

Orchestrating Digital Transformation Capability and Business Model Innovation to Turn External Pressure into Firm Performance

Kevin Khoe^{1*)}; Hesti Maheswari ²⁾

¹⁾ kevin.khoe.kk@gmail.com, Universitas Prasetiya Mulya, Jakarta, Indonesia

²⁾ hesti.maheswari@prasetyamulya.ac.id, Universitas Prasetiya Mulya, Jakarta, Indonesia

*) Corresponding Author

ABSTRACT

Objectives: In emerging economies it remains unclear how external pressure (EP) is associated with firm performance (FP), because prior studies treat pressure as a moderator and capabilities in isolation. This study examines the sequential mediation EP → digital transformation capability (DTC) → business model innovation (BMI) → FP. No moderation effects are tested.

Methodology: A higher-order PLS-SEM model grounded in the Technology–Organization–Environment framework and the Dynamic Capabilities View, with formative EP and DTC constructs, is estimated on survey data from 206 Indonesian manufacturers, controlling for firm size.

Finding: EP is strongly associated with DTC ($\beta = 0.864$), DTC with BMI ($\beta = 0.709$), and BMI with FP ($\beta = 0.846$). The indirect EP–BMI association through DTC ($\beta = 0.612$) is over three times the direct one ($\beta = 0.192$; VAF = 76.1%). The DTC–FP association is consistent with full mediation by BMI, as the direct path is not significant when estimated ($\beta = 0.173$, $p = 0.363$). PLSpredict and CVPAT indicate predictive relevance.

Conclusion: External pressure is associated with higher performance mainly when it is accompanied by digital capability and business model renewal. Because the data are cross-sectional, these relationships are read as associations, not causal effects.

Keywords: Digital Transformation Capability; Business Model Innovation; External Pressure; Manufacturing Industry; Firm Performance.

Submitted: 17-06-2026

Revised: 25-09-2026

Accepted: 13-10-2026

Article Doi:

http://dx.doi.org/10.22441/jurnal_mix.2026.v16i3.002

INTRODUCTION

A simple paradox sits at the heart of the digital transformation literature. External pressure on firms keeps rising, yet about 70% of digital transformations fall short (Forth et al., 2020), and 88% of business transformations miss their original ambitions (Bain & Company, 2024). Since the pandemic, the spread of artificial intelligence, Industry 4.0 automation, and platform competition has given firms far less time to adapt (Iansiti & Lakhani, 2020). This compression is most acute in emerging economies, where institutional weakness, limited infrastructure, and survival-level pressure converge. The real puzzle, then, is not whether pressure pushes firms to change, because it clearly does. The puzzle is why the same pressure produces such different results from one firm to the next, and why existing frameworks explain this only in part.

This study argues that the missing piece is a firm's dynamic capability to sense opportunities, seize them, and reconfigure digital resources into renewed value (Teece, 2007; Davenport & Westerman, 2018). Drawing on the microfoundations of dynamic capabilities (Helfat & Raubitschek, 2018), we call this bundle Digital Transformation Capability (DTC). It is a higher-order capacity that brings organizational readiness, digital capability, and digital supply-chain coordination together into one orchestrated whole (Li et al., 2018; Warner & Wäger, 2019). DTC is therefore not a mere portfolio of digital tools. It is the capability through which external pressure (EP) is expected to relate to business model innovation (BMI) and, in turn, to firm performance (FP). The sequence we test is $EP \rightarrow DTC \rightarrow BMI \rightarrow FP$.

External pressure here combines technological turbulence, competitive pressure, and government regulation, which in Indonesian manufacturing often act together and are therefore modeled jointly (Tornatzky et al., 1990). Manufacturing still generates 18.7% of national value added (World Bank, 2023), yet 61 textile factories closed in 2023 and 2024, leaving about 14,000 workers idle (BenarNews, 2024; Jakarta Globe, 2024). Firms under similar pressure end up in different places. Fujifilm met the collapse of the film market by reconfiguring its capabilities and renewing its business model (Teece, 2018). Sri Rejeki Isman, once the country's largest textile producer, went bankrupt under import competition and regulatory change without comparable renewal (Tempo, 2024), and Sepatu Bata closed its plant after seven decades (Detik, 2024). The difference lies less in the pressure itself than in whether it was met with capability building and business model innovation.

Three streams of research speak to this puzzle, but each leaves it unresolved on its own. The technology, organization, and environment (TOE) framework treats adoption as the joint product of three forces, yet it usually casts pressure as a moderator rather than a force that actually builds capability (Tornatzky et al., 1990; Chatterjee et al., 2022). The dynamic capabilities view (DCV) describes renewal as sensing, seizing, and reconfiguring, but it often measures capabilities as scattered first-order resources instead of one orchestrated whole (Teece, 2007; Warner & Wäger, 2019). The business model innovation literature points to value-creation logic as the mechanism that converts effort into results, yet it rarely tests the full pathway from pressure to performance (Foss & Saebi, 2017; Hanelt et al., 2021). What is still missing, especially in emerging-economy manufacturing, is an integrated model that shows how pressure relates to orchestrated capability, which is in turn associated with business model innovation and performance.

Two research questions guide the study. First (RQ1), is external pressure associated with firm performance mainly through DTC and BMI rather than directly? Second (RQ2),

does BMI fully mediate the link between DTC and firm performance? Using PLS-SEM on 206 Indonesian manufacturers, the study combines TOE and the dynamic capabilities view in one sequential model; its contributions are set out in the Theoretical Implications. The paper now turns to the literature review, the method, the results and discussion, and the conclusion.

LITERATURE REVIEW

Theoretical Foundation

The study rests on two complementary lenses that answer different questions. The technology, organization, and environment (TOE) framework explains why firms act, and it points to environmental forces as the decisive trigger (Tornatzky et al., 1990). The dynamic capabilities view (DCV) explains how firms renew themselves, by sensing, seizing, and transforming their resources as the environment shifts (Teece, 2007; Schilke, 2014). Read together, the two lenses suggest a natural sequence in which environmental pressure sets capability-building in motion.

External Pressure

External pressure (EP) is the bundle of environmental forces that reshape a firm's strategic choices, namely technological turbulence, competitive pressure, and government regulation (Tornatzky et al., 1990). Institutional theory adds detail here. Coercive, normative, and mimetic pressures all push firms toward digital alignment in search of legitimacy (DiMaggio & Powell, 1983; Oliver, 1991). In emerging economies this pressure speeds up adoption, but it stalls when firms do not have the absorptive capacity to act on it (Chatterjee et al., 2022).

Digital Transformation Capability

DTC is the answer to that shortfall. Li et al. (2018) define it as a firm's ability to integrate digital technologies, internal processes, and coordination across organizations while the environment keeps shifting, and Warner and Wäger (2019) stress that this ability has to be reconfigured continuously. More recent work treats DTC as one orchestrated configuration that weaves together organizational readiness, digital capability, and digital supply chain (Helfat & Raubitschek, 2018). Its three dimensions are the organizational domains in which the sensing, seizing, and reconfiguring processes of the DCV take place: digital capability supports sensing, organizational readiness supports seizing, and digital supply chain supports reconfiguring across firm boundaries (Teece, 2007, 2018). We measure the domains rather than the processes because managers can assess them more reliably; the mapping is a correspondence, not a formal decomposition.

Business Model Innovation

If capability is the engine, business model innovation (BMI) is where that engine does its work. BMI is about how a firm creates, delivers, and captures value, whether through new activities or a reworked revenue logic (Foss & Saebi, 2017). Within a transformation, it is the step that turns capability into operational and strategic advantage (Helfat & Raubitschek, 2018). In emerging-economy manufacturing in particular, business model innovation tends to follow the consolidation of digital capability rather than precede it (Balta et al., 2024).

Firm Performance

Firm performance (FP) is the outcome the chain has to reach. It is a multidimensional construct that spans efficiency, competitiveness, and operational effectiveness (Venkatraman & Ramanujam, 1986; Bharadwaj et al., 2013). The link between digital investment and performance is not automatic. It depends on how digital resources are reconfigured, and this is especially true in emerging economies (Chatterjee et al., 2022). Recent evidence singles out business model innovation as the main channel that converts digital capability into performance (Hanelt et al., 2021; Vial, 2019).

State of the Art and Research Gap

Evidence from emerging-economy manufacturing points the same way. Industry 4.0 readiness in Indonesian manufacturing depends on organizational as well as technological factors (Ginting et al., 2026), Brazilian manufacturers gain from digital technologies only when these are integrated with operations (Frank et al., 2019), and large Colombian manufacturers show a gap between readiness and adoption (Alpala et al., 2026). Among Indonesian SMEs, competition is associated with performance partly through digital transformation (Prihandono et al., 2024). Putting these literatures side by side exposes a tension. TOE treats pressure as a moderating backdrop rather than a force that actively builds capability (Tornatzky et al., 1990). DCV treats capability as the engine of renewal, yet it rarely tests the antecedents that feed the DTC bundle (Warner & Wäger, 2019). The BMI literature treats innovation as a lever for performance, but says little about the capability that sits upstream of it. To close this gap, we test a sequential model that links external pressure, DTC, BMI, and firm performance, and we ask whether capability is what carries pressure through to performance.

Hypothesis Development

External Pressure and Digital Transformation Capability

Institutional and adaptation logics point the same way. Environmental pressure is expected to set capability-building in motion. Coercive regulation, mimetic responses, and technological turbulence all raise the cost of standing still, and that cost pushes firms to invest in digital readiness and in coordination across organizations (DiMaggio & Powell, 1983; Tornatzky et al., 1990). The association is expected to be stronger where institutional volatility persists (Chatterjee et al., 2022; Wang et al., 2020).

H1: EP is positively associated with digital transformation capability.

Digital Transformation Capability and Business Model Innovation

Within the dynamic capabilities view, capability is what makes reconfiguration possible in the first place. Firms with stronger DTC already hold the routines they need to redesign how value is created, delivered, and captured (Teece, 2007, 2018), and they can integrate partners into renewed value architectures rather than acting in isolation (Li et al., 2018).

H2: Digital transformation capability is positively associated with business model innovation.

Business Model Innovation and Firm Performance

Business model innovation is where capability is expected to show in results. By realigning the value proposition, the cost structure, and the revenue logic around digital opportunities (Foss & Saebi, 2017), BMI gives a firm the flexibility, efficiency, and differentiation that translate into stronger performance (Peng & Tao, 2022).

H3: Business model innovation is positively associated with FP.

Mediating Role of Digital Transformation Capability

Taken together, the first three links imply a chain. If pressure is associated with innovation mainly through capability (H1 and H2), then DTC should carry the association between external pressure and BMI. This is exactly the role the dynamic capabilities view gives to capability, as the mechanism that converts an environmental stimulus into strategic renewal (Teece, 2007; Warner & Wäger, 2019).

H4: Digital transformation capability mediates the relationship between EP and business model innovation.

Direct Effect of External Pressure on Business Model Innovation

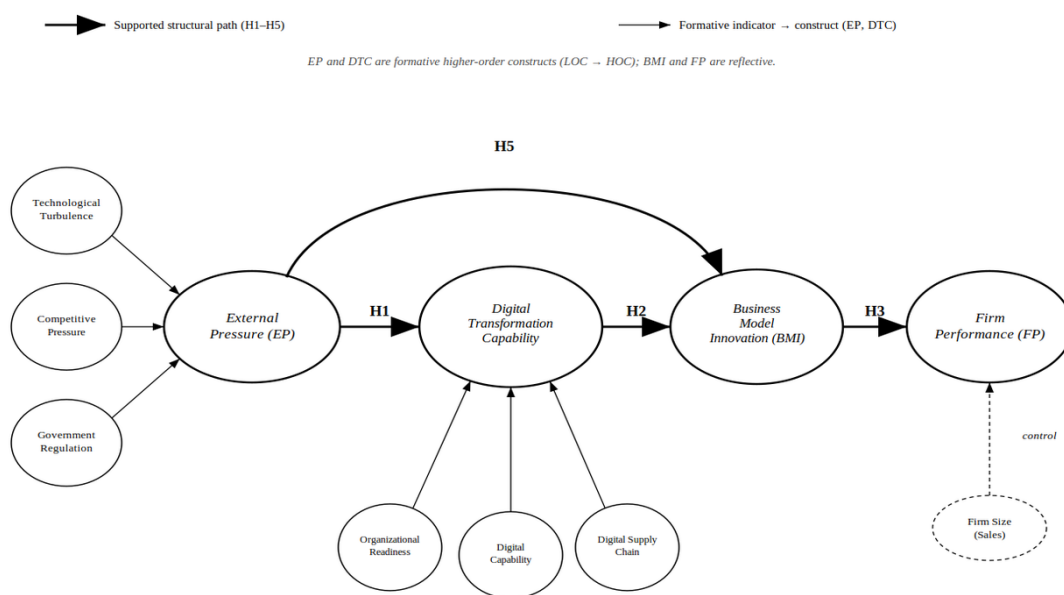
Pressure does not always wait for capability to mature. When capability is still developing, firms can respond to acute pressure with model adjustments that do not need deep digital orchestration, such as reactive repricing, channel reconfiguration, or the repackaging of products and services, all of which fit business model innovation under uncertainty (Foss & Saebi, 2017). Testing this direct path tells us whether business model change runs entirely through DTC, or also appears as an independent, reactive response to pressure, which would point to complementary partial mediation (Zhao et al., 2010).

H5: EP is directly and positively associated with business model innovation.

Theoretical Framework

Drawing the threads together, we propose that external pressure is associated with digital transformation capability, this capability with business model innovation, and innovation with firm performance. Digital transformation, on this account, is a sequential, capability-building process, and we test it in emerging-economy manufacturing (Figure 1).

Figure 1. Research Conceptual Model for the Present Study



Source: Authors' conceptualization

METHOD

Research Design

The study uses a quantitative, explanatory design to test the relationships among external pressure, DTC, BMI, and firm performance in Indonesian manufacturing. The design is grounded in the TOE framework and the dynamic capabilities view.

Sample and Data Collection Procedure

The target population was medium and large manufacturing firms in Indonesia. Because no register identifies managers with transformation experience, we used purposive sampling through business networks and professional relationships, reaching 250 prospective respondents from manufacturing and manufacturing-related businesses in DKI Jakarta, Banten, West Java, Central Java, East Java, and other regions; the records were not coded by KBLI subsector. A firm had to have adopted digital technologies in at least one operational, production, or managerial area and to have operated for at least five years; firm size was not screened but is controlled for. Invitations went out through WhatsApp and professional networks in November 2025, followed by two reminders. Of 219 returned questionnaires (87.6%), 13 failed the screening, leaving 206 usable responses from 206 firms (82.4%), collected between 6 and 17 November 2025.

We checked sample adequacy with the inverse square root method (Kock & Hadaya, 2018). With the most complex endogenous construct taking three predictors, a conservative minimum path coefficient of 0.2, a 5% significance level, and 80% power, the method calls for roughly 155 observations. Our sample of 206 clears that bar and also passes the ten-times rule (Hair et al., 2021), so statistical power is adequate.

Measurement Instruments

Data came from a structured questionnaire built on five-point Likert scales. We measured external pressure through technological turbulence, competitive pressure, and government regulation. DTC bundled organizational readiness, digital capability, and digital supply chain, while BMI and firm performance used indicators adapted from prior work; firm performance reflects managers' perceptions of performance gains, several of them linked to digital technology. One firm-performance indicator, Y.5, was removed because it cross-loaded on BMI, and dropping it improved discriminant validity (Hair et al., 2021). Respondent demographics appear in Table 1.

Table 1. Respondent Characteristics

Variable	Category	N	%
Gender	Male	111	53.88%
	Female	95	46.12%
Age	≤30 Years	64	31.07%
	31–40 Years	82	39.81%
	41–50 Years	44	21.36%
	>50 Years	16	7.77%
Education	High School (SMA/SMK)	24	11.65%
	Diploma (D1–D4)	29	14.08%
	Bachelor's Degree (S1)	135	65.53%
	Master's Degree (S2)	16	7.77%
	Doctoral Degree (S3)	2	0.97%
Job Position	Manager	109	52.91%
	Supervisor	66	32.04%
	C-Level Executive /	22	10.68%
	Director		
Department	Senior Manager	9	4.37%
	Supply Chain / Logistics	68	33.01%
	Production / Operations	57	27.67%
	Finance / Accounting	26	12.62%
	Sales & Marketing	22	10.68%
	Engineering &	10	4.85%
	Maintenance		
	Other	23	11.17%
Average Annual Sales (Past Two Years)	< Rp 100 Billion	74	35.92%
	Rp 100–250 Billion	39	18.93%
	Rp 250–500 Billion	21	10.19%
	Rp 500 Billion–1 Trillion	18	8.74%
	≥ Rp 1 Trillion	54	26.21%

Source: Processed Data (2026)

Data Analysis Procedure

We analyzed the data with PLS-SEM using a two-stage hierarchical component model, specifying external pressure and DTC formatively and BMI and firm performance reflectively. Stage 1 produced latent-variable scores for the lower-order constructs that make up higher-order DTC, namely organizational readiness, digital capability, and digital supply chain. Stage 2 then estimated the full chain $EP \rightarrow DTC \rightarrow BMI \rightarrow FP$, with the direct $EP \rightarrow BMI$ path included. We obtained significance from 5,000-subsample bootstrapping with bias-corrected and accelerated confidence intervals (Hair et al., 2021), and we examined out-of-sample relevance with PLSpredict and CVPAT. Firm size, measured as annual sales on a 1–5 ordinal scale, was entered as a control. Because the design is cross-sectional, we read the estimated paths as associational rather than strictly causal. An initial model also included direct $EP \rightarrow FP$ and $DTC \rightarrow FP$ paths; neither was significant and $DTC \rightarrow FP$ showed collinearity (inner VIF = 6.08), so both were dropped. Because this choice was partly data-informed, the full model is reported in Appendix Table A1.

Common Method Bias Assessment

Because all the data came from a single self-report source, we took common method bias seriously. While designing the instrument, we varied item wording to discourage patterned responding. We then assessed bias with two complementary tests. Harman's single-factor test showed that the first unrotated factor explained 38.7% of the variance, comfortably below the 50% threshold. More rigorously, the full-collinearity approach (Kock, 2015), which detects common variance at both the method and the model level, returned every VIF below 3.3, the conservative cut-off for concluding that a model is free of common method bias. Together, the two tests indicate that common method bias is not a serious concern here.

External pressure and DTC are specified as formative, following Jarvis et al. (2003), Becker et al. (2012), and Sarstedt et al. (2019): each dimension captures a distinct source of pressure or domain of capability, the dimensions are not interchangeable, and dropping one would change the meaning of the construct. The estimates agree. All weights are significant but unequal (0.335–0.471 for external pressure; 0.327–0.401 for DTC), and government regulation has a lower loading (0.745) and VIF (1.39) than the other pressure dimensions. The weights, loadings, and VIFs appear in Table 2.

Table 2. Formative Measurement Assessment (External Pressure and Digital Transformation Capability)

Construct	Indicator	Outer weight	t	p	Outer loading	VIF
External Pressure	Competitive Pressure	0.471	6.57	<0.001	0.901	2.31
	Government Regulation	0.335	5.34	<0.001	0.745	1.39
	Technological Turbulence	0.366	4.41	<0.001	0.890	2.45
Digital Transformation Capability	Digital Capability	0.401	4.92	<0.001	0.949	4.03
	Digital Supply Chain	0.327	4.62	<0.001	0.922	3.43
	Organizational Readiness	0.345	4.92	<0.001	0.919	3.15

Note. VIFs above 3.3 (digital capability, digital supply chain) indicate moderate collinearity; all VIFs are below 5.

Source: Processed Data (2026)

RESULTS AND DISCUSSION

Results

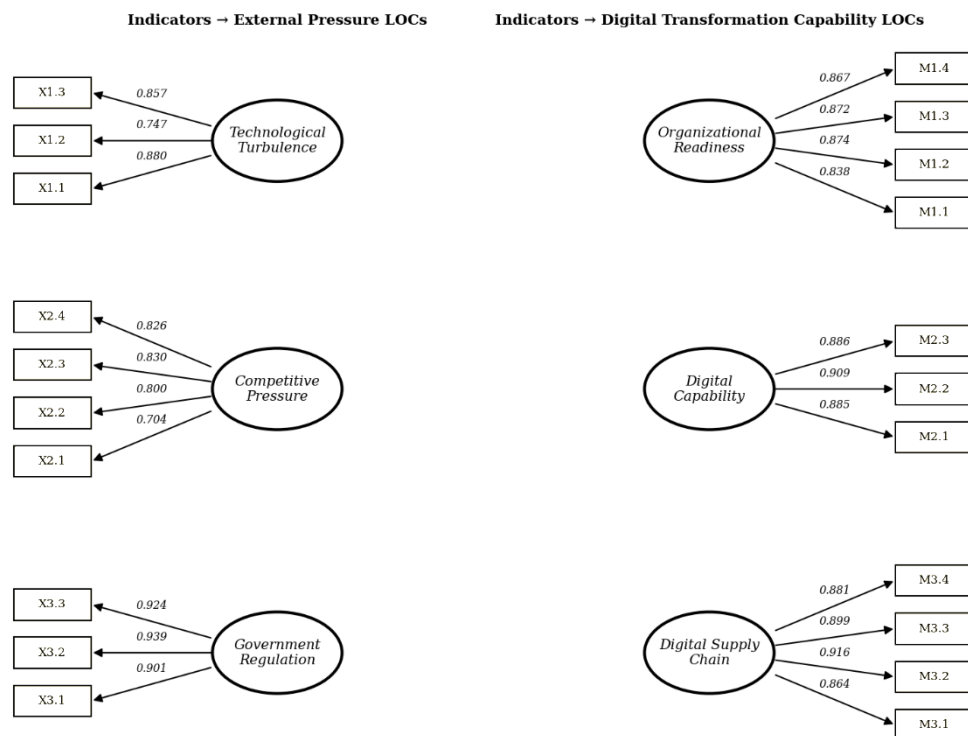
Respondent Characteristics

The 206 respondents cover a range of managerial and operational roles across Indonesian manufacturing, with managers making up 53%, supervisors 32%, C-level executives 11%, and senior managers 4%. They are concentrated in supply chain and logistics, production and operations, finance, and sales and marketing (Table 1).

Assessment of Measurement Model: Lower-Order Construct

We assessed the lower-order constructs in Stage 1 using outer loadings, Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and HTMT (Hair et al., 2021). We treated loadings, alpha, and CR above 0.70, AVE above 0.50, and HTMT below 0.85 as acceptable.

Figure 2. Modeling for Lower-Order Construct



Stage 1: Reflective measurement of the lower-order constructs (standardized loadings). LOC scores are then used as formative indicators of EP and DTC in Stage 2.

Source: Processed Data (2026)

The Stage 1 model is a measurement model: the first-order constructs were validated on their own (Figure 2), and their scores formed the higher-order constructs in Stage 2 (Becker et al., 2012).

Table 3 reports the Stage 1 results, and every construct clears the thresholds. Cronbach's alpha ranges from 0.772 to 0.913 and composite reliability from 0.869 to 0.944, both above 0.70, while AVE ranges from 0.627 to 0.849, above 0.50. The first-order constructs are therefore reliable and valid.

Table 3. Assessment of Reliability and Validity for LOC

Description	Cronbach's alpha	Composite reliability (rho a)	Composite reliability (rho c)	Average variance extracted (AVE)
Competitive Pressure	0.803	0.822	0.870	0.627
Digital Capability	0.874	0.874	0.922	0.798
Digital Supply Chain	0.913	0.915	0.939	0.793
Government Regulation	0.911	0.911	0.944	0.849
Organizational Readiness	0.886	0.886	0.921	0.745
Technological Turbulence	0.772	0.780	0.869	0.689

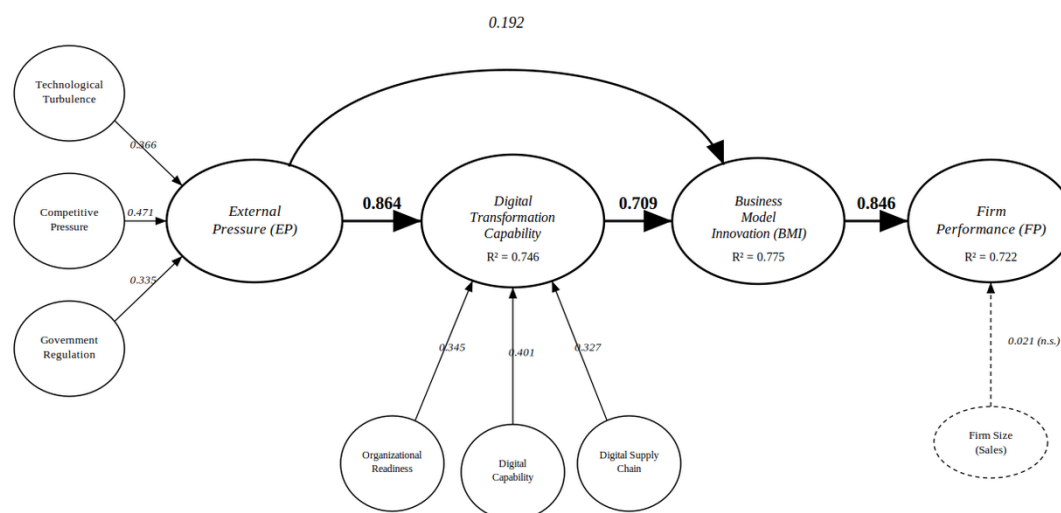
Source: Processed Data (2026)

Assessment of Measurement Model: Higher-Order Construct

In Stage 2, these dimension scores served as indicators of the two formative higher-order constructs, external pressure and Digital Transformation Capability. Because the constructs are formative, we assessed them through the significance of their indicator weights and through collinearity (VIF) rather than reflective criteria (Figure 3).

Figure 3. Modeling for Higher-Order Construct

Stage 2: Formative Higher-Order Structural Model (standardized estimates)



Control variable (firm size) added with a direct path to FP; effect non-significant. FP measured by four items (Y.1-Y.4) after removing Y.5.

Source: Processed Data (2026)

External pressure comprises Technological Turbulence, Competitive Pressure, and Government Regulation, and Digital Transformation Capability comprises Organizational Readiness, Digital Capability, and Digital Supply Chain. Both of these are formative, whereas Business Model Innovation and Firm Performance are reflective. In a formative construct, the dimensions define the construct rather than reflect it (Jarvis et al., 2003).

Table 4. Reflective Measurement Assessment (Business Model Innovation and Firm Performance)

Description	Cronbach's alpha	Composite reliability (rho _a)	Composite reliability (rho _c)	Average variance extracted (AVE)
Business Model Innovation	0.907	0.907	0.935	0.782
Firm Performance	0.890	0.894	0.924	0.752

Source: Processed Data (2026)

Table 4 indicates strong measurement quality for the two reflective constructs. Cronbach's alpha is 0.907 for Business Model Innovation and 0.890 for Firm Performance, composite reliability (rho_c) is 0.935 and 0.924 respectively, and average variance extracted is 0.782 and 0.752, both above 0.50.

Because external pressure and DTC are formative, we assess weight significance and collinearity. All weights are significant ($p < 0.001$) and loadings are high (0.745–0.949; Table 2). All VIFs are below 5 (Hair et al., 2022), but digital capability (4.03) and digital supply chain (3.43) exceed the stricter 3.3 threshold (Diamantopoulos & Siguaw, 2006), showing moderate overlap among the DTC dimensions. We keep all three, since dropping one would change the construct (Jarvis et al., 2003), but we do not read the DTC weights as a ranking of importance. External pressure and DTC are strongly associated ($\beta = 0.864$) yet distinct, as one captures environmental forces and the other organizational capabilities.

For the reflective constructs, the BMI–FP HTMT is 0.942 (95% CI [0.880, 0.986]; Table 5). The upper bound is below 1 (Henseler et al., 2015) but above 0.90, so the stricter test (Franke & Sarstedt, 2019) is not met. The square roots of AVE (BMI = 0.884; FP = 0.867) exceed the BMI–FP correlation (0.849) by a narrow margin, and every indicator loads higher on its own construct (Appendix Table A2). Three FP items mention digital technology, which may explain part of the overlap, so the BMI → FP coefficient is read as a strong association rather than a precise effect size.

Table 5. Discriminant Validity: Fornell-Larcker Criterion and HTMT (Reflective Constructs)

Construct	BMI	FP
Business Model Innovation	0.884	
Firm Performance	0.849	0.867

Note. Diagonal values (bold) are the square root of AVE; the off-diagonal value is the BMI–FP latent-variable correlation. Both $\sqrt{AVE}$ values (BMI = 0.884; FP = 0.867) exceed the inter-construct correlation (0.849), satisfying the Fornell-Larcker criterion. In addition, bootstrapping with 5,000 subsamples yields a 95% bias-corrected confidence interval for the BMI–FP HTMT of [0.880, 0.986]; the upper bound is below 1.0, meeting the HTMT inference criterion (Henseler et al., 2015), but above 0.90, so the stricter test (Franke & Sarstedt, 2019) is not met. HTMT values between the firm-size control (annual sales) and the reflective constructs are low (Sales–BMI = 0.161; Sales–FP = 0.156).

Source: Processed Data (2026)

The structural model has strong explanatory power. External pressure explains 74.6% of the variance in Digital Transformation Capability ($R^2 = 0.746$). External pressure and DTC together explain 77.5% of Business Model Innovation ($R^2 = 0.775$), and the model accounts for 72.2% of Firm Performance ($R^2 = 0.722$).

All five hypotheses are supported, in line with the EP → DTC → BMI → FP framework (two-tailed; Tables 6 and 7). The core paths are all significant: EP → DTC ($\beta =$

0.864), $DTC \rightarrow BMI$ ($\beta = 0.709$), and $BMI \rightarrow FP$ ($\beta = 0.846$), each at $p < 0.001$ (Table 6). The direct $EP \rightarrow BMI$ path is significant as well ($\beta = 0.192$; $p = 0.033$). In the full model (Appendix Table A1), neither direct path to performance is significant ($EP \rightarrow FP$: $\beta = 0.081$, $p = 0.357$; $DTC \rightarrow FP$: $\beta = 0.173$, $p = 0.363$), and the total indirect EP – FP association ($\beta = 0.656$, $p < 0.001$) far exceeds the direct one, which answers RQ1. $BMI \rightarrow FP$ is smaller there (0.630) than in the final model (0.846), so the latter is read as the estimate under the serial specification. Because $DTC \rightarrow FP$ is affected by collinearity, its non-significance, and hence full mediation, is read with caution.

Firm size showed no significant association with performance ($\beta = 0.021$; $t = 0.597$; $p = 0.551$; 95% BCa CI $[-0.047, 0.090]$), and the focal paths barely moved, which indicates robustness to firm size. Once business model innovation is in the model, larger firms hold no built-in advantage, so scale is neither a substitute for nor a precondition of the capability–performance link (Teece, 2018). The full estimates appear in Table 6.

Table 6. Structural Model Estimates with Firm-Size Control (Bootstrapping, 5,000 Subsamples)

Structural Path	β (O)	Mean (M)	STDEV	t	p	95% BCa CI
External Pressure $\rightarrow$ Digital Transformation Capability	0.864	0.863	0.026	33.527	<0.001	[0.805, 0.906]
Digital Transformation Capability $\rightarrow$ Business Model Innovation	0.709	0.716	0.090	7.865	<0.001	[0.508, 0.866]
External Pressure $\rightarrow$ Business Model Innovation	0.192	0.185	0.090	2.129	0.033	[0.031, 0.390]
Business Model Innovation $\rightarrow$ Firm Performance	0.846	0.844	0.032	26.368	<0.001	[0.774, 0.899]
Firm Size (Sales) $\rightarrow$ Firm Performance (control)	0.021	0.021	0.035	0.597	0.551	[-0.047, 0.090]

Note. BCa = bias-corrected and accelerated bootstrap confidence interval. R^2 (adjusted): $DTC = 0.746$ (0.745); $BMI = 0.775$ (0.773); $FP = 0.722$ (0.719). Effect sizes (f^2): $EP \rightarrow DTC = 2.934$; $DTC \rightarrow BMI = 0.567$; $EP \rightarrow BMI = 0.042$; $BMI \rightarrow FP = 2.510$; $Firm\ Size \rightarrow FP = 0.002$. All inner VIF values are below 5 (maximum = 3.934), indicating no problematic structural collinearity.

Source: Processed Data (2026)

The mediation analysis (Table 7) shows complementary partial mediation between external pressure and BMI through DTC. External pressure is associated with BMI both indirectly ($\beta = 0.612$; $p < 0.001$) and directly ($\beta = 0.192$; $p = 0.033$), and the indirect route accounts for 76.1% of the total effect. The direct paths from DTC and external pressure to performance are not significant in the full model (Appendix Table A1), so $DTC \rightarrow BMI \rightarrow FP$ is consistent with full mediation ($\beta = 0.600$), the serial chain $EP \rightarrow DTC \rightarrow BMI \rightarrow FP$ carries $\beta = 0.518$, and the total indirect effect of external pressure on performance is $\beta = 0.681$ (all $p < 0.001$).

Table 7. Specific and Total Indirect Effects with Bias-Corrected Confidence Intervals

Indirect Effect	β (O)	STDEV	t	p	95% BCa CI
EP → DTC → BMI	0.612	0.081	7.554	<0.001	[0.442, 0.763]
DTC → BMI → FP	0.600	0.085	7.061	<0.001	[0.424, 0.758]
EP → BMI → FP	0.163	0.076	2.138	0.033	[0.028, 0.333]
EP → DTC → BMI → FP (serial)	0.518	0.078	6.612	<0.001	[0.362, 0.673]
EP → FP (total indirect)	0.681	0.053	12.886	<0.001	[0.571, 0.773]

Note. EP = External Pressure; DTC = Digital Transformation Capability; BMI = Business Model Innovation; FP = Firm Performance. No bias-corrected confidence interval includes zero, indicating that all indirect effects are significant. The serial chain EP → DTC → BMI → FP accounts for 76.1% of EP's total indirect effect on FP (0.518/0.681), the remaining 23.9% via the direct EP → BMI → FP route (0.163).

Source: Processed Data (2026)

Robustness and Predictive Relevance

Beyond explanatory power, we examined out-of-sample relevance with PLSpredict and CVPAT (Table 8; Liengaard et al., 2021; Shmueli et al., 2019). Positive Q^2_{predict} values together with significant CVPAT loss differences point to predictive relevance, not merely explanatory fit.

Predictive Power Assessment (PLSpredict)

Every endogenous construct returns a positive Q^2_{predict} value, and DTC shows the strongest out-of-sample relevance (Q^2_{predict} 0.413–0.460), indicating predictive rather than merely explanatory power.

Cross-Validated Predictive Ability Test (CVPAT)

CVPAT (Table 8) yields the same conclusion. Every endogenous construct shows lower prediction loss than the indicator-average benchmark ($p < 0.001$), and at the overall model level the loss difference is negative and significant (-0.240 ; $t = 4.688$; $p < 0.001$), which indicates medium-to-strong out-of-sample predictive power.

Table 8. Cross-Validated Predictive Ability Test (CVPAT) Results

Construct	PLS Loss	IA Loss	Average Loss Difference	t-value	p-value	Interpretation
Business Model Innovation (BMI)	0.205	0.403	-0.198	4.744	<0.001	PLS significantly better
Digital Transformation Capability (DTC – HOC)	0.254	1.010	-0.756	5.000	<0.001	PLS significantly better
Firm Performance (FP)	0.232	0.381	-0.149	3.746	<0.001	PLS significantly better
Overall Model	0.228	0.468	-0.240	4.688	<0.001	Meaningful predictive relevance

Source: Processed Data (2026)

Discussion

The Pressure–Capability Pathway

Since the design is cross-sectional, these relationships are associational, and the directional language simply reflects the hypothesized sequence. External pressure is positively associated with DTC, which fits the TOE idea that pressure stimulates capability formation. DTC is associated with BMI, in line with the dynamic capabilities view that capabilities enable renewal (Teece, 2007). BMI is associated with higher performance through efficiency, responsiveness, and customer value (Teece, 2018).

Performance is associated mainly with BMI ($\beta = 0.846$ in the final model; 0.630 in the full model). Digital capability appears necessary but not sufficient on its own. In this sample, higher performance appears only alongside business model renewal, which qualifies the common assumption that simply accumulating capability is enough to improve performance (Li et al., 2018; Teece, 2018).

Dual Mechanisms in the Pressure–Innovation Link

External pressure relates to BMI through two paths, and the indirect path dominates. Pressure rarely changes a business model on its own. The pattern fits firms building capability before renewing their business models, although cross-sectional data cannot confirm this sequence. The direct $EP \rightarrow BMI$ path ($\beta = 0.192$) fits reactive adjustment, whereas the indirect route ($\beta = 0.612$) fits deliberate, capability-led renewal, which is consistent with dual-chain mediation evidence in manufacturing (Zhang et al., 2024).

The Central Role of Business Model Innovation as Mediator

This places BMI at the center of transformation, rather than treating it as a by-product of digitalization. In emerging economies, performance gains are capability- and path-dependent, and they tend to follow digital capability rather than precede it (Balta et al., 2024; Tetteh et al., 2025). That ordering helps explain why simply adopting technology so often fails to deliver (Verhoef et al., 2021; Vial, 2019).

Comparison with Prior Empirical Evidence

The findings both converge with and depart from prior work. The $EP \rightarrow DTC$ association ($\beta = 0.864$) is stronger than what Tetteh et al. (2025) and Chinese samples report (Zhang et al., 2023), which suggests that Indonesian manufacturers internalize pressure under survival conditions. The $DTC \rightarrow BMI$ link ($\beta = 0.709$) supports dynamic-capabilities arguments, and the $BMI \rightarrow FP$ link ($\beta = 0.846$) is consistent with BMI as the proximal antecedent of performance (Foss & Saebi, 2017). That DTC relates to performance only indirectly fits the view that capability stays latent until business model renewal puts it to use (Vial, 2019).

Digital supply chain shows strong out-of-sample relevance ($Q^2_{\text{predict}} = 0.413$), consistent with integration across organizations being a precondition for business model innovation (Queiroz et al., 2021). Programs such as Making Indonesia 4.0 may deliver more when they pair infrastructure with capability-building.

CONCLUSION

Why do so many transformation programs fall short under external pressure? Among 206 Indonesian manufacturers, about 76.1% of the total indirect association between external pressure and performance runs through the serial path $EP \rightarrow DTC \rightarrow BMI \rightarrow FP$ ($\beta = 0.518$

of 0.681). Performance under pressure is associated with what firms build rather than what they buy.

External pressure is strongly associated with DTC ($\beta = 0.864$), consistent with its role as an antecedent of capability formation rather than a moderator. BMI is the proximal path to performance: in the full model, neither pressure nor DTC has a significant direct association with performance. Because BMI and FP overlap (HTMT = 0.942) and the data are cross-sectional, single-source, and purposively sampled, these patterns are consistent with the proposed ordering but do not establish causation.

Theoretical Implications

Three theoretical contributions follow. First, the study reframes environmental pressure as an antecedent associated with capability formation, which is an empirical departure from TOE work that treats pressure as a moderator. Second, it specifies DTC as a single orchestrated higher-order capability, refining the dynamic capabilities view by replacing fragmented resource lists with one integrative construct. Third, it positions BMI as the mechanism through which capability relates to performance, tying external pressure, capability, BMI, and performance into one serial-mediation chain (Hanelt et al., 2021; Vial, 2019). The matching managerial routine is set out in the Managerial Implications.

Managerial Implications

Three practical lessons follow. First, managers can treat external pressure as a prompt for deliberate capability building, for example by scanning technological, competitive, and regulatory signals regularly and linking them to capability budgets. Second, readiness, digital capability, and digital supply chain work best as one bundle rather than as separate projects. Third, business model renewal is where capability becomes associated with performance, so regular reviews of the value proposition, revenue model, and delivery process, tracked against efficiency, growth, and profitability, deserve priority.

Limitations

Five boundary conditions qualify the findings. First, the cross-sectional design limits causal inference. Second, the Indonesian setting and purposive, non-probability sampling limit generalization; digitally engaged firms are probably over-represented, so the size, and possibly the pattern, of the associations may differ in the wider population, in a direction the data cannot establish. Third, all data come from one informant per firm at one point in time; Harman's test (38.7%) and full-collinearity VIFs below 3.3 (Kock, 2015) reduce but do not rule out common method bias (Conway & Lance, 2010), which may also inflate the strong EP–DTC association. Fourth, PLSpredict and CVPAT (Table 8) show predictive relevance but cannot rule out unmeasured confounders. Fifth, BMI and FP share substantial variance (HTMT = 0.942), partly because three FP items mention digital technology, so the BMI → FP coefficient should be read with caution.

Even so, the central message holds: in volatile economies, performance depends less on what firms acquire than on how they orchestrate capability into business model renewal.

Recommendations for Future Research

Three directions deserve priority. First, longitudinal designs, such as two- or three-wave panels, are needed to establish causal sequencing and to separate capability-building from deployment effects. Second, multi-source designs that pair managerial surveys with archival

financial indicators, or use performance items that do not mention digital technology, would address common-method concerns and strengthen the BMI → FP link. Third, comparative studies across emerging economies, for example Indonesia, Vietnam, and Brazil, would clarify how far the results generalize across institutional contexts. Together, these steps would turn cross-sectional evidence into a causally grounded theory of pressure-driven transformation.

REFERENCES

- Alpala, L. O., Quiroga-Parra, D. J., Hernández Arias, B. E., Mendoza Munar, L., & Valencia Ayala, H. (2026). Industry 4.0 adoption in large manufacturing companies: The readiness–adoption gap in an emerging economy. *Systems*, 14(7), 799. <https://doi.org/10.3390/systems14070799>
- Bain & Company. (2024). 88% of business transformations fail to achieve their original ambitions; those that succeed avoid overloading top talent. Bain & Company. <https://www.bain.com/about/media-center/press-releases/2024/>
- Balta, M. E., Papadopoulos, T., & Spanaki, K. (2024). Business model pivoting and digital technologies in turbulent environments. *International Journal of Entrepreneurial Behavior & Research*, 30(2–3), 773–799. <https://doi.org/10.1108/IJEBR-02-2023-0210>
- Becker, J.-M., Klein, K., & Wetzels, M. (2012). Hierarchical latent variable models in PLS-SEM: guidelines for using reflective-formative type models. *Long Range Planning*, 45(5–6), 359–394. <https://doi.org/10.1016/j.lrp.2012.10.001>
- BenarNews. (2024). Indonesia's textile industry struggles as thousands lose jobs. BenarNews.
- Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2013). Digital business strategy: toward a next generation of insights. *MIS Quarterly*, 37(2), 471–482. <https://doi.org/10.25300/MISQ/2013/37:2.3>
- Chatterjee, S., Mikalef, P., Khorana, S., & Kizgin, H. (2022). Assessing the Implementation of AI Integrated CRM System for B2C Relationship Management: Integrating Contingency Theory and Dynamic Capability View Theory. *Information Systems Frontiers*, 26(3), 967–985. <https://doi.org/10.1007/s10796-022-10261-w>
- Conway, J. M., & Lance, C. E. (2010). What reviewers should expect from authors regarding common method bias in organizational research. *Journal of Business and Psychology*, 25(3), 325–334. <https://doi.org/10.1007/s10869-010-9181-6>
- Davenport, T. H., & Westerman, G. (2018). Why so many high-profile digital transformations fail. Harvard Business Review.
- Detik. (2024). Sepatu Bata resmi tutup pabrik setelah 7 dekade beroperasi di Indonesia. Detik.com.
- Diamantopoulos, A., & Siguaw, J. A. (2006). Formative versus reflective indicators in organizational measure development: A comparison and empirical illustration. *British Journal of Management*, 17(4), 263–282. <https://doi.org/10.1111/j.1467-8551.2006.00500.x>
- DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, 48(2), 147–160. <https://doi.org/10.2307/2095101>
- Forth, P., Reichert, T., de Laubier, R., & Chakraborty, S. (2020). *Flipping the odds of digital transformation success*. Boston Consulting Group. <https://www.bcg.com/publications/2020/increasing-odds-of-success-in-digital->

- transformation
- Foss, N. J., & Saebi, T. (2017). Fifteen years of research on business model innovation: How far have we come, and where should we go? *Journal of Management*, 43(1), 200–227. <https://doi.org/10.1177/0149206316675927>
- Frank, A. G., Dalenogare, L. S., & Ayala, N. F. (2019). Industry 4.0 technologies: Implementation patterns in manufacturing companies. *International Journal of Production Economics*, 210, 15–26. <https://doi.org/10.1016/j.ijpe.2019.01.004>
- Franke, G., & Sarstedt, M. (2019). Heuristics versus statistics in discriminant validity testing: A comparison of four procedures. *Internet Research*, 29(3), 430–447. <https://doi.org/10.1108/IntR-12-2017-0515>
- Ginting, M., Zagloel, T., & Zulkarnain. (2026). Industry 4.0 readiness and maturity in Indonesia's manufacturing industries: An empirical study of key success factors. *The South African Journal of Industrial Engineering*, 37(1), 1–16. <https://doi.org/10.7166/37-1-3399>
- Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*. Springer Nature.
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage.
- Hanelt, A., Bohnsack, R., Marz, D., & Antunes Marante, C. (2021). A systematic review of the literature on digital transformation: Insights and implications for strategy and organizational change. *Journal of Management Studies*, 58(5), 1159–1197.
- Helfat, C. E., & Raubitschek, R. S. (2018). Dynamic and integrative capabilities for profiting from innovation in digital platform-based ecosystems. *Research Policy*, 47(8), 1391–1399. <https://doi.org/10.1016/j.respol.2018.01.019>
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
- Iansiti, M., & Lakhani, K. R. (2020). *Competing in the age of AI: Strategy and leadership when algorithms and networks run the world*. Harvard Business Review Press.
- Jakarta Globe. (2024). Textile industry crisis: Factory closures and nearly 14,000 layoffs due to imported goods. Jakarta Globe.
- Jarvis, C. B., MacKenzie, S. B., & Podsakoff, P. M. (2003). A critical review of construct indicators and measurement model misspecification in marketing and consumer research. *Journal of Consumer Research*, 30(2), 199–218. <https://doi.org/10.1086/376806>
- Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration*, 11(4), 1–10. <https://doi.org/10.4018/ijec.2015100101>
- Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Information Systems Journal*, 28(1), 227–261. <https://doi.org/10.1111/isj.12131>
- Li, L., Su, F., Zhang, W., & Mao, J. (2018). Digital transformation by SME entrepreneurs: A capability perspective. *Information Systems Journal*, 28(6), 1129–1157. <https://doi.org/10.1111/isj.12153>
- Liengaard, B. D., Sharma, P. N., Hult, G. T. M., Jensen, M. B., Sarstedt, M., Hair, J. F., & Ringle, C. M. (2021). Prediction: coveted, yet forsaken? Introducing a cross-validated

- predictive ability test in partial least squares path modeling. *Decision Sciences*, 52(2), 362–392. <https://doi.org/10.1111/deci.12445>
- MacKenzie, S. B., & Podsakoff, P. M. (2012). Common method bias in marketing: causes, mechanisms, and procedural remedies. *Journal of Retailing*, 88(4), 542–555. <https://doi.org/10.1016/j.jretai.2012.08.001>
- Oliver, C. (1991). Strategic responses to institutional processes. *Academy of Management Review*, 16(1), 145–179. <https://doi.org/10.5465/amr.1991.4279002>
- Peng, Y., & Tao, C. (2022). Can digital transformation promote enterprise performance?—From the perspective of public policy and innovation. *Journal of Innovation & Knowledge*, 7(3), 100198. <https://doi.org/10.1016/j.jik.2022.100198>
- Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903. <https://doi.org/10.1037/0021-9010.88.5.879>
- Prihandono, D., Wijaya, A. P., Wiratama, B., Prananta, W., & Widia, S. (2024). Digital transformation to enhance Indonesian SME performance: Exploring the impact of market competition and digital strategy. *Problems and Perspectives in Management*, 22(2), 103–113. [https://doi.org/10.21511/ppm.22\(2\).2024.09](https://doi.org/10.21511/ppm.22(2).2024.09)
- Queiroz, M. M., Wamba, S. F., & Branski, R. M. (2021). Supply Chain Resilience During the COVID-19: Empirical Evidence From an Emerging Economy. *Benchmarking: An International Journal*, 29(6), 1999–2018. <https://doi.org/10.1108/bij-08-2021-0454>
- Sarstedt, M., Hair, J. F., Cheah, J.-H., Becker, J.-M., & Ringle, C. M. (2019). How to specify, estimate, and validate higher-order constructs in PLS-SEM. *Australasian Marketing Journal*, 27(3), 197–211. <https://doi.org/10.1016/j.ausmj.2019.05.003>
- Schilke, O. (2014). On the contingent value of dynamic capabilities for competitive advantage: The nonlinear moderating effect of environmental dynamism. *Strategic Management Journal*, 35(2), 179–203. <https://doi.org/10.1002/smj.2099>
- Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *European Journal of Marketing*, 53(11), 2322–2347. <https://doi.org/10.1108/EJM-02-2019-0189>
- Teece, D. J. (2007). Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28(13), 1319–1350. <https://doi.org/10.1002/smj.640>
- Teece, D. J. (2018). Business models and dynamic capabilities. *Long Range Planning*, 51(1), 40–49. <https://doi.org/10.1016/j.lrp.2017.06.007>
- Tempo. (2024). Sritex resmi pailit: Kronologi dan penyebab kebangkrutan. Tempo.
- Tetteh, F. K., Gyamerah, K. K., Nyamekye, B., Atiki, G., & Ashia, R. (2025). Digital transformation and business model innovation: the relevance of strategic orientations under varying conditions of competitive intensity. *Journal of Manufacturing Technology Management*, 36(3), 621–650. <https://doi.org/10.1108/JMTM-07-2024-0394>
- Tornatzky, L. G., Fleischer, M., & Chakrabarti, A. K. (1990). *The processes of technological innovation*. Lexington Books.
- Venkatraman, N., & Ramanujam, V. (1986). Measurement of business performance in strategy research: A comparison of approaches. *Academy of Management Review*, 11(4), 801–814. <https://doi.org/10.5465/amr.1986.4283976>

- Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, 122, 889–901. <https://doi.org/10.1016/j.jbusres.2019.09.022>
- Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems*, 28(2), 118–144. <https://doi.org/10.1016/j.jsis.2019.01.003>
- Wang, Y., Chen, Y., Wang, N., Nevo, S., Kou, G., & Alsaadi, F. E. (2020). Impact of the strategic role of IT on explorative and exploitative innovation activities: The role of environmental uncertainty. *Decision Sciences*, 51(3), 542–574. <https://doi.org/10.1111/deci.12377>
- Warner, K. S. R., & Wäger, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Planning*, 52(3), 326–349.
- World Bank. (2023). Manufacturing, value added (% of GDP) – Indonesia [Data set]. World Bank Open Data. <https://data.worldbank.org/indicator/NV.IND.MANF.ZS?locations=ID>
- Zhang, Y., Ma, X., Pang, J., Xing, H., & Wang, J. (2023). The impact of digital transformation of manufacturing on corporate performance—The mediating effect of business model innovation and the moderating effect of innovation capability. *Research in International Business and Finance*, 64, 101890. <https://doi.org/10.1016/j.ribaf.2023.101890>
- Zhang, Z., Ye, B., Hu, A., & Zhang, H. (2024). Unlocking the potential of digital transformation: A dual-chain mediation model for product innovation performance in manufacturing. *Technology Analysis & Strategic Management*. Advance online publication. <https://doi.org/10.1080/09537325.2024.2320824>
- Zhao, X., Lynch, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research*, 37(2), 197–206. <https://doi.org/10.1086/651257>