architecture, Z2 is an organizational capability involving sensing, strategic flexibility, and resource reallocation. Dynamic-capabilities research suggests that such reconfiguration is especially important when firms must translate new information into coordinated responses (Teece, 2007; Warner & Wäger, 2019).

Recent SME research portrays digital transformation as a cyclical process in which technological and organizational capabilities co-evolve. Japanese SME evidence highlights the interaction of dynamic capabilities with external resource mobilization, while emerging-market research identifies resource-adaptive capabilities as important across phases of digital transformation (Yamamoto et al., 2026; Yao et al., 2026). Organizational adaptability may therefore increase the value of integrated systems and, more directly, increase the value of analytical insight by enabling firms to act on emerging information.

H5a: Organizational Adaptive Capability (Z2) positively moderates the relationship between Integrated Adaptive Digital Systems (X1) and MSME Competitiveness (Y1).

H5b: Organizational Adaptive Capability (Z2) positively moderates the relationship between Digital Data Analytics Capability (X2) and MSME Competitiveness (Y1).

The complete conceptual model is presented in Figure 1. The model separates three direct digital capabilities from two complementary moderators and limits moderation to the system and analytics paths specified in H4a–H5b.

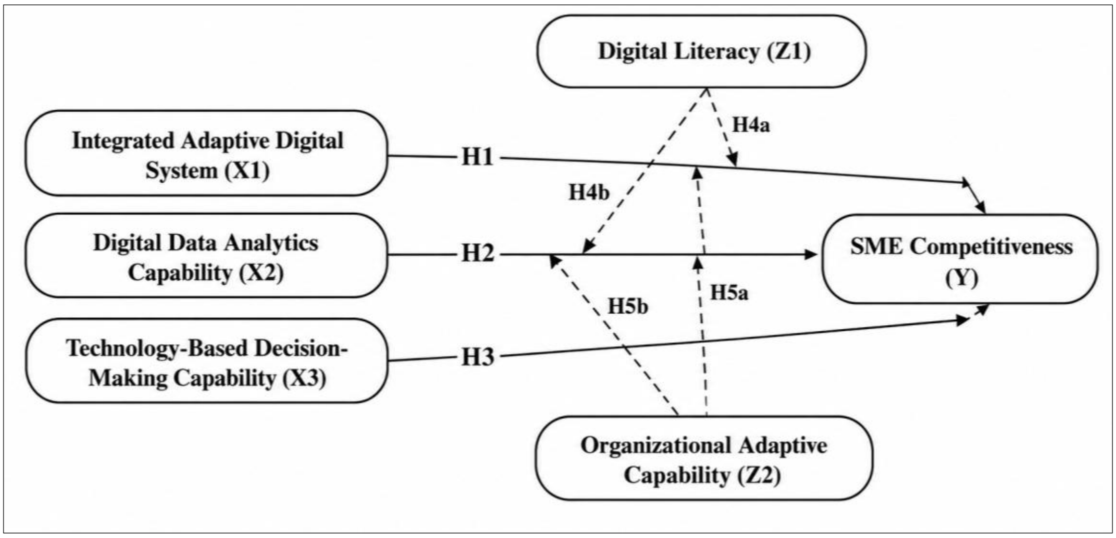

Figure 1. Conceptual framework of digital capabilities, complementary capabilities, and MSME competitiveness

3. Methodology

3.1. Research design

The study employed a quantitative cross-sectional correlational survey design. Numerical responses were collected on Likert-type scales and analyzed with partial least squares structural equation modeling (PLS-SEM). The design is appropriate for estimating multivariate associations among latent constructs and interaction terms, but the single-time-point structure does not establish temporal precedence; coefficients are therefore interpreted as associations rather than causal effects.

PLS-SEM was used to evaluate both the measurement and structural models in SmartPLS 4. The analysis followed the two-stage logic commonly recommended for PLS-SEM: measurement quality was assessed before structural relationships were interpreted (Hair et al., 2019, 2020). Moderation was represented through latent interaction terms corresponding to H4a, H4b, H5a, and H5b, consistent with established approaches to interaction analysis in PLS path models (Henseler & Chin, 2010).

3.2. Sampling and data collection

The target population comprised Indonesian micro, small, and medium enterprises operating across multiple sectors. Respondents were drawn from DKI Jakarta, West Java, East Java, South Sulawesi, and North Sumatra. The sampling procedure combined purposive eligibility screening for MSMEs that had adopted digital technologies with stratification by business sector and firm size. The resulting sample is therefore treated as a stratified purposive sample across the selected provinces, with eligibility based on prior digital-technology adoption.

The study targeted 400 MSMEs and retained 340 usable responses, corresponding to a reported response rate of 85%. This rate is comparatively high for organizational survey research (Baruch & Holtom, 2008). The sample-size planning reported an a priori G*Power calculation using $f^2 = 0.15$, $\alpha = .05$, and power = .80, with a minimum planning value of 92 cases. The final sample of 340 substantially exceeded that planning threshold, although the complexity of the moderation model should be considered when interpreting interaction effects.

Table 1 presents the respondent and firm profile. The sample is concentrated in food-and-beverage businesses, firms with five or fewer employees, enterprises younger than three years, low-turnover firms, and beginner-level digital adopters. These characteristics are important boundary conditions and are considered explicitly in the interpretation of the results.

Table 1. Demographic and business characteristics of the MSME sample

Variable	Category	n	%
Respondent role	Owner	175	51.50
Respondent role	Co-owner	85	25.00
Respondent role	Manager	55	16.20
Respondent role	Employee	25	7.40
Business sector	Manufacturing	3	0.88
Business sector	Retail & e-commerce	54	15.88
Business sector	Services (consulting, IT, finance)	2	0.59
Business sector	Food & beverage	223	65.59
Business sector	Logistics & transportation	20	5.88
Business sector	Other	38	11.18

Variable	Category	n	%
Firm size (employees)	1–5	235	69.12
Firm size (employees)	6–25	95	27.94
Firm size (employees)	26–75	10	2.94
Years in business	< 3 years	210	61.76
Years in business	3–5 years	62	18.24
Years in business	6–10 years	47	13.82
Years in business	11–20 years	12	3.53
Years in business	> 20 years	9	2.65
Digital technology adoption	Low (beginner)	297	87.35
Digital technology adoption	Moderate (intermediate)	41	12.06
Digital technology adoption	High (advanced)	2	0.59
Annual turnover	< Rp 2 billion	334	98.24
Annual turnover	> Rp 2–15 billion	4	1.18
Annual turnover	> Rp 15–50 billion	2	0.59

The distribution confirms that the empirical setting is dominated by micro-scale and early-stage firms rather than by digitally advanced SMEs. The findings should therefore be generalized primarily to MSMEs with similar structural and digital-maturity characteristics.

3.3. Measures

All six constructs were specified as reflective measurement models and measured on a five-point scale from 1 (strongly disagree) to 5 (strongly agree). The initial instrument contained 18 indicators, three for each construct. The indicator domains were adapted from established literature and contextualized for MSMEs. One organizational adaptive capability indicator was removed during measurement-model refinement because its reported loading was below the retained threshold, leaving 17 indicators in the final model.

Table 2 summarizes the construct domains and conceptual boundaries. The distinction between X1 and Z2 is particularly important: X1 captures the adaptability and integration of the digital system itself, whereas Z2 captures the organization's broader capacity to sense change and reconfigure resources. Similarly, X2 concerns the production and interpretation of analytical insight, while X3 concerns the use of digital intelligence in decisions.

Table 2. Construct operationalization and conceptual boundaries

Construct	Indicator domains	Capability level	Literature basis
Integrated Adaptive Digital Systems (X1)	Digital integration; system adaptability; real-time information flow	Digital architecture	Garzoni et al. (2020); Lu & Shaharudin (2024); Firdaussiah et al. (2026)
Digital Data Analytics Capability (X2)	Data collection; analytical processing; actionable insights	Analytical capability	Gupta & George (2016); Akter et al. (2016); Khabaziyan & Ahuja (2026)
Technology-Based Decision-Making Capability (X3)	Data-driven decisions; digital-tool utilization; decision effectiveness	Decision-use capability	Ciasullo et al. (2026); Haryadi (2026)
MSME Competitiveness (Y1)	Market position; operational efficiency; business growth	Outcome construct	Hakim et al. (2026); Karadağ et al. (2026)
Digital Literacy (Z1)	Technical proficiency; information evaluation; digital application	Human digital capability	Wediawati et al. (2025); Ningsih et al. (2026)

Construct	Indicator domains	Capability level	Literature basis
Organizational Adaptive Capability (Z2)	Environmental sensing; strategic flexibility; resource reconfiguration	Organizational dynamic capability	Teece (2007); Warner & Wäger (2019); Yao et al. (2026)

Source: Construct domains adapted from the cited literature and the study instrument.

The reflective specification is retained because it corresponds to the empirical model that generated the reported PLS-SEM results. Given the multidimensional nature of several capabilities, future research should nevertheless compare reflective and composite specifications using explicit theoretical criteria rather than relying on statistical convenience alone.

3.4. Data analysis

Measurement-model assessment included Cronbach's alpha, rho_A, composite reliability (rho_C), outer loadings, and average variance extracted (AVE). Convergent validity was evaluated using the conventional AVE threshold of .50, and discriminant validity was examined with the Fornell–Larcker criterion (Fornell & Larcker, 1981). Because the heterotrait–monotrait ratio (HTMT) is generally more sensitive to discriminant-validity problems, the Fornell–Larcker results are interpreted cautiously where interconstruct correlations are high (Henseler et al., 2015).

The structural model included X1, X2, and X3 as direct predictors of Y1, Z1 and Z2 as constituent moderator terms, and four interaction terms corresponding to H4a, H4b, H5a, and H5b. Statistical significance was evaluated from the SmartPLS t statistics and p values reported for the focal paths. Collinearity was assessed using variance inflation factors (VIF), while R^2 and the reported approximate-fit indices were used as supplementary structural-model diagnostics (Hair et al., 2019).

$$Y1 = \beta 0 + \beta 1X1 + \beta 2X2 + \beta 3X3 + \beta 4Z1 + \beta 5Z2 + \beta 6(X1\times Z1) + \beta 7(X2\times Z1) + \beta 8(X1\times Z2) + \beta 9(X2\times Z2) + \varepsilon \quad (1)$$

In Equation (1), Y1 is MSME competitiveness; X1 is integrated adaptive digital systems; X2 is digital data analytics capability; X3 is technology-based decision-making capability; Z1 is digital literacy; and Z2 is organizational adaptive capability. The interaction terms test whether Z1 and Z2 alter the X1–Y1 and X2–Y1 relationships.

4. Result and Discussion

4.1. Measurement model

Figure 2 presents the final PLS-SEM measurement model and the reported outer loadings. The retained indicators generally exceed .70, with the lowest retained loadings appearing in the competitiveness construct. The figure also reports $R^2 = 0.752$ for MSME competitiveness, indicating that the modeled predictors and interaction structure jointly account for a substantial proportion of variance in the endogenous construct.

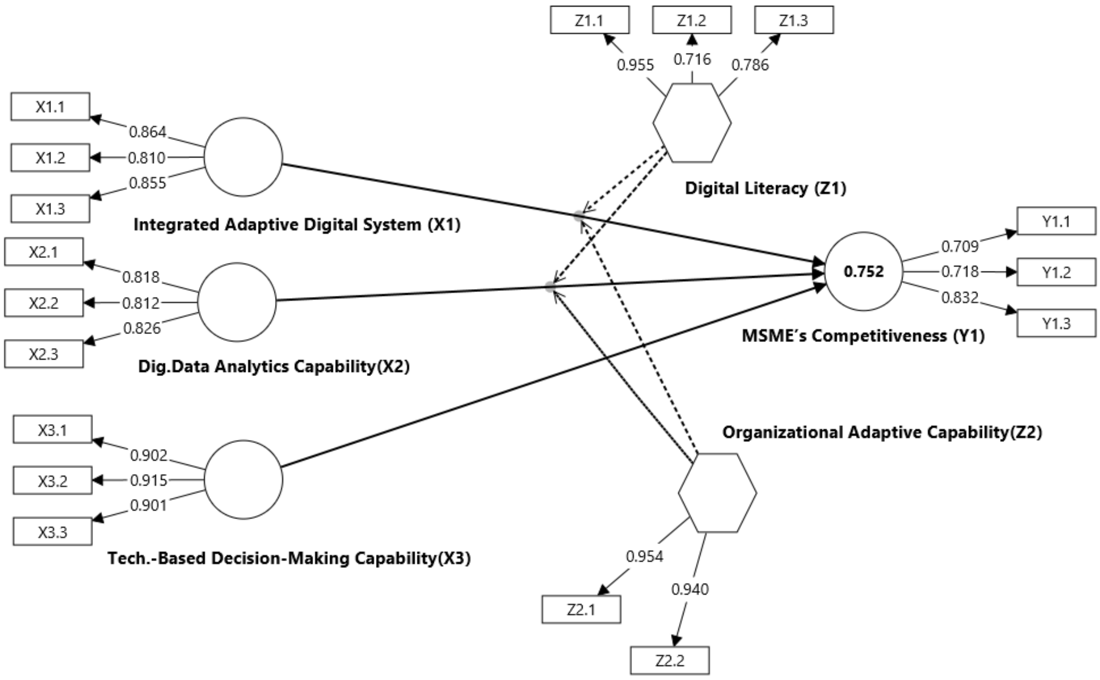

Figure 2. Final PLS-SEM measurement model and reported outer loadings

Construct-level reliability and convergent-validity statistics are shown in Table 3. Cronbach's alpha, rho_A, and rho_C exceed .70 for all constructs. To resolve a transcription inconsistency between the original AVE table, the reported loadings, and the Fornell–Larcker diagonal, AVE for Y1 and Z1 was recalculated from the retained loadings. The resulting values, .570 and .681 respectively, are consistent with the square roots of AVE shown on the diagonal of Table 4.

Table 3. Internal consistency reliability and convergent validity

Construct	α	rho_A	rho_C	AVE
X1 – Integrated Adaptive Digital Systems	0.797	0.798	0.881	0.711
X2 – Digital Data Analytics Capability	0.755	0.758	0.859	0.670
X3 – Technology-Based Decision-Making Capability	0.892	0.912	0.932	0.821
Y1 – MSME Competitiveness	0.774	0.887	0.878	0.570*
Z1 – Digital Literacy	0.771	0.812	0.863	0.681*
Z2 – Organizational Adaptive Capability	0.885	0.896	0.946	0.897

**AVE recalculated from the reported retained loadings to ensure consistency with the Fornell–Larcker diagonal.*

Source: Authors' SmartPLS 4 output and recalculation from reported loadings.

The reliability and AVE results support internal consistency and convergent validity. Discriminant validity, however, requires separate examination because high reliability does not establish that conceptually related constructs are empirically distinct.

Table 4 reports the Fornell–Larcker matrix. Diagonal entries are the square roots of AVE and off-diagonal entries are interconstruct correlations. Most construct pairs meet the intended criterion, but the analytics–competitiveness pair does not.

Table 4. Fornell–Larcker matrix and interconstruct correlations

Construct	X1	X2	X3	Y1	Z1	Z2
X1	0.843					

Construct	X1	X2	X3	Y1	Z1	Z2
X2	0.811	0.819				
X3	0.640	0.747	0.906			
Y1	0.719	0.843	0.688	0.755		
Z1	0.398	0.634	0.654	0.626	0.825	
Z2	0.385	0.522	0.634	0.618	0.412	0.947

Note: Diagonal values are square roots of AVE; off-diagonal values are interconstruct correlations.
Source: Authors' SmartPLS 4 output.

The correlation between X2 and Y1 is .843, exceeding both the X2 diagonal value (.819) and the Y1 diagonal value (.755). Under the Fornell–Larcker criterion, analytics capability and competitiveness therefore show inadequate empirical separation. The X2 structural coefficient remains reported because it is part of the prespecified model, but its substantive interpretation must remain cautious until HTMT and item-level cross-loading diagnostics are available (Henseler et al., 2015).

Figure 3 visualizes the interconstruct correlations. The heatmap makes the high X2–Y1 association and the relatively strong correlations among X1, X2, and X3 immediately visible, emphasizing both the substantive connectedness and the measurement-distinctiveness challenge among digital capability constructs.

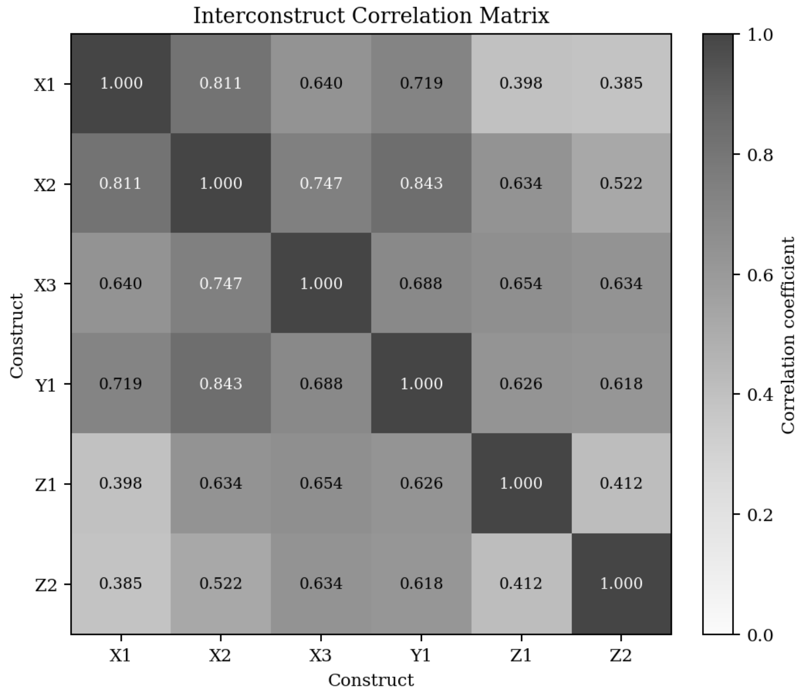

Figure 3. Heatmap of interconstruct correlations

4.2. Structural model and hypothesis testing

Collinearity statistics for the reported predictor constructs are presented in Table 5. All values are below 2.0, indicating no severe collinearity among the main-effect constructs. Because VIFs for the interaction terms were not reported, this conclusion applies only to the predictor constructs shown in the table.

Table 5. Variance inflation factors for predictor constructs

Predictor construct	VIF	Assessment
Integrated Adaptive Digital Systems (X1)	1.903	Acceptable
Digital Data Analytics Capability (X2)	1.478	Acceptable
Technology-Based Decision-Making Capability (X3)	1.959	Acceptable
Digital Literacy (Z1)	1.399	Acceptable
Organizational Adaptive Capability (Z2)	1.685	Acceptable

Source: Authors' SmartPLS 4 output.

The approximate model-fit statistics reported by SmartPLS are summarized in Table 6. These indices are treated as supplementary because PLS-SEM is not evaluated through global fit in the same way as covariance-based SEM (Hair et al., 2019).

Table 6. Reported approximate model-fit statistics

Criterion	Saturated model	Estimated model
SRMR	0.094	0.097
d_ULS	2.744	2.751
d_G	1.774	1.770
Chi-square	2.706	2.937
NFI	0.912	0.914

Source: Authors' SmartPLS 4 output.

The estimated SRMR is .097, which is below .10 but close to that boundary; it is therefore more appropriately described as marginal than as strong fit. NFI is .914. The d_ULS and d_G values are reported descriptively because bootstrap reference values are required for formal discrepancy assessment.

Table 7 presents the seven focal hypothesis tests. The model reports $R^2 = .752$ for MSME competitiveness. The three direct paths are statistically significant and positive, while only two of the four hypothesized moderation effects are supported.

Table 7. Structural path and moderation results

Hyp.	Path	β	Mean	SD	t	p	Decision
H1	X1 → Y1	0.620	0.601	0.068	9.084	< .001	Supported
H2	X2 → Y1	0.354	0.348	0.065	5.487	< .001	Supported
H3	X3 → Y1	0.148	0.153	0.049	3.039	.002	Supported
H4a	Z1 × X1 → Y1	0.159	0.136	0.117	1.350	.177	Not supported
H4b	Z1 × X2 → Y1	0.092	0.101	0.038	2.420	.016	Supported
H5a	Z2 × X1 → Y1	−0.131	−0.123	0.082	1.591	.112	Not supported
H5b	Z2 × X2 → Y1	0.282	0.277	0.056	4.997	< .001	Supported

Note: β = standardized path coefficient; SD = bootstrap standard deviation.
Source: Authors' SmartPLS 4 output.

H1–H3 are supported, and X1 has the largest direct coefficient. H4a is not supported, whereas H4b indicates a positive interaction between digital literacy and analytics capability. H5a is not supported and is negative in sign; H5b is supported and produces the largest interaction coefficient. Figure 4 compares the standardized direct and interaction coefficients.

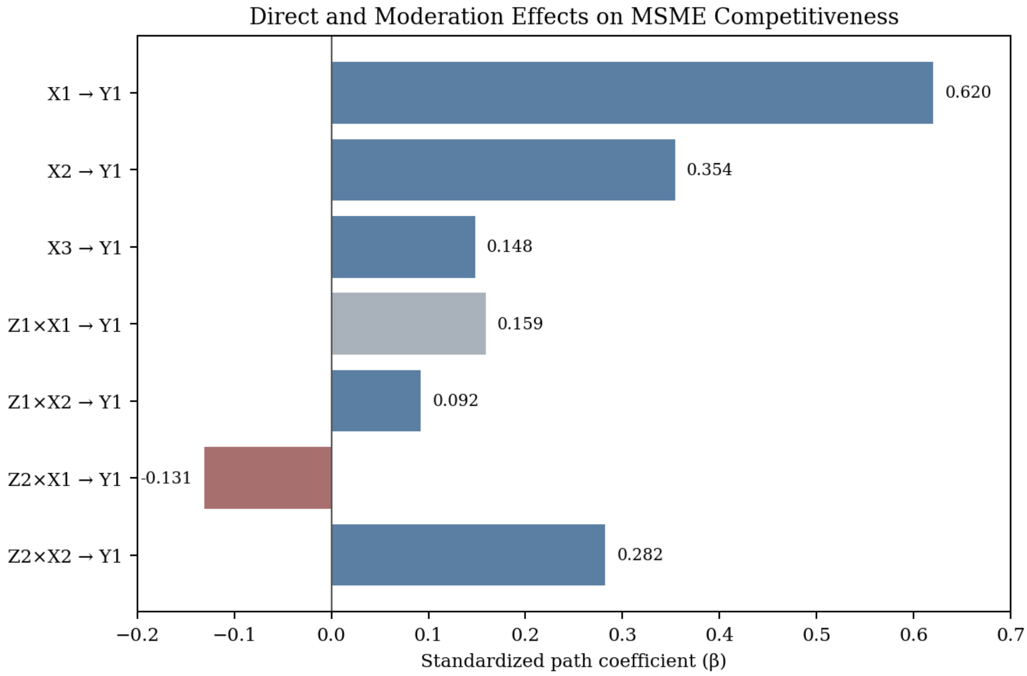

Figure 4. Standardized direct and interaction coefficients predicting MSME competitiveness

4.3. Discussion

The strongest direct association is observed for integrated adaptive digital systems (β = .620). This result supports the proposition that connected and flexible digital infrastructure can function as a foundational organizational resource by improving information continuity, coordination, and responsiveness. It is consistent with research describing SME digital transformation as a progression from isolated digital tools toward deeper process integration (Garzoni et al., 2020; Eller et al., 2020). The finding does not, however, establish that digital systems are intrinsically rare or inimitable. From an RBV perspective, competitive value depends on how these systems are embedded and combined with firm-specific routines rather than on technology ownership alone (Barney, 1991).

Digital data analytics capability also has a substantial positive coefficient (β = .354), consistent with research linking analytics capability to performance through improved sensing, strategic alignment, and decision support (Gupta & George, 2016; Akter et al., 2016; Wamba et al., 2017). Yet this result carries the study's most important measurement qualification: the X2–Y1 correlation of .843 exceeds the Fornell–Larcker diagonal values for both constructs. The strength of the analytics path may therefore partly reflect empirical overlap between how respondents perceive analytics capability and competitiveness. The result should be interpreted as supportive but provisional until HTMT and item-level diagnostics confirm distinctiveness (Henseler et al., 2015).

Technology-based decision-making capability has a smaller but statistically significant direct association with competitiveness (β = .148). The modest coefficient does not imply that decision-making is a mediator; no indirect effect was specified or tested. A more defensible interpretation is that technology-based decision use contributes incremental explanatory information after integrated systems and analytics are considered. This interpretation aligns with studies emphasizing that data-driven transformation requires managerial routines capable of translating insight into operational and strategic action (Ciasullo et al., 2026; Khabaziyan & Ahuja, 2026).

Digital literacy does not significantly moderate the integrated-systems path (H4a). This non-significant result should not be converted into a claim that system benefits are independent of human capability. The sample is heavily concentrated among beginner-level digital adopters, potentially limiting variation in both system sophistication and digital literacy. Prior Indonesian evidence continues to associate digital literacy with MSME performance and adaptability (Wediawati et al., 2025; Ningsih et al., 2026). The appropriate conclusion is therefore narrower: within the observed range of this sample, digital literacy did not significantly alter the X1–Y1 association.

By contrast, digital literacy positively moderates the analytics–competitiveness relationship (H4b; β = .092). This pattern is theoretically coherent because analytics requires users to evaluate data, understand analytical outputs, and translate them into contextually appropriate action. Human digital capability is therefore more directly implicated in the use of analytics than in the mere availability of connected systems. The effect is statistically significant but modest, so practical claims should remain proportionate. Nevertheless, it supports a complementary-capability interpretation in which analytical resources generate more value when users possess the literacy required to interpret them (Matarazzo et al., 2021; Kim & Jin, 2024).

Organizational adaptive capability does not significantly moderate the digital-systems path (H5a). Dynamic-capabilities theory does not predict that adaptability becomes irrelevant once infrastructure exists; instead, it emphasizes the reconfiguration of resources when circumstances change (Teece, 2007; Warner & Wäger, 2019). The non-significant interaction may indicate that the direct association of system integration with competitiveness is comparatively stable within this sample, or it may reflect restricted variance in a population dominated by young, low-digital-maturity firms. The result is therefore evidence of an undetected moderation effect, not evidence of automatic or unconditional system benefits.

The strongest interaction is H5b: organizational adaptive capability strengthens the analytics–competitiveness association (β = .282). This result fits dynamic-capabilities theory more directly. Analytics can support sensing by revealing trends, anomalies, and opportunities, but insight creates competitive value only when organizations can modify processes, redirect resources, and adjust strategic responses. Recent SME research similarly portrays digital transformation as a resource-reconfiguration process rather than a technology-adoption event (Yamamoto et al., 2026; Yao et al., 2026). The result therefore suggests that organizational adaptability is especially consequential for exploiting analytical insight.

Taken together, the moderation pattern refines the contribution of the study. Digital literacy and organizational adaptability do not emerge as universal amplifiers of every digital capability. Both supported interactions concern analytics, whereas neither moderator significantly conditions the integrated-systems path. This asymmetry suggests that foundational infrastructure and analytical value extraction occupy different positions in the digital capability architecture. It is consistent with configurational and systematic research that separates digital resources from the human and organizational capabilities required to mobilize them (Kraus et al., 2022; Lu & Shaharudin, 2024; Karadağ et al., 2026).

The practical implication is not a simple 'technology first' or 'people first' prescription. Integrated systems show the largest direct association with competitiveness, but the analytics pathway is more contingent on literacy and adaptability. For MSMEs—especially beginner-level adopters—investment decisions should therefore consider the compatibility of infrastructure, analytical ambition, workforce skills, and organizational flexibility. Business-support programs can facilitate this alignment by coupling digital infrastructure initiatives with digital-literacy development and managerial support, an approach consistent with Indonesian evidence on the role of institutional support in digital performance (Haryadi, 2026).

Finally, the sample composition provides an important contextual boundary. Approximately two-thirds of the firms are in food and beverage, nearly seven in ten employ no more than five people, more than three-fifths are younger than three years, and 87.35% are classified as beginner-level digital adopters. These characteristics make the study especially informative about early-stage digital capability building in micro-scale MSMEs but limit generalization to mature, technology-intensive, or medium-sized firms. Replication across sectors and maturity levels is necessary before treating the observed capability pattern as universal.

5. Conclusion and Suggestion

This study advances MSME digital-transformation research by separating integrated digital systems, analytics capability, and technology-based decision-making and by testing digital literacy and organizational adaptability as capability-specific moderators. The evidence is consistent with a differentiated architecture: integrated adaptive digital systems show the largest direct association with competitiveness, while literacy and adaptability are especially relevant to the analytics pathway. This pattern provides a more precise explanation than the generic proposition that digital transformation uniformly improves performance.

The principal theoretical contribution is conditional complementarity. Human and organizational capabilities do not strengthen all digital relationships equally; instead, the supported moderation effects are concentrated on analytics. For practice, the results suggest that MSMEs should align digital infrastructure with the level of analytical sophistication, user literacy, and organizational flexibility they can realistically sustain. Policy and support programs can similarly integrate technology access with capability development rather than treating digital adoption as a stand-alone intervention. The measurement overlap between analytics capability and competitiveness, however, requires that the X2 result be treated cautiously until construct distinctiveness is confirmed with stronger diagnostics.

6. Limitations and Future Research

Several limitations qualify the findings. First, the cross-sectional design does not establish temporal order, and reverse causality remains plausible because more competitive MSMEs may have greater resources to invest in integrated systems and analytics. Longitudinal or panel designs are needed to determine whether capability development precedes competitiveness or co-evolves with it.

Second, the sampling design combines purposive eligibility screening and stratification across selected provinces and is strongly concentrated in food-and-beverage, micro-scale, young, low-turnover, and low-digital-maturity firms. In addition, respondents include owners, co-owners, managers, and employees, creating potential variation in access to firm-level strategic information. Future studies should use more balanced sectoral samples, explicit key-informant criteria, and multi-informant designs. The use of a single questionnaire for focal constructs also means that common-method bias cannot be excluded (Podsakoff et al., 2003).

Third, discriminant validity between analytics capability and competitiveness is not established under the reported Fornell–Larcker criterion. Future reanalysis should report

HTMT, cross-loadings, interaction-term VIFs, conditional slopes and confidence intervals for significant interactions, f^2 effect sizes, Q^2, and out-of-sample predictive metrics. More comprehensive item sets are also needed for organizational adaptive capability because its final measurement relies on two retained indicators. Objective outcome measures—such as verified revenue growth, productivity, or market-share change—would further reduce conceptual overlap between capabilities and perceived competitiveness.

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Declaration of AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used QuillBot and ChatGPT for language editing, condensation, and structural refinement. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the accuracy, integrity, and final content of the publication. AI-assisted tools were not treated as sources of empirical data.

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