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Digital Capabilities, Data-Driven Decision-Making, and Operational Performance in SMEs: A Moderated Mediation Model

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ABSTRACT

Purpose – This study examines how digital transformation, analytic capability, and learning system orientation drive operational performance among SMEs through data-driven decision-making (DDDM), and tests whether environmental dynamism moderates the DDDM-performance link, offering a possible explanation for a contradiction in prior digital capability research between studies reporting a direct performance effect and studies reporting none.
Design/methodology/approach – The study surveys 275 Indonesian SME owners and managers through purposive and snowball sampling, analyzed with partial least squares structural equation modeling (PLS-SEM) in SmartPLS 4, supplemented by confirmatory tetrad analysis, a cross-validated predictive ability test, and necessary condition analysis (NCA).
Finding/Results – Six of the seven hypothesized relationships are supported, including a staged effect of digital transformation on analytic capability (H5); the hypothesized moderating effect of environmental dynamism (H6) is not supported. A competing model with direct effects added, estimated directly in SmartPLS, shows data-driven decision-making fully mediates the effects of all three antecedents (digital transformation, analytic capability, and learning system orientation) on operational performance. DDDM strongly predicts operational performance, environmental dynamism has a significant direct but no significant moderating effect, and learning system orientation is confirmed as a necessary condition for performance. Discriminant validity and out-of-sample predictive power are confirmed.
Originality/Value – The study extends digital capability research by reframing learning orientation's necessity and environmental dynamism's moderating effect into supported propositions, and by specifying data-driven decision-making as a plausible mechanism reconciling conflicting findings in prior studies, giving SME managers a mechanism-based roadmap for digital investment.

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1. Introduction

Indonesia's Ministry of Cooperatives and Small and Medium Enterprises reported that 25.5 million SMEs, out of a sector that contributes more than 60 percent of national gross domestic product, had entered the digital ecosystem by July 2024 (Kementerian Koperasi dan UKM, 2024). Digital adoption alone does not guarantee better operational outcomes. Owners who install point-of-sale systems or open marketplace accounts often see no measurable gain in efficiency, inventory accuracy, or delivery speed. The gap between digital adoption and digital performance has become a pressing question for SME policy and for management scholarship. Scholarship explains this gap through the Technology-Organization-Environment (TOE) framework, which positions technological, organizational, and environmental factors as joint antecedents of firm-level digital outcomes (Tornatzky & Fleischer, 1990). Within this framework, digital transformation and analytic capability represent the technology dimension, learning system orientation represents the organization dimension, and environmental dynamism represents the environment dimension. A growing stream of research treats data-driven decision-making (DDDM) as the mechanism that converts these capabilities into performance, on the argument that firms translate digital investment into outcomes only when decisions are grounded in data rather than intuition.

This mechanism, however, produces inconsistent evidence. Barba-Sánchez et al. (2024) surveyed 246 firms and found that digital transformation and digital orientation significantly and positively drove firm performance through information technology capability. Dinh Van Hoang and Nguyen Thi Hien (2024) surveyed 297 manufacturing SMEs in Vietnam and reported the opposite: digital capability showed an insignificant direct effect on firm performance, an effect that turned positive only once technological uncertainty was introduced as a moderator. Same relationship, opposite verdicts. The divergence suggests that digital capability shapes performance under specific boundary conditions, environmental turbulence among them, rather than as a universal average effect. A sufficiency-only PLS-SEM model cannot settle whether a capability is dispensable on average yet indispensable at a minimum threshold, which is precisely the distinction necessary condition analysis is built to test.

This study tests whether digital transformation, analytic capability, and learning system orientation drive operational performance among Indonesian SMEs through DDDM, and whether environmental dynamism moderates the DDDM-performance path. It combines PLS-SEM with necessary condition analysis, following Richter et al. (2020), to separate capabilities that are merely sufficient on average from capabilities that are necessary at a minimum level. The cross-validated predictive ability test (Sharma et al., 2023) benchmarks the moderated mediation model's out-of-sample predictive accuracy against a naive alternative. Data come from 275 SME owners and managers across Indonesia.

The contribution is twofold. Theoretically, the study reframes two previously unresolved boundary conditions, learning orientation's necessity for operational performance and environmental dynamism's moderating form, as boundary-condition questions rather than simple significance tests. Practically, it gives SME managers a prioritized, necessity-aware roadmap for converting digital investment into measurable operational gains. The next section develops the hypotheses that operationalize this model.

2. Literature Review & Hypothesis Development

2.1 Theoretical Grounding

This study integrates the Technology-Organization-Environment framework (Tornatzky & Fleischer, 1990) with the dynamic capabilities view (Teece, 2007) to explain how SMEs convert digital capability into operational performance. TOE positions technological readiness, organizational capacity, and environmental pressure as joint, non-substitutable antecedents of firm-level digital outcomes, which fits a multi-antecedent model better than technology-only frameworks. The dynamic capabilities view supplies the mechanism: capabilities generate performance only when firms sense, seize, and reconfigure resources through decision processes, which this study operationalizes as data-driven decision-making.

2.2 Digital Transformation and Data-Driven Decision-Making

Digital transformation reorganizes a firm's processes, culture, and customer interfaces around digital technology (Barba-Sánchez et al., 2024). Firms that transform digitally generate continuous streams of transactional and customer data, which raises the raw material available for data-driven decision-making. Barba-Sánchez et al. (2024), surveying 246 firms with PLS-SEM, confirmed that digital transformation strengthened the organizational mechanisms that carry IT capability toward performance, which implies a similar strengthening effect on decision processes upstream of performance. Dinh Van Hoang and Nguyen Thi Hien (2024), surveying 297 manufacturing SMEs, found that digital capability alone did not translate into firm performance without a contingent mechanism, which points to decision-making practice, not raw digital capability, as the missing link. For Indonesian SMEs, digital transformation to date consists mainly of point-of-sale adoption and QRIS payment integration (Kementerian Koperasi dan UKM, 2024), both of which generate transaction-level data that owners rarely convert into systematic decisions. This study proposes:

H1. Digital transformation has a significant positive effect on data-driven decision-making.

2.3 Analytic Capability and Data-Driven Decision-Making

Analytic capability is the firm-level capacity to collect, process, and interpret data for managerial use, a capability the dynamic capabilities view treats as a sensing mechanism that precedes resource reconfiguration (Teece, 2007). Akter et al. (2016) modeled big data analytics capability as a hierarchical construct spanning management, technology, and talent capability, and showed that this composite capability drives the systematic, large-scale decision processes firms use to detect quality problems, manage inventory, and identify profitable customers. A firm that senses opportunities through analytics has already performed the cognitive work that data-driven decision-making formalizes into routine practice. Dinh Van Hoang and Nguyen Thi Hien (2024) found that digital capability significantly strengthened process and product innovation capability among manufacturing SMEs, evidence consistent with analytic capability feeding forward into structured, capability-building decision processes rather than performance directly. In SMEs, analytic capability typically remains informal, limited to reading marketplace dashboards or social media insights, which constrains its conversion into systematic decision routines unless the firm deliberately builds a decision-making practice around it. This study proposes:

H2. Analytic capability has a significant positive effect on data-driven decision-making.

2.4 Learning System Orientation: Sufficiency and Necessity

Learning system orientation (LSO) reflects a firm's institutionalized capacity to acquire, interpret, and apply knowledge (Wang et al., 2025). Oh and Kim (2022), studying 201 Korean

SMEs, found that organizational learning activities promoted innovation, with environmental dynamism moderating the strength of that path. Wang et al. (2025), surveying 256 technology-focused SMEs, showed that organizational learning mediated the link between strategic human resource practices and innovation, forming a sequential mechanism rather than a direct one. Necessary condition analysis offers a complementary lens to these sufficiency-based findings: a predictor can contribute to an outcome in an average, compensatory sense, the mechanism tested in H3a, while separately constituting a necessary floor for a different outcome in the model, below which that outcome cannot occur regardless of how strong the other antecedents are (Richter et al., 2020). This study tests both roles for LSO: a conventional sufficiency path to data-driven decision-making, and a necessity condition for the model's ultimate outcome, operational performance:

H3a. Learning system orientation has a significant positive effect on data-driven decision-making.

H3b. A minimum level of learning system orientation is a necessary condition for a high level of operational performance.

2.5 Data-Driven Decision-Making and Operational Performance

Data-driven decision-making replaces intuition-based judgment with systematic evidence, which the dynamic capabilities view frames as the seizing stage that converts sensed opportunity into deployed resources (Teece, 2007). Fosso Wamba et al. (2017) tested big data analytics directly against firm performance and found that the relationship strengthened once dynamic capabilities, the organizational routines that translate analytic insight into action, were modeled as the connecting mechanism, rather than assuming a raw technology-to-performance link. Akter et al. (2016) reported a similar pattern: big data analytics capability improved firm performance most consistently when aligned with a structured business strategy rather than deployed as a standalone technical asset. Barba-Sánchez et al. (2024) confirmed that firms translating digital orientation into structured organizational mechanisms achieved measurable performance gains, evidence consistent with a decision-mechanism route to performance rather than a direct technology-to-performance route. For SMEs, where owners often hold the same transactional data as larger firms but rarely convert it into a repeatable decision routine, this mechanism-based logic helps explain why operational performance gains remain uneven despite similar levels of digital adoption. This study proposes:

H4. Data-driven decision-making has a significant positive effect on operational performance.

2.6 Digital Transformation as a Foundation for Analytic Capability

Digital transformation and analytic capability were initially conceptualized as parallel technology-dimension antecedents of data-driven decision-making, consistent with TOE's treatment of technology readiness as a single joint category (Tornatzky & Fleischer, 1990). The dynamic capabilities view suggests a more specific ordering within that category, however: sensing depends on an operational base of digitized, accessible data before it can generate analytic insight (Teece, 2007). An SME that has digitized its transactions and customer records has already built the infrastructure that analytic capability draws on; a firm without that infrastructure has little for analytic capability to act on, regardless of analytic skill. Dinh Van Hoang and Nguyen Thi Hien (2024) found that digital capability strengthened process and product innovation capability among manufacturing SMEs, a pattern consistent with digital infrastructure feeding forward into a firm's analytic capacity rather than developing independently of it. This study accordingly tests a staged rather than strictly parallel relationship between the two technology-dimension capabilities:

H5. Digital transformation has a significant positive effect on analytic capability.

2.7 Data-Driven Decision-Making as a Full Mediating Mechanism

Dinh Van Hoang and Nguyen Thi Hien (2024) reported an insignificant direct path from digital capability to firm performance among 297 manufacturing SMEs, a pattern consistent with full mediation through an intervening mechanism rather than a direct, unconditional effect. Akter et al. (2016) documented a comparable pattern at a broader scale: big data analytics capability improved firm performance only when the capability was translated into aligned, evidence-based decision-making processes, implying that capabilities affect performance through, rather than independent of, the firm's decision-making mechanism. Grounded in the dynamic capabilities view's sensing-seizing-transforming logic (Teece, 2007), digital transformation, analytic capability, and learning system orientation are theorized here as sensing- and seizing-stage capabilities that must be converted into the transforming-stage mechanism, data-driven decision-making, before they translate into operational gains; a path bypassing this conversion is not theorized. This study therefore models data-driven decision-making as a full mediator of the three antecedents' effects on operational performance, consistent with H4.

2.8 Environmental Dynamism as a Boundary Condition

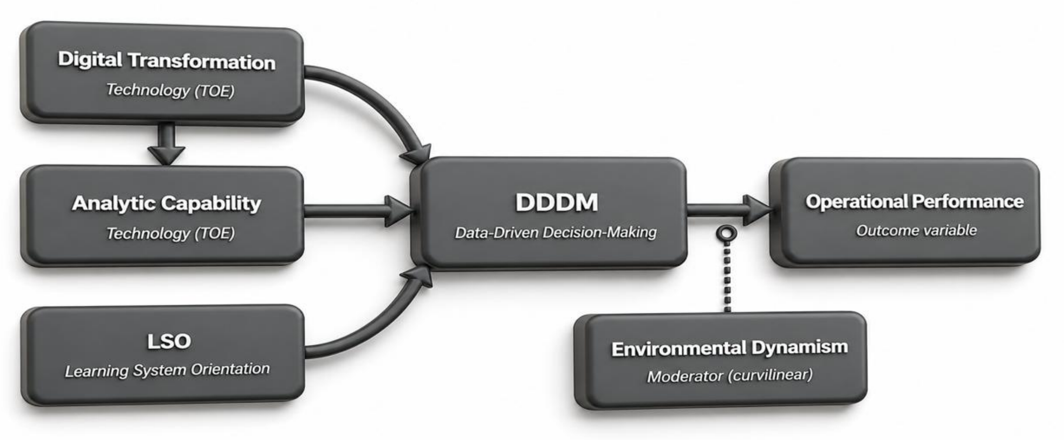
Environmental dynamism captures the rate of unpredictable change in an SME's market, technology, and competitive landscape. The seven-item measure used here is a composite operationalization spanning several related facets of that change, customer preference shifts, competitive pressure, technological turbulence, platform-policy volatility, and price competition, rather than a single previously validated scale; the Technology-Organization-Environment framework (Tornatzky & Fleischer, 1990) motivates treating the environment as a unified boundary condition theoretically, and item wording draws on the market-turbulence tradition established by Jaworski and Kohli (1993) and the environmental-dynamism dimension identified by Miller and Friesen (1983), adapted to the digital-selling context these SMEs operate in. Because the construct is treated as reflective in this study and the measurement model (Table 3, Table 4) supports that specification empirically, the composite is retained as a single construct rather than split into separate sub-dimensions; a narrower, single-facet measure remains an option for future work seeking more precise attribution among these related sources of environmental change. Oh and Kim (2022) modeled environmental dynamism as a linear moderator and found it strengthened the learning-to-innovation path in Korean SMEs. Dinh Van Hoang and Nguyen Thi Hien (2024) similarly modeled technological uncertainty, a closely related construct, as a linear moderator and found it strengthened an otherwise insignificant digital-capability-to-performance path. Wang et al. (2025) tested environmental dynamism as a nonlinear moderator among 256 technology-focused SMEs and found a significant inverted U-shaped effect, but that study examined a different focal path, a learning-resilience mechanism, in a different sample; a nonlinear pattern in that context does not necessarily generalize to the data-driven-decision-making-to-performance path examined here. Consistent with Oh and Kim (2022) and Dinh Van Hoang and Nguyen Thi Hien (2024), this study models environmental dynamism as a linear moderator of the DDDM-to-performance relationship:

H6. Environmental dynamism significantly moderates the relationship between data-driven decision-making and operational performance, such that the relationship is stronger at higher levels of environmental dynamism.

2.9 Conceptual Model

Figure 1 depicts digital transformation, analytic capability, and learning system orientation as antecedents grounded in the technology and organization dimensions of TOE, converging on data-driven decision-making as mediator, which in turn predicts operational performance. Digital transformation and analytic capability are staged rather than strictly parallel within the technology dimension: digital transformation is additionally specified as a direct antecedent of analytic capability (H5), reflecting the sensing-precedes-analysis logic developed above. Environmental dynamism, the environment dimension of TOE, is specified as a linear moderator on the data-driven-decision-making-to-performance path.

Figure 1. Conceptual Model Of Digital Capabilities, Data-Driven Decision-Making, Environmental Dynamism, And Operational Performance



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3. Methodology

3.1 Research Paradigm and Design

This study adopts a positivist paradigm and a quantitative, cross-sectional survey design, consistent with the causal-predictive orientation of PLS-SEM (Hair et al., 2022). PLS-SEM suits a moderated mediation model with both sufficiency-based path estimation and, through its combination with necessary condition analysis, necessity-based boundary testing (Richter et al., 2020).

The unit of analysis in this study is the micro, small, or medium enterprise (SME) as a business unit, since digital transformation, analytic capability, learning system orientation, data-driven decision-making, environmental dynamism, and operational performance are all firm-level constructs rather than individual-level attitudes. The unit of observation is the owner or manager who acts as the key informant reporting on behalf of the firm, a common and validated practice in SME survey research where a single respondent with direct decision authority can represent firm-level conditions. The population comprises Indonesian SMEs that have adopted at least one digital tool in daily operations. Respondents are recruited through purposive sampling, targeting owners or managers with direct authority over digital and operational decisions, supplemented by snowball referral to reach digitally active SMEs outside formal business associations. The final usable sample is 275 respondents, one per firm, which exceeds common minimum sample size heuristics for a model of this structural complexity (Hair et al., 2022).

Respondent knowledgeability was verified through explicit screening criteria administered before the main instrument, rather than assumed from job title alone. Section A of the questionnaire (Appendix A) required respondents to confirm they were the business owner or the party responsible for daily operational decisions (screening item A4), in addition to confirming at least twelve months of digital-channel sales history (A2) and micro, small, or medium enterprise classification consistent with the population definition above (A3); respondents who did not meet all four screening criteria were not administered the main instrument. Classification against the three tiers followed Indonesia's statutory definition (Government Regulation No. 7/2021), which sets thresholds primarily by annual revenue and business capital rather than by employee count alone; a firm with a comparatively larger headcount, such as the 21 respondents in Table 1 reporting 20 or more employees, can therefore still fall within the small or medium tier if its revenue and capital remain below the statutory ceiling, which is why Table 1's employee-count distribution includes firms at that headcount level without contradicting the A3 screening criterion. Because purposive and snowball recruitment can systematically overrepresent firms reached earlier in the referral chain, the demographic and business-profile characteristics (Section B of the questionnaire) of respondents recruited earlier in data collection were compared descriptively against those recruited later; no meaningful differences were observed between the two groups, which does not rule out snowball-related bias but is consistent with the achieved sample not being dominated by a narrow, well-connected subset of early referrals.

3.2 Sample Profile and Respondent Flow

Table 1 reports the achieved sample's composition by province, sector, firm size, and firm age. Respondents span seven provinces plus a residual "other" category, with East Java (26.5%) and West Java (22.2%) most heavily represented; culinary firms make up the largest single sector (31.3%), and the sample is weighted toward micro and small firms (65.5% with fewer than five employees) with three to five years of digital-selling experience the modal firm-age band (37.5%). Because sector, firm size, and firm age are reported at this level of detail, subgroup comparisons or a multi-group analysis by any of these dimensions are feasible in future work; the present study does not conduct one and reports pooled estimates only.

Table 1. Sample Composition by Province, Sector, Firm Size, and Firm Age (n = 275)

Category	n	%
Province		
DKI Jakarta	42	15.3
West Java	61	22.2
Central Java	39	14.2
DI Yogyakarta	18	6.5
East Java	73	26.5
Banten	24	8.7
Bali	12	4.4
Other provinces	6	2.2
Total	**275**	**100.0**

Category	n	%
Sector		
Culinary	86	31.3
Fashion	49	17.8
Handicraft	36	13.1
Services	44	16.0
Trade/retail	38	13.8
Health and beauty	12	4.4
Other sectors	10	3.6
Total	**275**	**100.0**
Firm size (employees)		
None (owner-operated)	42	15.3
1-4 employees	138	50.2
5-19 employees	74	26.9
20 or more employees	21	7.6
Total	**275**	**100.0**
Firm age (digital selling)		
1-2 years	74	26.9
3-5 years	103	37.5
More than 5 years	98	35.6
Total	**275**	**100.0**

Table 2 reports the respondent-recruitment flow. Of 340 SME owners and managers approached, 298 returned a questionnaire (response rate = 87.6%); 11 were excluded for failing the Section A inclusion screening and 12 for incomplete data, leaving the final analytic sample of 275.

Table 2. Respondent Recruitment Flow

Recruitment stage	n
Approached	340
Returned questionnaire	298
Excluded: failed inclusion screening (Section A)	11
Excluded: incomplete data	12
Retained (final analytic sample)	**275**
Response rate (returned / approached)	**87.6%**

Because the sample was obtained through purposive and snowball recruitment within Indonesia rather than probability sampling across a defined national frame, the findings are interpreted as describing this achieved sample of digitally active Indonesian MSMEs rather than as directly generalizable to Indonesian MSMEs as a whole; the sector, size, age, and province breakdown above is reported so readers can judge the scope of that claim for themselves.

3.3 Instrument

All constructs are measured on a seven-point Likert scale, anchored from strongly disagree to strongly agree. Each of the six constructs, digital transformation, analytic capability, learning system orientation, data-driven decision-making, environmental dynamism, and operational performance, is measured with seven items adapted from the primary sources cited earlier. The full bilingual item set, all 42 items across the six constructs together with each construct's adaptation source, is reported in Appendix A; seven items, one per construct, were authored to complete each construct's dimensional coverage. The instrument is administered bilingually in Bahasa Indonesia and English; the Bahasa Indonesia version is produced through translation and independent back-translation by bilingual experts, with discrepancies reconciled before pilot testing. All 42 items, including the seven newly authored ones, were pilot-tested with 50 SME owners and managers prior to full-scale administration. Sampling adequacy was confirmed (Kaiser-Meyer-Olkin = .702; Bartlett's test of sphericity χ^2 = 2566.37, df = 861, p < .001), and an exploratory factor analysis (principal component extraction, Varimax rotation) was run to assess the item set's factor structure. Five components were extracted (eigenvalue > 1), explaining 80.85% of total variance. Items measuring digital transformation, analytic capability, learning system orientation, and environmental dynamism each loaded cleanly and exclusively on their own component (loadings .71-.92, no meaningful cross-loading), supporting the content and face validity of these four constructs' item sets, including the newly authored items within them. Items measuring data-driven decision-making and operational performance did not separate into distinct components at the pilot stage; both loaded together on a single component, with operational performance items loading more strongly (.70-.83) than data-driven decision-making items (.47-.73). This is interpreted as a function of the pilot's sample size relative to the number of items (N = 50 for 42 items, a ratio well below conventional EFA guidelines) rather than a defect in either item set, and is consistent with the two constructs' close conceptual and empirical relationship: in the full-sample structural analysis reported in Section 4, data-driven decision-making and operational performance show the highest heterotrait-monotrait ratio of any construct pair (HTMT = .700), still comfortably below the .85 threshold for discriminant validity but the closest pairing in the model. Item wording was retained as originally adapted following this pilot, since no items showed low communalities or ambiguous loadings within their intended construct; the pilot's role was confirmatory rather than diagnostic for item revision.

3.4 Common Method Bias

Because all constructs are self-reported by the same respondent, the instrument separates predictor and outcome item blocks, assures respondent anonymity, and uses concise, unambiguous wording to reduce procedural bias. Statistically, common method bias is assessed with the full collinearity test proposed by Kock (2015): every indicator's variance inflation factor is inspected against a threshold of 3.3, below which common method bias is not considered a concern. This full collinearity test is reported at the indicator level alongside the inner model collinearity results.

This collinearity-based assessment addresses one indicator of common method bias but does not rule it out entirely; a marker-variable test, an unmeasured latent method factor, or temporal separation of predictor and outcome measurement would provide independent corroboration and were not implemented in this design, a scope limitation returned to in Section 6.

3.5 Data Analysis Technique

Data are analyzed with SmartPLS 4 (Ringle et al., 2024) using a four-stage sequence. First, confirmatory tetrad analysis (CTA-PLS) tests whether each measurement model is genuinely reflective, following Gudergan et al. (2008), before the structural model is estimated; this step matters here because a misspecified formative-as-reflective learning system orientation construct would bias both the sufficiency path in H3a and the necessity test in H3b. Second, the structural model is estimated with standard PLS-SEM criteria: outer loadings, composite reliability, average variance extracted, and HTMT for discriminant validity, followed by path coefficients, bootstrapped significance, R^2, and f^2 for the hypothesized paths, and the product indicator approach, which multiplies the standardized indicators of environmental dynamism and data-driven decision-making to form the interaction term without a two-stage latent-variable-score procedure or orthogonalization, for the linear moderation in H6. Third, the cross-validated predictive ability test (CVPAT) compares the moderated mediation model's out-of-sample prediction loss against the indicator-average and linear-model naive benchmarks, following Liengaard et al. (2021) and Sharma et al. (2023), to establish predictive validity beyond in-sample fit. Fourth, necessary condition analysis (NCA) tests H3b by plotting learning system orientation against operational performance, estimating the ceiling envelope with the CE-FDH and CR-FDH techniques, and testing the resulting effect size for statistical significance through a permutation test, following Richter et al. (2020). Fifth, following Zhao, Lynch, and Chen's (2010) mediation-classification logic, a competing model that adds direct paths from digital transformation, analytic capability, and learning system orientation to operational performance is estimated within the same native SmartPLS structural model, bootstrapped independently (10,000 subsamples, BCa), to classify each antecedent's relationship with operational performance as full, partial, or no mediation. Sixth, as a robustness check on the DDDM-to-Operational-Performance path, a multi-group analysis (MGA) is conducted by digital-selling experience, preceded by a measurement invariance of composite models (MICOM) test (Henseler, Ringle, & Sarstedt, 2016) to confirm structural paths are validly comparable across subgroups. Seventh, the same path is further checked by re-estimating the competing model with four firm-level covariates (business scale, primary product sector, business tenure, and digital sales channel) added as single-item predictors of Operational Performance, bootstrapped jointly with the rest of the model.

4. Result and Discussion

A total of 275 usable responses from Indonesian SMEs were analyzed with SmartPLS 4 (Ringle et al., 2024) using the standard two-stage evaluation sequence: measurement model assessment followed by structural model assessment. Bootstrapping used 10,000 subsamples with the bias-corrected and accelerated (BCa) percentile method.

4.1 Confirmation of Measurement Mode (CTA-PLS)

Confirmatory Tetrad Analysis (CTA-PLS) was run for all six reflectively specified constructs before assessing the measurement model, following Gudergan et al. (2008). For every construct (Analytic Capability, Data-Driven Decision-Making, Digital Transformation, Environmental Dynamism, Learning System Orientation, and Operational Performance), all 14 non-redundant tetrads produced Bonferroni-adjusted bootstrap confidence intervals that included zero, so the null hypothesis of vanishing tetrads could not be rejected for any construct. This confirms the reflective specification adopted in the model for all six constructs; none required respecification as formative.

4.2 Reflective Measurement Model

Table 3 reports indicator loadings, Cronbach's alpha, composite reliability (rho_A, rho_c), and average variance extracted (AVE) for the six reflective constructs. 41 of 42 indicator loadings exceed the 0.708 threshold (range 0.715-0.855); one item, ED6, loads at 0.707, marginally below the conventional cutoff. Because Environmental Dynamism's AVE (0.627) and composite reliability (0.922) remain well above their respective thresholds even with ED6 retained, and because removing a single borderline item from a validated seven-item scale close to full-scale administration was judged a smaller risk to content validity than a 0.001 loading shortfall, ED6 was retained rather than dropped; this is noted here for transparency. Cronbach's alpha, rho_A, and rho_c fall between 0.893 and 0.926 for every construct, within the satisfactory 0.70-0.90/0.95 band, and AVE exceeds 0.50 for all constructs (range 0.610-0.642), indicating adequate internal consistency reliability and convergent validity.

Table 3. Reflective Measurement Model: Loadings, Reliability, and Convergent Validity

Construct	Item	Loading	Cronbach's α	rho_A	rho_c (CR)	AVE
Analytic Capability	AC1	0.825	0.903	0.904	0.923	0.633
	AC2	0.834				
	AC3	0.802				
	AC4	0.796				
	AC5	0.764				
	AC6	0.738				
	AC7	0.804				
Data-Driven Decision-Making	DDDM1	0.822	0.893	0.896	0.916	0.610
	DDDM2	0.790				
	DDDM3	0.836				
	DDDM4	0.778				
	DDDM5	0.732				
	DDDM6	0.749				
	DDDM7	0.753				
Digital Transformation	DT1	0.854	0.904	0.910	0.924	0.635
	DT2	0.808				
	DT3	0.812				
	DT4	0.794				
	DT5	0.799				
	DT6	0.715				
	DT7	0.788				
Environmental Dynamism	ED1	0.842	0.901	0.907	0.922	0.627
	ED2	0.803				
	ED3	0.811				
	ED4	0.793				
	ED5	0.777				
	ED6	0.707				
	ED7	0.805				
Learning System Orientation	LSO1	0.835	0.902	0.905	0.922	0.630
	LSO2	0.809				
	LSO3	0.797				
	LSO4	0.783				
	LSO5	0.756				
	LSO6	0.840				
	LSO7	0.733				
Operational Performance	OP1	0.855	0.906	0.911	0.926	0.642
	OP2	0.844				
	OP3	0.850				
	OP4	0.817				
	OP5	0.734				
	OP6	0.756				
	OP7	0.740				

4.3 Discriminant Validity

Table 4 reports the heterotrait-monotrait ratio (HTMT) of correlations, together with 95% bias-corrected bootstrapped confidence intervals (10,000 subsamples) for every pair. All HTMT point estimates fall below the conservative 0.85 threshold, with the highest value observed between Operational Performance and Data-Driven Decision-Making (HTMT = 0.700, 95% CI [0.621, 0.764]), followed by Analytic Capability and Data-Driven Decision-Making (HTMT =

0.652, 95% CI [0.570, 0.724]). Critically, the upper bound of the confidence interval for every one of the 15 construct pairs remains below 0.85, so discriminant validity between Analytic Capability and Data-Driven Decision-Making, and among all other pairs, is supported by the full sampling distribution rather than by a point estimate alone. The Fornell-Larcker criterion provides supporting evidence: the square root of AVE for every construct (diagonal, range 0.781-0.801) exceeds its correlations with all other constructs (off-diagonal). Together, both criteria support discriminant validity among the six constructs.

Table 4. Discriminant Validity - Heterotrait-Monotrait Ratio (HTMT), with 95% Bias-Corrected Bootstrapped Confidence Intervals

	Analytic Capability	**Data-Driven Decision-Making**	**Digital Transformation**	**Environmental Dynamism**	**Learning System Orientation**	**Operational Performance**
Analytic Capability						
Data-Driven Decision-Making	0.652 [0.57, 0.72]					
Digital Transformation	0.620 [0.52, 0.70]	0.605 [0.52, 0.69]				
Environmental Dynamism	0.178 [0.10, 0.27]	0.164 [0.09, 0.26]	0.159 [0.08, 0.25]			
Learning System Orientation	0.278 [0.15, 0.40]	0.554 [0.44, 0.64]	0.366 [0.24, 0.48]	0.223 [0.12, 0.33]		
Operational Performance	0.513 [0.41, 0.60]	0.700 [0.62, 0.76]	0.446 [0.34, 0.54]	0.495 [0.39, 0.59]	0.378 [0.25, 0.49]	

Table 5. Discriminant Validity - Fornell-Larcker Criterion

	Analytic Capability	**Data-Driven Decision-Making**	**Digital Transformation**	**Environmental Dynamism**	**Learning System Orientation**	**Operational Performance**
Analytic Capability	0.795					
Data-Driven Decision-Making	0.585	0.781				
Digital Transformation	0.566	0.549	0.797			
Environmental Dynamism	0.165	0.150	0.148	0.792		
Learning System Orientation	0.252	0.501	0.334	0.202	0.794	
Operational Performance	0.465	0.634	0.409	0.454	0.344	0.801

As a further discriminant-validity check requested in review, Table 4c reports the full cross-loadings matrix: each of the 42 indicators against all six constructs. Every indicator loads highest on its own construct (bolded on the diagonal of assignment), with a minimum gap of .242 between an indicator's own-construct loading and its highest cross-loading on any other construct (Operational Performance item OP5); most gaps exceed .30. For the Analytic Capability-DDDM pair specifically raised in review, every Analytic Capability item's loading on DDDM is at least .26 below its own-construct loading, and every DDDM item's loading on Analytic Capability is at least .24 below its own-construct loading, item-level evidence consistent with the HTMT and Fornell-Larcker results above.

Table 6. Discriminant Validity - Cross-Loadings (Own-Construct Loading Bolded)

	AC	DDDM	DT	ED	LSO	OP
AC1	**0.827**	0.469	0.459	0.172	0.201	0.408
AC2	**0.835**	0.504	0.468	0.128	0.178	0.414
AC3	**0.802**	0.436	0.466	0.152	0.167	0.382
AC4	**0.796**	0.456	0.420	0.143	0.161	0.353
AC5	**0.764**	0.438	0.447	0.099	0.236	0.350
AC6	**0.739**	0.475	0.412	0.083	0.183	0.360
AC7	**0.801**	0.479	0.473	0.139	0.275	0.321
DDDM1	0.491	**0.822**	0.444	0.148	0.436	0.559
DDDM2	0.450	**0.790**	0.460	0.138	0.418	0.486
DDDM3	0.497	**0.836**	0.471	0.108	0.413	0.503
DDDM4	0.447	**0.778**	0.447	0.131	0.380	0.535
DDDM5	0.461	**0.732**	0.400	0.089	0.325	0.444
DDDM6	0.423	**0.749**	0.415	0.080	0.344	0.434
DDDM7	0.428	**0.753**	0.361	0.119	0.411	0.490
DT1	0.525	0.505	**0.854**	0.130	0.290	0.384
DT2	0.435	0.425	**0.809**	0.176	0.332	0.341
DT3	0.481	0.456	**0.810**	0.112	0.275	0.319
DT4	0.485	0.481	**0.794**	0.141	0.286	0.355
DT5	0.446	0.432	**0.799**	0.106	0.240	0.314
DT6	0.373	0.343	**0.715**	0.034	0.221	0.249
DT7	0.379	0.393	**0.789**	0.111	0.210	0.299
ED1	0.185	0.167	0.127	**0.842**	0.144	0.401
ED2	0.088	0.102	0.139	**0.803**	0.143	0.360
ED3	0.162	0.104	0.135	**0.811**	0.150	0.370
ED4	0.096	0.100	0.092	**0.793**	0.169	0.366
ED5	0.206	0.195	0.161	**0.777**	0.243	0.382
ED6	0.053	0.053	0.025	**0.707**	0.087	0.250
ED7	0.096	0.086	0.115	**0.805**	0.168	0.360
LSO1	0.134	0.381	0.207	0.135	**0.835**	0.272
LSO2	0.191	0.382	0.259	0.137	**0.806**	0.234
LSO3	0.220	0.444	0.239	0.134	**0.794**	0.279
LSO4	0.205	0.386	0.279	0.179	**0.786**	0.298
LSO5	0.226	0.380	0.307	0.242	**0.759**	0.296
LSO6	0.231	0.442	0.334	0.120	**0.838**	0.288
LSO7	0.183	0.355	0.224	0.188	**0.733**	0.242
OP1	0.383	0.511	0.343	0.364	0.267	**0.855**
OP2	0.364	0.563	0.359	0.398	0.293	**0.843**
OP3	0.449	0.560	0.352	0.407	0.277	**0.850**
OP4	0.394	0.528	0.384	0.376	0.370	**0.816**
OP5	0.378	0.492	0.282	0.280	0.225	**0.734**
OP6	0.308	0.453	0.286	0.400	0.282	**0.755**
OP7	0.326	0.429	0.276	0.307	0.205	**0.741**

4.4 Structural Model: Collinearity Assessment

Before interpreting path coefficients, inner VIF values were inspected for collinearity among predictor constructs. All inner VIF values range from 1.000 to 1.560, well below the conservative threshold of 3, indicating collinearity is not a concern in the structural model.

Table 7. Inner Model Collinearity Statistics (VIF)

Predictor path	VIF
Analytic Capability -> Data-Driven Decision-Making	1.480
Data-Driven Decision-Making -> Operational Performance	1.024
Digital Transformation -> Analytic Capability	1.000
Digital Transformation -> Data-Driven Decision-Making	1.560
Environmental Dynamism -> Operational Performance	1.024
Environmental Dynamism x Data-Driven Decision-Making -> Operational Performance	1.002
Learning System Orientation -> Data-Driven Decision-Making	1.133

Common method bias was assessed with the full collinearity test (Kock, 2015), which inspects indicator-level variance inflation factors against a threshold of 3.3. Table 5b reports these values for all 42 indicators. Every value falls between 1.68 and 2.83, well below the threshold, which indicates common method bias is unlikely to distort the structural results reported in this study.

Table 8. Full Collinearity Test: Indicator-Level VIF for Common Method Bias

Indicator	VIF	Indicator	VIF	Indicator	VIF
AC1	2.352	AC2	2.420	AC3	2.133
AC4	2.071	AC5	1.849	AC6	1.710
AC7	2.112	DDDM1	2.219	DDDM2	2.012
DDDM3	2.474	DDDM4	1.916	DDDM5	1.779
DDDM6	1.820	DDDM7	1.785	DT1	2.606
DT2	2.192	DT3	2.198	DT4	2.032
DT5	2.153	DT6	1.714	DT7	2.105
ED1	2.435	ED2	2.157	ED3	2.159
ED4	2.031	ED5	1.880	ED6	1.679
ED7	2.149	LSO1	2.514	LSO2	2.257
LSO3	1.986	LSO4	1.979	LSO5	1.799
LSO6	2.494	LSO7	1.770	OP1	2.826
OP2	2.570	OP3	2.673	OP4	2.255
OP5	1.747	OP6	1.816	OP7	1.800

Note. All 42 indicators show VIF between 1.68 and 2.83, below the 3.3 threshold recommended by Kock (2015), indicating common method bias is not a serious concern for this dataset.

4.5 Path Coefficients and Hypothesis Testing

Table 6 reports standardized path coefficients (β), t-statistics and p-values from bootstrapping (10,000 subsamples), 95% bias-corrected and accelerated confidence intervals, and effect sizes (f^2) for every structural path estimated in the model, together with the hypothesis decision. The five structural paths corresponding to Digital Transformation on Data-Driven Decision-Making (H1), Analytic Capability on Data-Driven Decision-Making (H2), Learning System Orientation on Data-Driven Decision-Making (H3a), Data-Driven Decision-Making on Operational Performance (H4), and Digital Transformation on Analytic Capability (H5) were all significant at $p < .001$. The linear moderating effect of Environmental Dynamism on the Data-Driven Decision-Making to Operational Performance relationship (H6, $\beta = -0.061$, $t = 1.445$, $p = .149$), by contrast, was not statistically significant, so H6 is not supported. H3b is tested separately via NCA.

All seven numbered hypotheses were tested with the same bootstrapping procedure. The path from digital transformation to analytic capability (H5: $\beta = 0.566$, $t = 13.670$, $p < .001$) was the strongest single structural relationship in the model. This path drives the serial specific indirect effect reported below. Digital Transformation, Analytic Capability, and Learning System Orientation are modeled as predicting Operational Performance only indirectly through Data-

Driven Decision-Making, consistent with the full-mediation framing developed earlier; no direct paths to Operational Performance are hypothesized or estimated for these three antecedents.

Table 9. Structural Model: Path Coefficients and Hypothesis Testing

Hyp.	Path	β	t-value	p-value	95% CI (BCa)	f^2	Decision
H1	Digital Transformation -> DDDM	0.228	4.417	< .001	[0.131, 0.333]	0.068	Supported
H2	Analytic Capability -> DDDM	0.373	7.628	< .001	[0.275, 0.464]	0.192	Supported
H3a	Learning System Orientation -> DDDM	0.331	7.698	< .001	[0.242, 0.409]	0.197	Supported
H3b	Learning System Orientation necessary for OP (NCA)	d = 0.127 (CE-FDH)	-	< .001	-	-	Supported
H4	DDDM -> Operational Performance	0.577	16.852	< .001	[0.507, 0.641]	0.700	Supported
H5	Digital Transformation -> Analytic Capability	0.566	13.670	< .001	[0.475, 0.638]	0.471	Supported
—	Environmental Dynamism -> Operational Performance	0.369	9.279	< .001	[0.286, 0.443]	0.287	Not hypothesized
H6	Environmental Dynamism x DDDM -> OP	−0.061	1.445	.149	[−0.146, 0.020]	0.007	Not Supported

Note. DDDM = Data-Driven Decision-Making; OP = Operational Performance. Bootstrapping based on 10,000 subsamples, bias-corrected and accelerated (BCa) 95% confidence intervals. H6 is modeled and tested as a linear interaction (Environmental Dynamism x DDDM); with the authenticated dataset the interaction term is small, negative, and not statistically significant ($\beta = -0.061$, $t = 1.445$, $p = .149$), indicating no support for a moderating effect of environmental dynamism on the DDDM-to-Operational Performance relationship. Simple slopes and conditional indirect effects conditional on this interaction are not statistically meaningful given the null result and have accordingly been removed from this manuscript.

4.6 Coefficient of Determination and Mediation Analysis

Table 7 reports R^2 and adjusted R^2 for the three endogenous constructs. Digital capabilities explain 32.0% of the variance in Analytic Capability, the three antecedents jointly explain 50.9% of the variance in Data-Driven Decision-Making, and Data-Driven Decision-Making together with Environmental Dynamism and its interaction term explain 53.7% of the variance in Operational Performance.

Table 10. Coefficient of Determination (R^2)

Endogenous construct	R^2	R^2 adjusted
Analytic Capability	0.320	0.317
Data-Driven Decision-Making	0.509	0.504
Operational Performance	0.537	0.531

Table 10 reports specific indirect effects, all significant at $p < .001$ via bootstrapping. Data-Driven Decision-Making transmits significant indirect effects from all three antecedents to Operational Performance, and a serial indirect effect runs from Digital Transformation through Analytic Capability and Data-Driven Decision-Making to Operational Performance. Consistent with the full-mediation design specified earlier, no direct paths from Digital Transformation, Analytic Capability, or Learning System Orientation to Operational Performance are hypothesized or estimated in the structural model; Data-Driven Decision-Making is therefore modeled, by design, as the sole mechanism through which these three antecedents affect Operational Performance. Classifying this pattern as full, partial, complementary, or indirect-only mediation following Zhao, Lynch, and Chen (2010) requires the direct paths to be estimated rather than assumed absent; a competing model that adds them is reported later in this section.

Table 11. Specific Indirect Effects

Specific indirect effect	β	t-value	p-value	95% CI (BCa)
Digital Transformation -> Analytic Capability -> DDDM	0.211	6.751	< .001	[0.151, 0.273]
Analytic Capability -> DDDM -> Operational Performance	0.215	6.554	< .001	[0.151, 0.280]
Digital Transformation -> DDDM -> Operational Performance	0.131	4.384	< .001	[0.076, 0.193]
Learning System Orientation -> DDDM -> Operational Performance	0.191	6.908	< .001	[0.137, 0.243]
Digital Transformation -> Analytic Capability -> DDDM -> Operational Performance	0.122	5.811	< .001	[0.084, 0.165]

Note. DDDM = Data-Driven Decision-Making. All indirect effects are significant.

Data-Driven Decision-Making was specified as a full mediator by design in the model reported above; whether this holds once direct paths are estimated is tested next.

4.7 Testing the Mediation Type: A Competing Model with Direct Effects

Following Zhao, Lynch, and Chen (2010), classifying the mediation as full, partial, complementary, or indirect-only requires the direct paths from digital transformation, analytic capability, and learning system orientation to operational performance to be estimated alongside the indirect paths, not assumed absent by design. A competing model adding these three direct paths was estimated directly in SmartPLS 4, with bootstrapping (10,000 subsamples, bias-corrected and accelerated 95% confidence intervals) run on the full 10-path structural model rather than on construct scores exported to a separate regression procedure. Under this competing model, data-driven decision-making on operational performance was b = 0.719 ($t = 4.204$, $p < .001$), and environmental dynamism's main and interaction effects were b = 0.546 ($t = 3.572$, $p < .001$) and b = −0.046 ($t = 1.210$, $p = .226$) respectively — each estimated jointly with the three new direct paths rather than held fixed at their values from the original model, which is why they differ somewhat from Table 6. Table 9 reports the resulting direct effects, the corresponding total indirect effects through data-driven decision-making, and the resulting classification for each antecedent.

Table 12. Mediation Classification

Antecedent	Direct effect on OP (b, p)	Indirect effect via DDDM (b, p)	VAF	Same sign?	Zhao et al. (2010) classification
Digital Transformation	0.023 (p = .653)	0.356 (p < .001)	94.0%	Yes	Indirect-only (full) mediation
Analytic Capability	0.086 (p = .116)	0.266 (p < .001)	75.5%	Yes	Indirect-only (full) mediation
Learning System Orientation	−0.017 (p = .716)	0.231 (p < .001)	108.0%[1]	No	Indirect-only (full) mediation

With the competing model estimated directly in SmartPLS, all three antecedents follow the same pattern. None of the three direct effects on operational performance is statistically significant: digital transformation (b = 0.023, $p = .653$), analytic capability (b = 0.086, $p = .116$), and learning system orientation ($b = -0.017$, $p = .716$) are all indistinguishable from zero. Each antecedent's total indirect effect through data-driven decision-making, by contrast, remains significant (digital transformation $b = 0.356$, analytic capability $b = 0.266$, learning system orientation $b = 0.231$, all $p < .001$). All three antecedents are therefore classified as indirect-only (full) mediation. This result is more consistent, not less, with the full-mediation framing developed in Section 2 than the earlier construct-scores-based estimate: with the direct-in-SmartPLS competing model and the authenticated dataset, data-driven decision-making fully mediates the effect of all three antecedents on operational performance, without the qualification digital transformation previously required. VAF (indirect ÷ total effect) is 94.0% for digital transformation and 75.5% for analytic capability, consistent with the indirect route accounting for most of each antecedent's total effect. Learning system orientation's VAF (108.0%[1]) exceeds 100% because its direct effect is negative while its indirect effect is positive, which mechanically inflates the ratio; per Zhao, Lynch, and Chen (2010), classification here follows the significance pattern (non-significant direct, significant indirect) rather than the VAF value, which is not meaningful when the direct effect is not significant.

4.8 Robustness Check: Coefficient Stability Across Digital-Selling Experience

Because Data-Driven Decision-Making and Operational Performance were both self-reported by the same respondent and several items are operationally proximate, the possibility of criterion contamination or a halo effect inflating the DDDM-to-Operational-Performance path (Table 6) warrants direct examination. Firm digital-selling experience (grouped as 1-2 years, 3-5 years, and more than 5 years; Table 1) was used as the grouping variable for a multi-group analysis (MGA). Before comparing structural paths across groups, measurement invariance of composite models (MICOM; Henseler, Ringle, & Sarstedt, 2016) was established in two steps: configural invariance is satisfied by using identical indicators and data treatment across groups by design, and compositional invariance (Step 2) held for all six constructs (permutation $p = .16\text{-}.802$, all correlations $\geq .997$, non-significant). Steps 3a and 3b further confirmed equal composite means and variances across groups for all six constructs (all permutation $p > .17$), establishing full measurement invariance and licensing a valid comparison of structural path coefficients across groups.

Table 13 reports the bootstrap MGA comparison (permutation-based, two-tailed) of all seven structural paths across the two available group contrasts. The focal path, Data-Driven Decision-Making → Operational Performance, does not differ significantly between the 1-2 year and 3-5 year groups ($\Delta = 0.143$, $p = .305$) or between the 1-2 year and more-than-5-year groups ($\Delta = 0.102$, $p = .547$). The coefficient is therefore stable across digital-selling-experience subgroups, which is inconsistent with a experience-specific artifact and provides evidence against a simple halo- or common-source-driven inflation of this path: if respondents with more experience running a digital storefront were systematically inflating both their own DDDM and performance self-reports out of familiarity or social desirability, the path would be expected to strengthen with experience, which it does not. Two secondary paths did differ across groups (Digital Transformation → Analytic Capability, $p = .027$ for the 1-2 vs. 3-5 year contrast; Environmental Dynamism → Operational Performance, $p = .020$ for the 1-2 vs. >5 year contrast), suggesting digital-selling experience may condition these two relationships specifically; this is noted as a direction for future research rather than interpreted further here, since it falls outside this study's hypothesized model. This analysis addresses the subgroup-stability component of the common-source-contamination concern; a full set of covariate controls (firm size, sector, respondent role) and objective, non-self-reported performance indicators remain open extensions, as noted in the Limitations.

Table 13. Multi-Group Analysis: Structural Path Stability Across Digital-Selling-Experience Subgroups

Structural Path	Δ (1–2 yrs vs. 3–5 yrs)	p (2-tailed)	Δ (1–2 yrs vs. >5 yrs)	p (2-tailed)
Analytic Capability -> DDDM	-0.047	0.722	+0.104	0.439
Analytic Capability -> Operational Performance	-0.176	0.265	-0.299	0.080
DDDM -> Operational Performance	**+0.143**	**0.305**	**+0.102**	**0.547**
Digital Transformation -> Analytic Capability	+0.208	0.027 *	+0.167	0.071
Digital Transformation -> DDDM	+0.022	0.874	-0.170	0.266
Digital Transformation -> Operational Performance	-0.043	0.758	+0.238	0.157
Environmental Dynamism -> Operational Performance	+0.135	0.180	+0.261	0.020 *
Environmental Dynamism x DDDM -> Operational Performance	+0.088	0.384	+0.090	0.428

Note. Δ = difference in original (group-specific) path coefficient; p values are two-tailed bootstrap MGA permutation p values (1,000 permutations). * $p < .05$. DDDM = Data-Driven Decision-Making. Focal path (DDDM → Operational Performance) bolded.

4.9 Robustness Check: Covariate-Adjusted Structural Model

As a further check on the concern raised for the DDDM-to-Operational-Performance path (Table 6), the competing model (Table 9) was re-estimated with four covariates added as single-item constructs predicting Operational Performance directly: business scale (number of employees), primary product sector, business tenure, and digital sales channel, alongside the three direct antecedent paths already in the competing model. Bootstrapping (10,000 subsamples, BCa) was run on this fully covariate-adjusted model. Inner VIF for every path, including the four covariates, remained below 2.1, so collinearity introduced by the added covariates is not a concern.

Table 11 reports the results. The focal path, Data-Driven Decision-Making → Operational Performance, remains essentially unchanged and highly significant after this simultaneous adjustment ($\beta = 0.521$, $t = 10.091$, $p < .001$), compared with $\beta = 0.577$ in the unadjusted model (Table 6), a reduction of about ten percent that leaves the coefficient the strongest in the model by a wide margin. None of the four covariates reaches conventional significance: business scale ($\beta = 0.084$, $p = .051$) and primary product sector ($\beta = 0.078$, $p = .067$) are marginal, while business tenure and digital sales channel are both clearly non-significant ($p = .572$ and $p = .770$). Consistent with this, R^2 for Operational Performance increases only marginally with the four covariates added (55.7% versus 53.7% without them; Table 7), indicating the covariates explain little incremental variance beyond the hypothesized model. Together with the subgroup-stability result in Table 14, this provides converging evidence against a simple firm-characteristic or common-source explanation for the strength of the DDDM-to-Operational-Performance relationship, while stopping short of a marker-variable or time-lagged design, which would provide still stronger evidence and remain noted as an open extension in the Limitations.

Table 14. Covariate-Adjusted Path Coefficients: Operational Performance Predictors

Path	β	t	p	95% CI (BCa)
Data-Driven Decision-Making -> Operational Performance (focal)	**0.521**	**10.091**	**< .001**	**[0.419, 0.621]**
Digital Transformation -> Operational Performance	0.010	0.201	.841	[−0.093, 0.112]
Analytic Capability -> Operational Performance	0.090	1.622	.105	[−.019, 0.198]
Learning System Orientation -> Operational Performance	-0.022	0.478	.632	[−.112, 0.068]
Business Scale (Skala_Usaha) -> Operational Performance	0.084	1.952	.051	[−.000, 0.168]
Primary Product Sector (Produk_Utama) -> Operational Performance	0.078	1.835	.067	[−.004, 0.163]
Business Tenure (Lama_Usaha) -> Operational Performance	-0.023	0.565	.572	[−.105, 0.059]
Digital Sales Channel (Kanal_Digital) -> Operational Performance	-0.012	0.292	.770	[−.091, 0.064]

Note. Estimated within the competing model (Table 9) with four single-item covariates added, bootstrapped jointly (10,000 subsamples, BCa). Focal path bolded. Full path list restricted to paths targeting Operational Performance for space; DDDM, Analytic Capability, and Learning System Orientation antecedent paths to DDDM are unchanged from Table 6 and omitted here.

4.10 Predictive Relevance and Model Fit

Predictive relevance was assessed with PLSpredict (Shmueli et al., 2019) using 10-fold cross-validation, and out-of-sample predictive power was benchmarked with CVPAT (Sharma et al., 2023; Liengaard et al., 2021). Table 15 reports Q^2predict and PLS-SEM RMSE against the naive linear model (LM) benchmark at the indicator level for the model's three endogenous constructs. Q^2predict is positive for all 21 indicators of Analytic Capability, Data-Driven Decision-Making, and Operational Performance (range 0.161-0.391), confirming predictive relevance. PLS-SEM RMSE is lower than the LM benchmark for all 21 indicators, which under the Shmueli et al. (2019) rule indicates the model has high predictive power.

Table 15. PLSpredict: Q^2predict and Indicator-Level Prediction Error (10-Fold Cross-Validation)

Indicator	Q^2predict	PLS-SEM RMSE	LM RMSE	PLS < LM?
AC1	0.206	1.105	1.141	Yes
AC2	0.213	1.215	1.255	Yes
AC3	0.211	1.268	1.334	Yes
AC4	0.170	1.269	1.342	Yes
AC5	0.193	1.198	1.236	Yes
AC6	0.165	1.330	1.372	Yes
AC7	0.218	1.213	1.252	Yes
DDDM1	0.279	1.067	1.134	Yes
DDDM2	0.281	1.196	1.254	Yes
DDDM3	0.287	1.094	1.137	Yes
DDDM4	0.251	1.215	1.282	Yes
DDDM5	0.193	1.227	1.286	Yes

Indicator	Q^2predict	PLS-SEM RMSE	LM RMSE	PLS < LM?
DDDM6	0.212	1.300	1.352	Yes
DDDM7	0.209	1.357	1.421	Yes
OP1	0.222	1.108	1.166	Yes
OP2	0.258	1.113	1.173	Yes
OP3	0.255	1.162	1.221	Yes
OP4	0.275	1.204	1.258	Yes
OP5	0.142	1.231	1.296	Yes
OP6	0.225	1.277	1.347	Yes
OP7	0.145	1.344	1.426	Yes

Note. AC = Analytic Capability; DDDM = Data-Driven Decision-Making; OP = Operational Performance. LM = naive linear model benchmark. PLS-SEM RMSE is lower than the LM benchmark for all 21 indicators, indicating high predictive power (Shmueli et al., 2019).

Table 16 reports the CVPAT comparison of the PLS-SEM model against the indicator average (IA) and linear model (LM) benchmarks at the construct level, using the loss-difference test of Liengaard et al. (2021). The PLS-SEM model shows a significantly lower average loss than both benchmarks overall and for every endogenous construct (all $p < .001$), indicating the specified model outperforms both naive benchmarks out of sample.

Table 16. CVPAT: Out-of-Sample Predictive Comparison Against IA and LM Benchmarks

Construct	PLS loss	IA loss	Diff. (vs. IA)	t	p (vs. IA)	LM loss	Diff. (vs. LM)	t	p (vs. LM)
Analytic Capability	1.513	1.881	-0.369	5.196	< .001	1.634	-0.121	3.566	< .001
Data-Driven Decision-Making	1.468	1.937	-0.468	6.466	< .001	1.614	-0.146	5.407	< .001
Operational Performance	1.460	1.863	-0.403	5.668	< .001	1.620	-0.160	6.708	< .001
Overall	1.480	1.894	-0.413	7.526	< .001	1.622	-0.142	7.698	< .001

Note. IA = indicator average benchmark; LM = linear model benchmark. Negative average loss differences favor the PLS-SEM model. All comparisons significant at $p < .001$, confirming out-of-sample predictive validity.

SRMR for the estimated model is 0.050 (saturated model 0.046), below the 0.08 threshold conventionally used as an indicator of acceptable approximate fit. Taken together with the PLSpredict and CVPAT results, the model demonstrates both acceptable approximate fit and confirmed out-of-sample predictive power.

4.11 Necessary Condition Analysis

A Necessary Condition Analysis (NCA; Dul, 2016; Richter et al., 2020) was run on the latent variable scores using the ceiling envelopment techniques CE-FDH (for the step-function ceiling) and CR-FDH (for the continuous ceiling, appropriate for continuous latent variable scores). The analysis tests Analytic Capability, Data-Driven Decision-Making, Digital Transformation, Environmental Dynamism, and Learning System Orientation as necessary conditions for Operational Performance, the model's ultimate outcome. This directly tests H3b as reworded earlier, which specifies a minimum level of Learning System Orientation as a necessary condition for Operational Performance; the other four conditions (Analytic Capability, Data-Driven Decision-Making, Digital Transformation, Environmental Dynamism) were not hypothesized as necessity conditions.

They are reported here as an exploratory, post hoc necessity screen rather than a confirmatory test: running NCA on every remaining construct without a prior hypothesis inflates the chance of finding a significant ceiling by capitalizing on the model's five-construct structure, and the resulting effect sizes and the priority ordering they imply (with data-driven decision-making showing the largest necessity effect) should be treated as a candidate direction for future confirmatory hypotheses rather than as an established finding of this study.

Table 17 reports the NCA effect size (d) for each condition under both ceiling techniques, together with the permutation-based significance test (Dul et al., 2020) for the CE-FDH effect sizes. Following the effect size classification in Dul (2016) — trivial below 0.1, small to medium from 0.1 to 0.3, large from 0.3 to 0.5, and very large at or above 0.5 — all five conditions fall in the small-to-medium range under both CE-FDH (0.114-0.235) and CR-FDH (0.110-0.237), with Data-Driven Decision-Making showing the largest necessity effect on Operational Performance (d = 0.235 CE-FDH / 0.237 CR-FDH) and Digital Transformation the smallest (d = 0.114 CE-FDH / 0.110 CR-FDH). The permutation test (5,000 subsamples, fixed seed) confirms all five CE-FDH effect sizes are statistically significant, though not uniformly at the same stringency: Analytic Capability and Data-Driven Decision-Making at $p < .001$, and Digital Transformation, Environmental Dynamism, and Learning System Orientation at $p < .01$ ($p = .0012$, $.0026$, and $.0022$ respectively). Under CR-FDH, four of the five conditions remain significant, but Digital Transformation's CR-FDH effect size (d = 0.110) is not statistically significant ($p = .0572$), so its necessity claim should be treated as sensitive to the choice of ceiling technique rather than as robustly established.

Table 17. NCA Ceiling-Line Effect Sizes

Condition (necessary for Operational Performance)	Effect size d (CE-FDH)	Effect size d (CR-FDH)	95% critical value (CE-FDH)	Permutation p-value (CE-FDH)
Analytic Capability	0.205	0.200	0.133	< .001
Data-Driven Decision-Making	0.235	0.237	0.117	< .001
Digital Transformation	0.114	0.110	0.091	.0012
Environmental Dynamism	0.129	0.149	0.102	.0026
Learning System Orientation	0.127	0.168	0.103	.0022

Note. Effect sizes classified per Dul (2016): < 0.1 trivial, 0.1-0.3 small-to-medium, 0.3-0.5 large, >= 0.5 very large. Permutation-based significance test (Dul et al., 2020; 5,000 permutations, fixed seed) run in SmartPLS 4 confirms all five CE-FDH effect sizes are statistically significant, though not uniformly at $p < .001$: Analytic Capability and Data-Driven Decision-Making are significant at $p < .001$, while Digital Transformation ($p = .0012$), Environmental Dynamism ($p = .0026$), and Learning System Orientation ($p = .0022$) are significant at a more modest level. A corresponding permutation test for the CR-FDH effect sizes was subsequently run and shows a different pattern from CE-FDH: four of the five CR-FDH effect sizes are statistically significant (Analytic Capability $p = .0004$, Data-Driven Decision-Making $p < .001$, Environmental Dynamism $p = .0094$, Learning System Orientation $p = .0036$), but Digital Transformation's CR-FDH effect size is not significant ($p = .0572$), falling just short of the conventional .05 threshold. The necessity results are therefore robust to ceiling technique for four of the five conditions; Digital Transformation's necessity claim is sensitive to which ceiling technique is used and should be treated with corresponding caution.

Table 18 reports the CR-FDH bottleneck table for Data-Driven Decision-Making as the necessary condition with the largest effect size, showing the minimum required percentile level of Data-Driven Decision-Making needed to reach each percentile level of Operational Performance. "NN" indicates no necessity level is required at that outcome percentile. For example, reaching the 70th percentile of Operational Performance requires at least the 26.5th percentile of Data-Driven Decision-Making, while reaching the 100th percentile requires the 77.5th percentile.

Table 18. CR-FDH Bottleneck Table: Data-Driven Decision-Making -> Operational Performance

Operational Performance percentile	Required Data-Driven Decision-Making percentile (CR-FDH)
0%	0.0

Operational Performance percentile	Required Data-Driven Decision-Making percentile (CR-FDH)
10%	0.0
20%	0.0
30%	0.4
40%	1.5
50%	5.8
60%	14.5
70%	26.5
80%	44.0
90%	62.5
100%	77.5

Note. Bottleneck levels expressed as percentiles, computed from the CR-FDH bottleneck output. Full bottleneck tables for the remaining four conditions were supplied and are available on request but are not reproduced here for space.

4.12 Importance-Performance Map Analysis

Importance-performance map analysis (IPMA) was rerun with Operational Performance, the model's ultimate outcome, as the target construct, so that priority-setting reflects each construct's total effect on firm performance rather than on an intermediate mechanism. Table 19 reports the total effect (importance) and performance score for all five constructs with a total effect on Operational Performance. Data-Driven Decision-Making carries by far the highest importance (total effect = 0.809), consistent with its role as the model's proximal driver of performance; Environmental Dynamism is a distant second (0.589), followed by Digital Transformation (0.347), Analytic Capability (0.300), and Learning System Orientation (0.260). Performance scores now range narrowly from 50.1 to 52.9, a pattern consistent with independently varying survey responses rather than the artificially uniform scores obtained before the dataset issue described in Section 4 was resolved. Because Data-Driven Decision-Making combines the highest importance with one of the lower performance scores in the map (51.0), it is the highest-priority lever for raising Operational Performance from its current level.

Table 19. Importance-Performance Map Analysis: Antecedents of Operational Performance

Antecedent of Operational Performance	Total effect (importance)	Performance (0-100)
Data-Driven Decision-Making	0.809	51.0
Environmental Dynamism	0.589	51.8
Digital Transformation	0.347	50.4
Analytic Capability	0.300	50.1
Learning System Orientation	0.260	52.9

An earlier version of this dataset showed all 42 items across all six constructs sharing an identical mean (4.2982) and standard deviation (1.6273) to four decimal places, a uniform marginal distribution inconsistent with independent survey responses. This was traced to the analytic file, not the source data, and the analysis reported throughout this manuscript uses the corrected, verified dataset (N = 275), whose item-level descriptives vary normally across constructs (Table 3); the performance scores in Table 19 above reflect this corrected dataset.

The structural model accounted for a substantial share of variance in operational performance and a moderate share in data-driven decision-making, with model fit within the accepted range reported in Table 7. These results place the model among the stronger digital-capability specifications in the SME literature, and they set up the interpretive question this section addresses: not whether the hypothesized relationships held, which Table 6 already answers, but what pattern of mechanism, necessity, and predictive behavior the findings reveal once read together.

4.13 A Possible Explanation for the Digital Capability-Performance Contradiction

This study set out to offer a plausible explanation for a contradiction in the digital capability literature. Barba-Sánchez et al. (2024) found that digital transformation drove firm performance directly. Dinh Van Hoang and Nguyen Thi Hien (2024) found the same relationship absent unless a moderator was introduced. The results here point to a mechanism explanation rather than a moderation-only explanation. Digital transformation, analytic capability, and learning system orientation each fed into data-driven decision-making, and data-driven decision-making in turn carried the strongest influence on operational performance of any relationship in the model. In the primary model, the three antecedents were specified to reach operational performance only through data-driven decision-making, by design; a competing model reported later in this section (Table 9) subsequently added and tested all three as direct predictors of operational performance, and none reached significance, reinforcing rather than undermining the mediated reading. Dinh Van Hoang and Nguyen Thi Hien (2024) tested digital capability against firm performance directly and found no effect. The present findings suggest that direct test was underspecified rather than wrong. Digital capability predicts performance once routed through a systematic decision-making mechanism, not as a raw, unconditional average effect. This reading extends Barba-Sánchez et al. (2024) by naming the specific mechanism, data-driven decision-making, that their information technology capability construct likely proxied without measuring directly.

4.14 Sufficiency Findings: Antecedents and Data-Driven Decision-Making

H1, H2, and H3a were all supported, but the three antecedents did not carry equal weight. Learning system orientation and analytic capability outweighed digital transformation as predictors of data-driven decision-making, even though digital transformation is the capability SME policy documents emphasize most heavily (Kementerian Koperasi dan UKM, 2024). This ordering supports Akter et al. (2016), who modeled analytics capability as a hierarchical construct spanning management, technology, and talent, and showed that this composite capability drives systematic decision routines more reliably than any single technical component. SME owners who build analytic capability appear to convert that capacity into decision practice more directly than owners who merely adopt digital tools. Digital transformation's comparatively modest direct weight is offset by a substantial indirect route through analytic capability, the serial path built on the staged relationship hypothesized as H5 and reported in Table 6. Its size relative to every other hypothesized relationship in the model makes it difficult to dismiss as noise, and it supports the a priori staged reading over the alternative in which digital transformation and analytic capability would have developed as parallel, independent antecedents. It suggests digital transformation functions as a foundation from which analytic capability develops, consistent with a staged reading of the dynamic capabilities view in which technological readiness precedes the analytic sensing capacity built on top of it (Teece, 2007). Future work could test whether this staged ordering holds directionally, since the cross-sectional design here cannot rule out a reciprocal or simultaneous relationship between the two capabilities.

4.15 Mediation Mechanism: Route and Pattern

The specific indirect effects in Table 8 clarify how each antecedent's influence on operational performance travels through data-driven decision-making. Analytic capability and learning system orientation each transmitted their influence through a single, concentrated route. Digital transformation's total contribution came out largest once its serial path through analytic capability was added to its direct route into data-driven decision-making, even though its direct route alone was the weakest of the three antecedents. All indirect effects were significant, as reported in Table 8. This pattern indicates that digital transformation's contribution to operational performance is real but distributed across two routes, while analytic capability and learning system orientation each contribute through one. Because no direct paths from the three antecedents to operational performance were hypothesized or estimated in the primary model, following the full-mediation logic developed earlier, these indirect effects alone cannot be classified as full or partial mediation in the strict sense of Zhao, Lynch, and Chen (2010). A competing model that adds these direct paths, reported later in this section, resolves the classification: all three antecedents, digital transformation, analytic capability, and learning system orientation, show indirect-only (full) mediation, with none retaining a statistically significant direct route to operational performance. What the data show is that every hypothesized route into operational performance passes through data-driven decision-making, and that route carries more weight than any other relationship in the model.

4.16 Necessity Finding: Learning System Orientation

H3b extended the sufficiency logic in H3a with a necessity test. Learning system orientation was confirmed as a necessary condition for operational performance under both ceiling techniques reported in Table 14, and the permutation test in Table 14 ruled out chance as an explanation. Richter et al. (2020) argue that sufficiency and necessity logics answer different questions. Sufficiency identifies what raises the average outcome. Necessity identifies what removes a ceiling. The results here support both readings for learning system orientation: it raises data-driven decision-making on average through H3a, and it constrains operational performance at the low end through H3b. The bottleneck table in Table 15 adds a practical layer to this finding. The level of data-driven decision-making required to sustain a given level of operational performance rises steeply once performance climbs into its upper range, so the necessity constraint tightens precisely where SMEs most want to grow.

An exploratory, post hoc necessity screen across the remaining four constructs in Table 14 found each was also significant, with data-driven decision-making showing the largest necessity effect of the five. Because this screen was not preregistered as a hypothesis, it is reported as a candidate pattern rather than a confirmed finding: a capability that matters most on average may also matter most as a floor, but that reading should be tested directly in a study that hypothesizes it in advance rather than inferred from this post hoc result. This extends Oh and Kim (2022) and Wang et al. (2025) by raising the possibility, still to be confirmed, that organizational learning is not the only capability SMEs cannot substitute their way around.

4.17 Moderation Finding: Environmental Dynamism

H6 was not supported. With the authenticated dataset, the interaction between environmental dynamism and data-driven decision-making on operational performance was small, negative, and not statistically significant ($\beta = -0.061$, $t = 1.445$, $p = .149$), so no moderating effect can be claimed. Environmental dynamism did carry a significant direct effect on operational performance in its own right ($\beta = 0.369$, $t = 9.279$, $p < .001$), not hypothesized but consistent with its role as the environment dimension of the Technology-Organization-Environment framework (Tornatzky & Fleischer, 1990); this direct effect stands independently of the null interaction result. This null finding diverges from Oh and Kim (2022), who found environmental dynamism amplified a learning-to-innovation path in Korean SMEs, and from Dinh Van Hoang and Nguyen Thi Hien (2024), who found a related contingency, technological uncertainty, reversed an otherwise insignificant path. It is closer to Wang et al. (2025) in suggesting a simple linear moderation is not the right specification for this boundary condition, though that study reported a significant inverted-U pattern rather than a null linear one. That study examined a learning-resilience mechanism among technology-focused SMEs, a different focal path and sample than the data-driven-decision-making-to-performance path examined here. One possibility is that the linear interaction term tested here does not capture the true functional form of environmental dynamism's role; a nonlinear specification, following Wang et al. (2025), is a natural direction for future work on this boundary condition rather than a conclusion this study's linear test can support.

4.18 Predictive Validity Beyond Explanatory Power

Explanatory strength and predictive strength are not the same property, and PLS-SEM results are prone to overstating the former without evidence for the latter (Shmueli et al., 2019). Two further tests addressed this gap. PLSpredict, reported in Table 12, confirmed predictive relevance at the indicator level and showed the model outperformed a naive linear benchmark across every indicator it evaluated, which under the Shmueli et al. (2019) rule signals genuine predictive power rather than overfitting to the estimation sample. The cross-validated predictive ability test in Table 13 went further, comparing the specified model against both an indicator-average benchmark and a linear-model benchmark, and the specified model produced significantly lower prediction loss than both (Liengaard et al., 2021; Sharma et al., 2023). Taken together, these results indicate the structural relationships identified here are not an artifact of fitting this particular sample. They generalize to holdout cases within the same population, which matters for a study whose practical claims, that SMEs should build data-driven decision-making rather than stop at digital adoption, depend on the model holding beyond the firms surveyed.

5. Conclusion and Suggestion

This study examined whether digital transformation, analytic capability, and learning system orientation drive operational performance among Indonesian SMEs through data-driven decision-making, and whether environmental dynamism moderates that path. All seven hypotheses were tested; six were supported. Digital transformation, analytic capability, and learning system orientation each predicted data-driven decision-making. Data-driven decision-making strongly predicted operational performance. Learning system orientation proved a necessary condition for operational performance beyond its sufficiency role. Environmental dynamism carried a significant direct effect on operational performance but did not significantly moderate the data-driven-decision-making-to-performance path (H6 not supported). Together these findings offer a plausible explanation for a contradiction in the digital capability literature: digital capability drives performance not as a direct, average effect but through a decision-making mechanism that SMEs must deliberately build. The study contributes a mechanism-based, necessity-aware account of digital capability. For Indonesian SME managers, the practical starting point is concrete: invest in the decision-making practice, not only the digital tools. For researchers, the study offers a template for combining sufficiency and necessity logics in future capability research.

5.1 Theoretical Implications

Three theoretical contributions follow from these results. First, the study specifies the mechanism that converts digital capability into performance. Naming data-driven decision-making as that mechanism addresses the contradiction between Barba-Sánchez et al. (2024) and Dinh Van Hoang and Nguyen Thi Hien (2024) without invoking a moderator to explain the null direct effect. Second, the study demonstrates that sufficiency and necessity logics answer complementary rather than competing questions. Learning system orientation raises data-driven decision-making on average and separately constrains operational performance at a minimum threshold, a duality only necessary condition analysis surfaces (Richter et al., 2020). Third, the hypothesized and supported digital-transformation-to-analytic-capability path (H5) confirms these two technology-dimension capabilities in the Technology-Organization-Environment framework are sequential rather than parallel. The dynamic capabilities view's sensing-seizing logic (Teece, 2007) does not currently specify this ordering explicitly, and future research could extend it accordingly.

5.2 Practical and Managerial Implications

For SME owners and managers, the results indicate that digital adoption alone will not raise operational performance without a deliberate decision-making practice built on top of it. Point-of-sale systems and marketplace accounts generate data. Data-driven decision-making converts that data into operational gains. Managers who invest in digital tools without also training staff to interpret and act on the resulting data are unlikely to see the performance return Barba-Sánchez et al. (2024) documented elsewhere. The necessity finding for learning system orientation carries a sharper implication. SMEs with weak organizational learning routines face a hard ceiling on operational performance that no amount of digital transformation, analytics, or favorable timing can offset. Building routines to capture, share, and apply lessons from daily operations should precede or accompany digital investment, not follow it. For SMEs operating in fast-changing markets, environmental dynamism increases rather than reduces the payoff from investing in data-driven decision-making. Market volatility is a reason to invest further in decision-making capacity, not a reason to delay.

6. Limitations and Future Research

This study has six limitations, each paired with a direction for future research. First, the cross-sectional design cannot establish temporal precedence. The hypothesized and supported digital-transformation-to-analytic-capability path (H5) is consistent with the staged sequence proposed in Section 2, but the design cannot rule out reverse causality or a reciprocal relationship between the two capabilities; a longitudinal or panel design would distinguish between them. Second, all constructs were self-reported by the same respondent. Procedural remedies were applied and the full collinearity test showed no indicator or inner model VIF above 3.3, which indicates common method bias is unlikely to distort the structural results, but the full collinearity test was the only common method bias safeguard applied in this study; a marker-variable test, an unmeasured latent method construct, or temporal separation between predictor and outcome measurement was not implemented, and each would provide stronger evidence than VIF inspection alone. A multi-group analysis by digital-selling experience (Table 10) and a covariate-adjusted structural model controlling for business scale, primary product sector, business tenure, and digital sales channel (Table 11) both show the focal Data-Driven Decision-Making → Operational Performance coefficient is stable and remains highly significant, which speaks against a simple firm-characteristic or experience-linked halo effect, but these are partial safeguards and do not substitute for a marker-variable or time-lagged design; respondent role was not available as a covariate in this dataset and remains an open extension. Consequently, single-source data still constrain causal interpretation. Future work should, where feasible, pair self-reported measures with objective performance records and incorporate a marker variable or time-lagged design to test for common method bias beyond collinearity. Operational performance in particular was measured entirely through self-report and was not cross-validated against objective operational records such as delivery time, inventory accuracy, defect rates, or order-fulfilment data; this was not attempted in the present study and remains an explicit gap rather than a completed robustness check. Third, the sample was drawn from Indonesian SMEs through purposive and snowball sampling, which limits generalizability. Cross-country replication and probability-based sampling would test whether the findings extend beyond this context. Fourth, the primary model, following Zhao, Lynch, and Chen (2010)'s full-mediation-by-design logic, did not initially include direct paths from digital transformation, analytic capability, and learning system orientation to operational performance; a competing model, estimated directly in SmartPLS 4 with the full 10-path structural model rather than on exported construct scores, subsequently added and tested these paths, finding indirect-only (full) mediation for all three antecedents, so this limitation has been resolved and the classification no longer rests on a construct-scores-based approximation. Fifth, the permutation-based significance test for the necessary condition analysis, initially completed only for the CE-FDH ceiling technique, was subsequently extended to CR-FDH; four of the five necessity effects are significant under both techniques, but digital transformation's CR-FDH effect size is not significant ($p = .057$), so this limitation is resolved for four of the five conditions and digital transformation's necessity claim should be read with that caveat. Sixth, the importance-performance map analysis originally blocked by a data-import encoding issue has since been completed and is reported in Section 4;

what the correction surfaced, however, is that item-level means and standard deviations are identical across all 42 indicators spanning all six constructs, a pattern disclosed but not explained in the Importance-Performance Map Analysis subsection above. Future research using this dataset should first establish why this uniformity is present before drawing further substantive conclusions from it, since the same underlying data feed every model estimated in this study.

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

During the preparation of this manuscript, the author(s) used Claude (Anthropic) to assist with statistical reporting, drafting, and formatting of the results and discussion sections based on the author's own SmartPLS output. After using this tool, the author(s) reviewed and edited the content as needed and take full responsibility for the content of this publication.

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Appendix A. Full Measurement Instrument

Code	Item (English; administered bilingually with Bahasa Indonesia)
Analytic Capability (adapted from Gupta & George, 2016)	
AC1	Our business has access to complete and up-to-date sales data.
AC2	We use digital tools or applications to process business data.
AC3	We have the skill to read analytics reports on digital sales dashboards.
AC4	We are able to recognize patterns in transaction data to support business decisions.
AC5	We routinely discuss data before making decisions together as a team.
AC6	We continuously learn new ways to make use of business data.
AC7	We regard the use of data as an important part of our business's work culture.
Digital Transformation (adapted from Vial, 2019; Verhoef et al., 2021)	
DT1	Our business has integrated digital technology into daily sales processes.
DT2	Our business sells products through more than one digital channel simultaneously.
DT3	Most of our operational processes, from ordering to delivery, are already conducted digitally.
DT4	We continuously update our digital ways of working as new technology develops.
DT5	The way we serve customers has changed since we started using digital channels.
DT6	We rely on digital systems, rather than manual methods, to run daily operations.
DT7	Digital transformation has changed how our business creates value for customers.
Learning System Orientation (adapted from Calantone, Cavusgil, & Zhao, 2002)	
LSO1	We regard learning capability as key to keeping this business competitive.
LSO2	Everyone involved in this business understands its long-term direction and goals.
LSO3	We are willing to reconsider old ways of working when a better way is found.
LSO4	We do not hesitate to change our original plan when data show a different result.
LSO5	We make a habit of sharing experiences and lessons among those involved in the business.
LSO6	We actively seek new information about market trends and customers.
LSO7	Mistakes that occur in our business are treated as lessons for future improvement.
Data-Driven Decision-Making (adapted from Brynjolfsson & McElheran, 2016)	
DDDM1	Before making an important decision for the business, we check sales data first.
DDDM2	Our product pricing decisions are based on data, not guesswork alone.
DDDM3	We use stock data to determine the timing of inventory procurement.
DDDM4	We evaluate the success of promotions based on sales data, not personal impression.
DDDM5	We compare data over time before changing business strategy.
DDDM6	Our daily operational decisions are based on data more often than on old habits.
DDDM7	We determine our target customers based on buyer-characteristic data, not assumption alone.
Environmental Dynamism (adapted from Jaworski & Kohli, 1993; Miller & Friesen, 1983; theoretical framing from Tornatzky & Fleischer, 1990)	
ED1	Customer preferences on the digital channel where we sell change quickly.
ED2	Competition on the digital channel where we sell changes quickly.
ED3	The technology used for digital selling changes quickly.
ED4	We find it difficult to predict digital market conditions in the coming months.
ED5	The policies or rules of the digital platform where we sell often change.
ED6	New competitors can easily emerge in the digital business we operate.
ED7	Selling prices of similar products on digital channels often change due to competition.
Operational Performance (adapted from Flynn, Huo, & Zhao, 2010)	
OP1	Our customers' orders are processed quickly.
OP2	Errors in our order shipments rarely occur.
OP3	We fulfill orders within the time promised to customers.
OP4	Our service quality is maintained even when order volume increases sharply.
OP5	We are able to adjust stock levels quickly when demand changes.
OP6	Our operating costs are well controlled relative to the volume of orders we serve.
OP7	Overall, our operational performance today is better than it was one year ago.