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MOVE FAST OR BUILD TIES? WHICH STRATEGY TRULY DRIVES MSME PERFORMANCE?

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Abstract
How do small firms grow when markets shift? We surveyed 312 Micro, Small, and Medium Enterprises (MSMEs) in West Java and compared four simple "strategies" for turning capabilities into revenue growth: Agility-led, Relationship-led, Big-bet, and Dual-lever (relationships + scope + speed). For each firm, we estimated the four options and assigned the one that best explained its results. One pattern stood out: relationships with customers, suppliers, and local institutions matter most both directly and, even more, by helping firms diversify products, channels, and resources. Moving faster on its own was not a safe bet; speed helped only when combined with strong relationships and a clear plan to expand scope (the Dual-lever archetype). Sector patterns were modest: culinary firms tended to be Relationship-led, while technology firms were fully Dual-lever. We translate these findings into practical playbooks: build partner ties first, expand scope next, and add speed once the complements are in place.

Keywords: Business Strategy; MSME performance; relational capital; diversification; strategic archetypes.

Introduction

Micro, small, and medium enterprises (MSMEs) are the backbone of Indonesia's economy and a central lever for inclusive growth (Sinha, Sinha, & Sinha, 2024). In West Java—home to dense creative and manufacturing clusters—provincial plans increasingly emphasize digitalization and collaborative governance to raise productivity and market access (Fauzi & Faizien, 2024; Indrayani, Murdiyana, Nurnawati, Guntoro, & Nainggolan, 2024). Yet many MSMEs still face a capability gap: digital transformation proceeds unevenly, constrained by limited skills, weak partner linkages, and fragmented resources (Rupeika-Apoga & Petrovska, 2022; Arisena et al., 2024; Lei, Indıran, & Kohar, 2023; Purnomo, Nurmalitasari, & Nurchim, 2024).

Strategic management research suggests that performance in turbulent contexts hinges on dynamic capabilities—sensing, seizing, and reconfiguring—to convert technological options and market signals into outcomes (Bitencourt, De Oliveira Santini, Ladeira, Santos, & Teixeira, 2020; Hernández-Linares, Kellermanns, & López-Fernández, 2020; Weaven et al., 2021; Dejardin et al., 2022; Troise, Corvello, Ghobadian, & O'Regan, 2022). For Indonesian MSMEs, recent evidence echoes this: digitalization and agility capabilities correlate positively with resilience and performance (Putritamara et al., 2023; Setiawan, Pamungkas, Mekaniwati, & Kusuma, 2025).

Within this broad lens, three capability domains repeatedly surface in MSME settings. Speed of adaptation—the ability to make, implement, and evaluate changes quickly—can raise innovation speed and, in turn, financial outcomes (Wang, Cai, Liang, Wang, & Xiang, 2018). Diversification—across products, markets, and organization/resources—has nuanced effects: it can buffer shocks and open growth paths, but benefits depend on scope and execution (Miocevic, 2021; Arte & Larimo, 2021; Wu, Chen, & Jiao, 2016). Relational capital—deep customer feedback, partner collaboration, and ecosystem embeddedness—both accelerates capability development and links to performance (Yi, Li, Hitt, Liu, & Wei, 2016; Long & Zhao, 2022; Corvino, Caputo, Pironti, Doni, & Martini, 2019). These strands motivate our comparative focus on Speed, Diversification, and Relational Capital as proximal drivers of MSME financial performance.

Despite rich case and single-model studies, two gaps remain. First, most analyses test one causal story at a time (e.g., "relationships help performance") rather than adjudicating rival strategic logics that specify different directions and mediating channels among Speed, Diversification, and Relational Capital. Second, external usefulness is seldom verified without out-of-sample prediction, which is critical for policy and managerial deployment in MSME programs. Addressing both gaps is practically important in West Java, where public and private actors must prioritize tools (e.g., partner matchmaking, diversification discipline, capability coaching) to the realities of varied MSME pathways (Indrayani et al., 2024; Fauzi & Faizien, 2024).

We therefore compare four rival models (A–C, E) that encode distinct, theory-based mechanisms linking these capabilities to Financial Performance. Each model is estimated on a common measurement backbone using a two-stage PLS-SEM with formative higher-order composites for the three capability domains, and tested with consistent PLS (PLSc) and bias-corrected bootstrap inference. To establish practical value, we evaluate predictive validity via PLSpredict (10-fold ×10 repetitions) and baseline comparisons (CVPAT). Finally, we translate rival-model evidence into an archetype mapping assigning each firm to the model that best predicts its performance so policymakers and mentors can target interventions (e.g., strengthening partner ties vs. focusing diversification magnitude/frequency vs. execution speed) to the archetype most consistent with a firm's data (Putritamara et al., 2023; Setiawan et al., 2025).

Our contributions are threefold. Substantively, we provide West Java–grounded evidence on which strategic logic most plausibly underpins MSME financial performance, while also speaking to MSME policy in Indonesia and comparable emerging regions (Sinha et al., 2024; Indrayani et al., 2024). Methodologically, we integrate rival-model testing with predictive validation, moving beyond in-sample fit. Managerially and for policy, the archetype lens yields actionable guidance for capability investments and partner engagement tailored to local industry structures.

Methods

Data Sampling

The written-informed consents to the participants in the study have been declared prior to filling out questionnaires, interviews, and discussions. The questionnaire was filled up by 312 MSME owners or managers in West Java, Indonesia. Agrofood, creative industries, services, fashion, handicrafts, herbal, and culinary were among the sectors represented by the respondents. West Java had a significant number of MSMEs and played a vital role in the national economy. According to 2023 data, with a number of more than 4.63 million, MSMEs in West Java contributed over 60% to national GDP and employed 97% of the workforce. The questionnaire was developed by adapting pre-existing MSME survey instruments and conducting a literature analysis to guarantee the instrument's validity and contextual relevance. To find any ambiguous or unclear elements, a pilot test was carried out on a small group of MSME owners in West Java. Five MSME owners, each chosen to represent one of the primary industries covered by the study, participated in in-depth interviews after the pilot test.

These interviews gave direct input on the questionnaire's practicality, relevance, and clarity, ensuring that the instrument addressed the unique characteristics and needs of different industries. Insights from these interviews were used to further refine and finalize the questionnaire. Respondents for the main survey were selected using judgmental (purposive) sampling, targeting MSME owners or managers who were active in their sector, located in West Java, and Indonesian citizens. Data collection was conducted online via Google Forms.

Statistical analyses such as Cronbach's alpha, composite reliability, average variance extracted (AVE), and Fornell-Larcker discriminant validity tests were used to further validate the validity of the instrument. By taking all these steps, the questionnaire's validity and reliability were guaranteed, and the data appropriately represented the target MSME population across key industry sectors.

Measures and Coding

As in Table 1, all items were coded so that higher values indicate more of the intended construct (faster speed, broader diversification, stronger relational capital, better performance). Reverse-worded items were recoded prior to analysis. As pre-registered, items Q9, Q12, Q15 are excluded from structural models and retained for descriptives/robustness.

Table 1: Constructs, item codes, response options, numeric coding, and scoring notes

Construct / variable	Items (Q#)	Response options shown to respondents (English)	Numeric code used in analysis	Scoring direction/notes
Firm age	Q7	Less than 1 year; 1–3 years; 3–5 years; More than 5 years	1; 2; 3; 4	Higher = older firm
Initial capital (excluding land/buildings)	Q8	< Rp 50 million; Rp 50–500 million; Rp 500 million–1 billion; > Rp 1–≤ Rp 5 billion; > Rp 5–≤ Rp 10 billion	1; 2; 3; 4; 5	Higher = larger initial capital
Decision speed (time to decide a change)	Q10–Q11	< 1 week; 1–2 weeks; 3–4 weeks; 1–2 months; > 2 months	5; 4; 3; 2; 1	Reverse-coded → higher = faster
(Dropped from structural analysis; retained for descriptives)	Q9, Q12, Q15	< 1 week; 1–2 weeks; 3–4 weeks; 1–2 months; > 2 months	5; 4; 3; 2; 1	Reverse-coded
Implementation speed (time to implement a change)	Q13–Q14	< 1 week; 1–2 weeks; 3–4 weeks; 1–2 months; > 2 months	5; 4; 3; 2; 1	Reverse-coded → higher = faster
Evaluation speed (frequency of review/benchmark/revision)	Q16–Q18	Never (not relevant); ≤ 1 time/year; 2 times/year; 3–4	0; 1; 2; 3; 4; 5; 6; 7	Higher = more frequent evaluation

Construct / variable	Items (Q#)	Response options shown to respondents (English)	Numeric code used in analysis	Scoring direction/notes
		times/year; 5–6 times/year; 7–9 times/year; 10–12 times/year; > 12 times/year		
Diversification *(Product/Service; Market/Channel; Organization/Resources)*	Q19–Q30	Never (not relevant); ≤ 1 time/year; 2 times/year; 3–4 times/year; 5–6 times/year; 7–9 times/year; 10–12 times/year; > 12 times/year	0; 1; 2; 3; 4; 5; 6; 7	Higher = broader/more frequent diversification activities
Relational capital *(Customer feedback intensity; Partner collaboration depth; Ecosystem & institutional embeddedness)*	Q31–Q38	Never (not relevant); ≤ 1 time/year; 2 times/year; 3–4 times/year; 5–6 times/year; 7–9 times/year; 10–12 times/year; > 12 times/year	0; 1; 2; 3; 4; 5; 6; 7	Higher = stronger/more frequent relational activities
Stakeholder trust/support	Q39	Not at all; Very low; Adequate; High; Very high	0; 1; 2; 3; 4	Higher = stronger perceived support
Industry trend speed (environmental dynamism)	Q41	Trend does not change; Trend persists > 2 years; Trend changes every 1–2 years; Trend changes in < 1 year	0; 1; 2; 3	Higher = faster trend turnover
Owner dominance in strategic decisions	Q43	Not dominant (team jointly decides); Moderately dominant (owner leads, team involved); Highly dominant (owner decides alone)	1; 2; 3	Higher = more centralized decisions

Construct / variable	Items (Q#)	Response options shown to respondents (English)	Numeric code used in analysis	Scoring direction/notes
External influence on strategic decisions	Q44	Not significant (decisions free of interference); Moderately significant (external input, firm makes final decision); Highly significant (external actors strongly shape decisions)	1; 2; 3	Higher = stronger external sway
Financial performance — revenue growth (last 12 months)	Q45	Declined < 0%; 0–5%; 6–15%; 16–30%; > 30%	−1; 1; 2; 3; 4	Preserves contraction (−) vs growth (+)
Personnel performance — change in employees (last 12 months)	Q46	Decreased (−1 or more); No change (stable); Increased (1–2); Increased (3–5); Increased (> 5)	−1; 0; 1; 2; 3	Ordered categorical
Digital customers — change in online customers/followers	Q47	Decreased > 10%; Decreased 1–10%; Stable (≈ 0%); Increased 1–10%; Increased > 10%	−2; −1; 0; 1; 2	Symmetrical around zero

Items Q9, Q12, Q15 were excluded from structural models and retained for descriptives/robustness.

Descriptive Statistics, Reliability, and Validity

This section reports descriptive statistics for the higher-order composites (HOCs) and outcomes, then evaluates reliability, convergent validity, discriminant validity, and common-method bias, as in Table 2.

Table 2
Distributions for stage-2 composites (SPEED, DIV, RC) and outcomes (PF, PP, PD)

Construct	N	Mean	SD	Min	Max	Skewness	Kurtosis (excess)
Speed of Adaptation	312	0	1	-1.844	2.012	0.184	-1.384
Diversification	312	0	1	-2.058	1.863	-0.046	-1.488
Relational Capital	312	0	1	-2.201	2.208	-0.028	-1.392
Financial Performance	312	2.301	0.987	-1	4	0.05	-0.712

Personnel Performance	312	1.551	1.058	-1	3	-0.037	-1.155
Digital Customers	312	0.638	1.158	-2	2	-0.581	-0.535

Because Stage-2 composites are standardized, SPEED/DIV/RC show mean ≈ 0, SD = 1; outcome variables retain their original scaling.

Result and Discussion

Estimation setup

As in Table 8, we estimated four rival structural models (A, B, C, E; D was estimated for completeness but screened from focal comparisons) at Stage-2 using Consistent PLS-SEM (PLSc) in SmartPLS 4. Stage-1 first estimated the reflective first-order facets and saved their latent scores; Stage-2 then formed formative higher-order composites (SPEED, DIV, RC) via Mode B and estimated structural paths to PF.

Uncertainty was assessed with Consistent PLS-SEM bootstrapping (two-tailed, BCa 95% confidence intervals, N = 10,000 resamples, fixed seed; sign changes = Individual). We report standardized path coefficients (β), BCa 95% CIs, *p*-values, and R^2(PF). Specific indirect effects are reported only when structurally implied by a model's arrows (A: none; B/E: RC→DIV→PF and RC→SPEED→PF; C: SPEED→MG→PF; D: RC→DIV→PF and RC→SPEED→PF). Out-of-sample predictive validity is evaluated via PLSpredict with 10-fold cross-validation × 10 repetitions (fixed seed) and CVPAT comparisons versus indicator-average and linear baselines.

Table 8 Estimation setup (Stage-2 PLSc; Consistent bootstrapping)

Field	**Value**
Sample size (N)	**312**
Software	SmartPLS 4
Stage & estimation	**Two-stage**: Stage-1 reflective facets → save scores; Stage-2 **PLSc** (Path weighting; standardized results)
Higher-order constructs	Stage-2 **formative** HOCs (**SPEED, DIV, RC**; Mode B)
First-order reflective blocks	**Speed**: DS, IS, ES; **Diversification**: DOR, DPS, DMC; **Relational**: RCP, RCE, RCC
Endogenous outcome	**Financial Performance (PF)** (Q45)
Bootstrapping	**Consistent PLS-SEM bootstrapping**, two-tailed, **BCa 95% CIs**, **N = 10,000** resamples, fixed seed; sign changes = **Individual.**
Predictive evaluation	**PLSpredict** (10-fold × 10 reps, fixed seed, target = PF) + **CVPAT** vs **indicator-average** & **linear** baselines
Rival models	**A, B, C, E** (reported); **D** estimated but **screened** from focal comparisons

Out-of-sample predictive performance (PLSpredict 10×10; CVPAT)

As in Table 9, we evaluate predictive validity using PLSpredict with 10-fold cross-validation × 10 repetitions (fixed seed; target = PF). For each rival $m \in \{A, B, C, E\}$ (Model D was estimated but is screened from focal comparisons), we report Q²_predict and MAE (PLS) and benchmark against linear (LM) and indicator-average (IA) baselines using CVPAT. Higher Q^2_predict and lower MAE indicate stronger predictive performance.

Table 9
Out-of-sample predictive quality (PLSpredict / CVPAT; LV level, PF only) (Lower MAE is better; PLS-SEM beats both LM and IA across models; Q^2_predict > 0 indicates meaningful predictive power.)

Model	Q^2_predict (PF)	MAE (PLS)	MAE (Linear Model)	MAE (Indicator Average)
Model A (Agility-led)	0.163	**0.728**	0.834	0.979
Model B (Relationship-led)	0.127	**0.774**	0.842	0.979
Model C (Big-bet)	0.162	**0.749**	0.824	0.979
Model E (Dual-lever)	0.125	**0.775**	0.842	0.979

Archetype assignment from PLSpredict

Each firm i is assigned an archetype (A, B, C, E) By comparing absolute prediction errors on PF across rivals and selecting the smallest error:

$$e_i^{(m)} = \left|y_i - \hat{y}_i^{(m)}\right|, \quad a_i = \arg\min_{m\in\{A,B,C,E\}} e_i^{(m)}$$

To guard against razor-thin wins, we also report an ε-ambiguity sensitivity: a case is labeled Ambiguous if the gap to the runner-up is $e_i^{(2)} - e_i^{(1)} < \varepsilon$, (here we use $\varepsilon = 0.02$ PF-units). Assignments use identical folds/repetitions and seed across rivals. We obtain the models in Table 10 (10 and 11).

Table 10
Empirical archetypes from PLSpredict (strict assignment, ε = 0.00)

Archetype	n	Share (%)
Model A — Agility-led	**151**	**48.4**
Model B — Relationship-led	**23**	**7.4**
Model C — Big-bet	**47**	**15.1**
Model E — Dual-lever	**91**	**29.2**
Ambiguous	**0**	**0**
Total	**312**	**100**

Notes: Assignment uses the winner-takes-best-prediction rule based on cross-validated absolute PF errors. ε is the minimum error-gap between the best and runner-up models, below which a case is flagged Ambiguous. Rounding may cause totals to differ by ±0.1.

Table 11 Robustness checks archetype shares (%) across ε

Archetype	ε = 0.00	ε = 0.01	ε = 0.02
Model A — Agility-led	48.4	43.9	39.7
Model B — Relationship-led	7.4	2.9	0.3
Model C — Big-bet	15.1	13.8	11.2

Model E — Dual-lever	29.2	20.5	7.7
Ambiguous	0	18.9	41
Sum	100	100	100

Hypothesis testing (Stage-2 PLSc; BCa 95% CIs)
We test directional and non-directional hypotheses using bias-corrected and accelerated (BCa) 95% confidence intervals from the Stage-2 PLSc models. Decision rules follow our preregistered criteria: for $\beta > 0$, support requires $\hat{\beta} > 0$ and BCa-CI entirely > 0; for $\beta < 0$, $\hat{\beta} < 0$ and CI entirely < 0; for $\beta \neq 0$, CI must exclude 0; for $\beta \leq 0$, the upper CI bound must be ≤ 0. Mediation hypotheses are evaluated on specific indirect effects; support requires the indirect BCa-CI to exclude 0 with the expected sign. We report model-wise results below and provide full coefficients and CIs in Tables 4.4a–4.4e.
Model A — Agility-led (parallel predictors)
The results are in Table 11 (11a and 11b).
Hypotheses: H_A1 (SPEED → PF, β > 0), H_A2 (DIV → PF, β > 0), H_A3 (RC → PF, β > 0). (No mediations.)
Findings: H_A3 supported (Relational Capital → PF); H_A1 and H_A2 not supported. This indicates that, within a purely *parallel specification, relational ties (not speed or diversification alone) explain variation in PF.*

Table 12 Direct-path hypothesis tests (Model A, PLSc; BCa 95% CI)

Path	**Expected**	**β**	**SE**	**t**	**p**	**LL_BCa**	**UL_BCa**	**Decision**
DIV → PF	β > 0	0.049	0.103	0.19	0.846	−0.178	0.209	Not supported
RC → PF	β > 0	0.205	0.088	2.44	0.015	0.028	0.37	**Supported**
SPEED → PF	β > 0	−0.163	0.195	1.26	0.207	−0.422	0.262	Not supported

R^2 (PF) for Model A: 0.210
Model B —Relationship-led
Direct paths: H_B1 (RC → DIV, β > 0), H_B2 (RC → SPEED, β ≠ 0), H_B3 (DIV → PF, β > 0), H_B4 (RC → PF, β > 0).
Mediation (implied by the diagram): H_B5 (RC → DIV → PF). *(Note: B does not include SPEED → PF, so RC → SPEED → PF is not modeled and is not tested.)*
Findings: H_B1, H_B3, H_B4 supported (RC strongly enables DIV; both DIV and RC raise PF); H_B2 not supported (RC does not exhibit a robust non-zero link to SPEED). H_B5 supported: RC improves PF indirectly via DIV, consistent with a relationship-enabled diversification mechanism.

Table 13 Direct-path hypothesis tests (Model B, PLSc; BCa 95% CI)

Path	**Expected**	**β**	**SE**	**t**	**p**	**LL_BCa**	**UL_BCa**	**Decision**
RC → DIV	β > 0	0.586	0.061	9.57	<.001	0.458	0.691	**Supported**
RC →	β ≠ 0	0.065	0.083	0.78	0.434	−0.122	0.233	Not

SPEED								supported
DIV → PF	β > 0	0.325	0.086	3.77	<.001	0.123	0.491	**Supported**
RC → PF	β > 0	0.271	0.088	3.07	0.002	0.083	0.46	**Supported**

R^2 (PF) for Model B: 0.289

Model C — Big-bet

The results are in Table 14.

Direct paths: H_C1 (SPEED → MG, β > 0), H_C2 (MG → PF, β > 0), H_C3 (FR → PF, β ≤ 0), H_C4 (RC → PF, β > 0).

Mediation (implied): H_C5 (SPEED → MG → PF).

Findings: The SPEED → MG link does not follow the expected positive direction, and MG → PF does not clear the BCa-CI threshold in this sample. FR → PF is not supported for the "≤ 0" claim, and RC → PF shows evidence consistent with a positive association in Big-bet only when the CI excludes zero (see Table 13 for exact bounds). The indirect chain SPEED → MG → PF is not supported. Overall, the pure Big-bet mechanism is weak in this dataset relative to relationship-enabled pathways.

Table 14 Direct-path hypothesis tests (Model C, PLSc; BCa 95% CI)

Path	Expected	β	SE	t	LL_BCa	UL_BCa	Decision
SPEED → MG	β > 0	0.262	0.096	2.73	0.048	0.06	**Supported**
MG → PF	β > 0	0.41	0.101	4.05	0.643	0.18	**Supported**
FR → PF	β ≤ 0	−0.110	0.091	1.21	−0.312	0.06	Not supported (UL_BCa ≥ 0)
RC → PF	β > 0	0.142	0.082	1.73	−0.014	0.302	Not supported

R^2 (PF) for Model C: 0.244

(**Note:** the p-value column in the C export isn't reliable across all rows, so decisions strictly follow BCa CIs and expected signs.)

Model E Dual-lever (no direct RC → PF)

The results are in Table 13.

Direct paths: H_E1 (RC → DIV, β > 0), H_E2 (RC → SPEED, β > 0), H_E3 (DIV → PF, β > 0), H_E4 (SPEED → PF, β > 0).

Mediations: H_E5 (RC → DIV → PF), H_E6 (RC → SPEED → PF).

Findings: H_E1 and H_E3 supported (RC strongly raises DIV; DIV raises PF). H_E2 and H_E4 are not supported (RC does not raise SPEED; SPEED does not raise PF). Yet, both mediations are supported—especially RC → DIV → PF—showing that relationships lift performance primarily by enabling scope (DIV) rather than by accelerating speed alone.

Table 15 Direct-path hypothesis tests (Model E, PLSc; BCa 95% CI)

Path	Expected	β	SE	t	p	LL_BCa	UL_BCa	Decision
RC → DIV	β > 0	0.612	0.056	10.87	<.001	0.497	0.706	**Supported**

RC → SPEED	β > 0	0.334	0.068	4.91	<.001	0.201	0.444	**Supported**
DIV → PF	β > 0	0.242	0.082	2.94	0.004	0.053	0.389	**Supported**
SPEED → PF	β > 0	0.227	0.081	2.79	0.005	0.057	0.374	**Supported**

R^2 (PF) for Model E: 0.172

Specific indirect effects (summary)

We compile the specific indirects, as in Table 14, only for the models where they are structurally implied: B: RC → DIV → PF; C: SPEED → MG → PF; E: RC → DIV → PF and RC → SPEED → PF. (As noted, B: RC → SPEED → PF is not modeled and is not tested.) Consistent with the model-wise results, relationship-enabled diversification emerges as the most reliable mediated pathway to PF, whereas speed-based chains do not generalize in this sample.

Table 16 Mediation tests (Models B, C, E; PLSc; BCa 95% CI)

Model	Indirect path	Expected	β_indirect	LL_BCa	UL_BCa	Decision
B	RC → DIV → PF	β > 0	0.311	0.08	0.569	**Supported**
C	SPEED → MG → PF	β > 0	−0.108	−0.416	0.086	Not supported
E	RC → DIV → PF	β > 0	0.184	0.023	0.35	**Supported**
E	RC → SPEED → PF	β > 0	0.176	0.037	0.296	**Supported**

Screened rival (Model D)

Model D, as in Table 15, is estimated for transparency and excluded from the focal comparisons in §§4.2–4.4. Its structure includes RC → DIV, RC → SPEED, DIV → PF, SPEED → PF, and RC → PF, with implied mediations RC → DIV → PF and RC → SPEED → PF. We use Stage-2 PLSc with BCa 95% CIs (10,000 resamples; standardized coefficients).

Direct paths. Results show a very strong positive RC → DIV (β = 0.889, BCa 95% CI [0.854, 0.917]); non-significant RC → PF (β = 0.028, [−0.246, 0.282]) and DIV → PF (β = 0.187, [−0.105, 0.500]); and reliably negative links for RC → SPEED (β = −0.770, [−0.802, −0.722]) and SPEED → PF (β = −0.223, [−0.382, −0.054]). The model explains R^2(PF) ≈ 0.172. Taken together, Model D does not overturn the main narrative: relationship assets enable scope (DIV), while greater speed is associated with lower PF in this specification.

Table 17 Model D — Direct paths (PLSc; BCa 95% CI)

Path	B	SE	t	LL_BCa	UL_BCa	Decision
RC → DIV	0.889	0.016	56.34	0.854	0.917	**Supported**
RC → SPEED	−0.770	0.02	38.18	−0.802	−0.722	**Supported (β≠0; CI<0)**
DIV → PF	0.187	0.154	1.17	−0.105	0.5	Not supported
SPEED → PF	−0.223	0.084	2.65	−0.382	−0.054	**Supported (β≠0; CI<0)**
RC → PF	0.028	0.135	0.25	−0.246	0.282	Not supported

R^2 (PF): 0.172.

Specific indirect effects. Consistent with the arrows, we test two chains:

1. RC → DIV → PF: β_indirect = 0.160, BCa 95% CI [−0.093, 0.454] → Not supported (CI includes 0).
2. RC → SPEED → PF: β_indirect = 0.171, BCa 95% CI [0.041, 0.295] → Supported (CI excludes 0).

This second mediation, as in Table 16, is formally positive because it is the product of two negatives (RC reduces SPEED; SPEED reduces PF); it does not imply that increasing SPEED is beneficial. Substantively, RC → DIV → PF remains the more intuitive route for translating relational assets into performance, aligning with our focal models.

Table 18 Model D — Specific indirect effects (PLSc; BCa 95% CI)

Indirect path	β_indirect	LL_BCa	UL_BCa	Decision
RC → DIV → PF	0.16	−0.093	0.454	Not supported
RC → SPEED → PF	0.171	0.041	0.295	**Supported**

Heterogeneity by Industry (Exploratory)

As in Table 17, we link the strict archetype assignments (ε = 0.00; winner = smallest median absolute error on PF across Models A–C–E) to the industry each MSME operates in. Table 18 reports the Industry × Archetype cross-tabulation (counts), and Table 4.8 reports row-normalized shares. A Pearson chi-square test using the counts indicates a modest association between industry and archetype ($\chi^2 = 35.106$, df = 21, $p = 0.027$; Cramér's V = 0.194), suggesting small-to-moderate differences in composition by sector.

Table 19 Industry × Archetype (counts; ε = 0.00)

Industry	A	B	C	E	Total
Agrofood Sector (Agriculture, Livestock, and Food Production)	2	4	5	1	12
Fashion and Apparel Industry	11	8	5	12	36
Creative Industries (Design,	1	1	4	1	7

Content, and Media)					
Service Sector (Agencies, Travel, Photography)	1	3	1	0	5
Handicraft Industry	12	7	3	6	28
Chemical and Herbal Industry	0	2	2	2	6
Culinary Industry (Food and Beverages)	35	83	56	43	217
Technology Sector (Information Technology and Digital Innovation)	0	0	0	1	1

Table 20 Industry × Archetype (row-normalized shares; ε = 0.00)

Industry	**A**	**B**	**C**	**E**
Agrofood Sector (Agriculture, Livestock, and Food Production)	0.167	0.333	0.417	0.083
Fashion and Apparel Industry	0.306	0.222	0.139	0.333
Creative Industries (Design, Content, and Media)	0.143	0.143	0.571	0.143
Service Sector (Agencies, Travel, Photography)	0.2	0.6	0.2	0
Handicraft Industry	0.429	0.25	0.107	0.214
Chemical and Herbal Industry	0	0.333	0.333	0.333
Culinary Industry (Food and Beverages)	0.161	0.382	0.258	0.198
Technology Sector (Information Technology and Digital Innovation)	0	0	0	1

From Table 20 (shares). Several regularities emerge:

1. Culinary Industry (largest sector, N = 217) shows a Relationship-led center of gravity (B = 0.382) with sizable Agility-led (A = 0.161) and Dual-lever (E = 0.198) minorities. This echoes our structural and predictive results that relational ties and scope dominate over stand-alone speed.
2. Fashion and Apparel is multi-modal, with a balanced split between Agility-led (A = 0.306) and Dual-lever (E = 0.333), and a smaller Relationship-led segment (B = 0.222). This suggests strategy variety (agility and scope) in markets with rapid design cycles and channel diversification.
3. Handicraft tilts Agility-led (A = 0.429) with Dual-lever as the secondary share (E = 0.214). Given small-batch, design-driven operations, faster decision/implementation cycles likely matter, but scope/partnerships still play a role.
4. Service Sector (agencies/travel/photography) leans heavily on Relationship-led (B = 0.600), consistent with reputation and client-network dependence.
5. Creative Industries are Big-bet heavy (C = 0.571), consistent with project-based bets on product/market fit and high variance in outcomes.
6. Technology is fully Dual-lever (E = 1.000), matching the idea that combining scope (diversification) and relational embedding outperforms pure speed.

We reveal that MSMEs in West Java, Indonesia, comprise four models, which are Agility-led (48.4%), Relationship-led (7.4%), Big-bet (15.1%), and Dual-level (29.2%). To attain a competitive advantage with the implications of high financial performance, MSME is supposed to integrate the resources and value-chain activities (Karna, Richter, & Riesenkampff, 2016). In this regard, the Relational Capital is pivotal in integrating them to attain the necessary competencies and implement the business strategy. The models that comply with the Relational Capital-intensive roles are Relationship-led and Dual-lever, encompassing 7.4% and 29.2%. In particular, the Dual-lever model, although it is not prevalent, may potentially spawn both speed and the related diversification.

The dominant Agility-led model in West Java is an unintegrated-manner which is unplausible to attain competitive advantage. Likewise, the Big-bet model has disadvantageous implications to performance since it emphasized solely on speed and frequency to performance and undermined the strategic investment and trade-off policies on competencies. In this model, ubiquitous experience in Indonesian MSMEs undertaking frequent changes of products and services, which are misaligned with strategy should be avoided.

Three themes cut across the four focal rivals estimated on a shared measurement backbone. First, Relational Capital (RC) is the pivotal enabler: it directly improves PF where specified (Models A and B) and it indirectly improves PF via Diversification (DIV) in models where RC builds scope first (B and E). In E, RC also raises SPEED, and both DIV→PF and SPEED→PF are positive, yielding two supported mediations (RC→DIV→PF and RC→SPEED→PF).

Second, Speed of Adaptation on its own is not a universally reliable driver of PF. In A it is not supported; in B it is not modeled to PF; in C, elements of the “big-bet” chain appear in the direct links but the overall SPEED→MG→PF indirect is not supported; in E, SPEED→PF is positive—but in tandem with RC and DIV. Taken together, speed “pays” when meshed with relationships and scope, not as a stand-alone lever.

Third, out-of-sample predictive validity is consistently positive across rivals (Q^2_predict > 0; PLS beats LM and IA), supporting practical usefulness for firm-level decision guidance. The archetype mapping from PLSpredict shows most MSMEs are best explained by Agility-led (A) or Dual-lever (E), with smaller Relationship-led (B) and Big-bet (C) segments; sectors differ in composition (e.g., Culinary → B-heavy; Technology → E-only), and the industry × archetype association is statistically significant with a small–moderate effect size.

Theoretical Contributions

Relational Capital is a fundamental driver, Speed of Adaptation is only useful when combined with other capabilities, and a prediction-based archetype approach offers a more nuanced lens for understanding firm performance.

1. Reconceptualizing Dynamic Capabilities: From a Monolithic View to an Archetype Approach

Traditionally, the literature on dynamic capabilities—the ability to sense, seize, and reconfigure resources—is often treated as a concept that tends to be uniform and always positive for performance. This study empirically challenges this view.

This study demonstrates that dynamic capabilities (Speed, Diversification, and Relational Capital) do not operate in parallel and independently, as tested in Model A (Agility-led), which appears to have a weak influence path. Instead, these capabilities operate in different configurations or "archetypes," where their interaction and sequence are crucial. The finding that speed alone is insufficient is an important correction to the often contextdeficient "move fast and break things" mantra. Future research should shift from examining dynamic capabilities as independent predictors to a configurational or archetype approach. Theory needs to be more explicit in modeling how different combinations of capabilities (such as Model E - Dual-lever) create competitive advantage.

There is a need to develop a theory on "capability sequencing" in MSMEs. This study implicitly suggests the sequence "Build Relationships → Expand Scope → Increase Speed." Future theory should validate whether this sequence is universally applicable or context-dependent, as suggested by Karna et al. (2016).

2. Elevating the Role of Relational Capital as an Antecedent "Meta-Capability"

The literature has long recognized the importance of relational capital for capability development and performance. However, this study provides strong evidence that its role is more than just one of many capabilities; it serves as a foundation.

In the models that most successfully explain performance (Models B and E), Relational Capital (RC) serves as an antecedent that enables or activates other capabilities such as Diversification (DIV) and Speed (SPEED). Without strong RC, diversification or speed-enhancing efforts are less effective. This aligns with the idea that relational embeddedness accelerates capability development, but this study positions it as a crucial starting point. Dynamic capability theory in MSMEs should explicitly model Relational Capital as a "meta-capability," or a higher-order antecedent capability that forms the conditions for the development of other operational (first-order) capabilities.

3. Researchers should test mediation mechanisms more systematically

Instead of testing RC → Performance, a more accurate theoretical model, as demonstrated by this study, is RC → Other Capabilities (e.g., Diversification) → Performance. This would help open the "black box" of how exactly social relationships translate into financial outcomes.

4. Theorizing the "Cost of Speed" and Context Dependence

Much of the literature assumes a positive linear relationship between speed and performance. This study provides strong counter-evidence, suggesting that speed can be irrelevant or even counterproductive if not managed in the right context. In Model A, the SPEED → PF path is insignificant. In the explored Model D, the SPEED → PF relationship is even significantly negative. Only in Model E, where SPEED is activated by RC and operates concurrently with DIV, does it have a positive impact. This implies a "cost of speed"—hasty action without relational support and strategic focus (diversification) can waste resources and harm performance. Future theory needs to move beyond the "faster is better" assumption and explicitly incorporate contingency factors that determine the outcomes of speed. Relational capital and the discipline of diversification should be theorized as key moderators that alter the relationship between speed and performance. Developing a theory of "optimal speed" for MSMEs. Rather than maximizing speed, theory should focus on synchronizing speed with the development of other complementary capabilities, in line with the findings of this study.

5. Integrating Rival Model Testing and Predictive Validation for Theory Building

This study methodologically critiques research that only tests a single causal hypothesis and relies on in-sample fit. The approach used here has profound implications for how theory is built and tested. By directly comparing four different "strategic logics" (Models A, B, C, E) and using out-of-sample predictive validation (PLSpredict) to determine which model is most practically useful, this study demonstrates a path to more robust and relevant theory. This process forces researchers to ask not simply "does X affect Y?" but "which causal logic best explains Y?". The field of strategic management, particularly in MSME studies, should adopt rival model testing as standard practice. This promotes theoretical rigor by requiring the clear specification of alternative causal mechanisms.

Predictive validation should be an additional criterion in addition to statistical significance for evaluating theories. A theory must not only be able to explain existing data (explanatory power), but also have the ability to predict outcomes on new data (predictive power). This ensures that the developed theory is not only academically elegant but also useful in the real world.

Managerial implications (archetype-specific playbooks)

These actions translate the structural and predictive evidence into "what to do next." They respect the Stage-2 formative nature of SPEED, DIV, RC, and the Stage-1 reflective validation.

Model A Agility-led (parallel predictors)

What the data say. RC→PF is supported; SPEED→PF and DIV→PF are not. What to do:

1. Invest in relationships first (customer feedback loops, partner co-development, institutional ties) to unlock direct PF gains.
2. Gate speed with readiness checks (capacity, cash, capability owner); accelerate only when bottlenecks are cleared.
3. Use short learning loops (post-launch debriefs, monthly KPI reviews) to prevent "fast-but-shallow" pivots.

Model B Relationship-led

What the data say. RC→DIV, DIV→PF, and RC→PF are supported; RC→SPEED is not robust; only the mediation RC→DIV→PF is implied and supported. What to do.

1. Channel RC into focused diversification (portfolio cap, stage-gate kill/scale decisions).
2. Govern partner work (joint steering, shared metrics) to keep scope expansion disciplined.
3. Monetize network access by prioritizing fewer, higher-return moves rather than broad expansion.

Model C Big-bet

What the data say. The tabled SPEED→MG and MG→PF links show support, yet the SPEED→MG→PF indirect link is not supported, and RC→PF is not supported in this structure.

What to do.

1. Concentrate on one or two major reconfigurations backed by anchor partners; avoid frequent tinkering.
2. Stage big bets with milestone funding and stop/go gates; measure realized impact, not activity volume.
3. Embed partners early so magnitude gains translate into PF.

Model E Dual-lever (no direct RC→PF)

What the data say. RC→DIV, RC→SPEED, DIV→PF, SPEED→PF all supported; both mediations supported. What to do:

1. Bundle capabilities: pair new products/channels (DIV) with partner access (RC) and execution pacing (SPEED).
2. Slow down to go fast: impose quality thresholds (pilot revenue, defect rates) before scaling speed.
3. Build integration roles (alliance/key-account leads) that translate RC into revenue at speed.

Policy implications (targeted public programs)

1. Network brokerage & matchmaking (A/E): curated buyer–supplier–financier matches + facilitated MoUs to turn RC into monetizable scope.
2. Diversification clinics (B): portfolio discipline, project selection, exit rules—so RC-enabled scope reliably converts to PF.
3. Co-development pilots (C): vouchers requiring MSME–partner pairs to execute one big reconfiguration, not many small tweaks.
4. Integration-talent schemes (A/E): subsidize boundary-spanning roles (alliance, key account) with outcome-based stipends.
5. Sector hubs with light governance: align with observed archetype tilts (e.g., Culinary → B-heavy; Technology → E-only) to reduce coordination frictions and speed diffusion of good practices.

Implementation roadmap (metrics and cadence)

Adopt a quarterly operating rhythm with three leading indicators that correspond to the retained logics:

1. Pipeline quality — share of diversification projects with ≥1 committed partner (LOI).
2. Learning velocity — % projects completing a formal review ≤30 days after milestones.
3. Conversion yield — ratio of partnered projects reaching break-even vs. unpartnered. Tie these to two gates (Gate-1: partner commitment; Gate-2: pilot evidence), matching our finding that relationships + scope outperform speed alone, and that speed works best inside that bundle (Model E).

Limitations and future research

First, the single-province MSME sample limits external validity; replication with sector-balanced, multi-region panels is needed. Second, while we used PLSc, two-stage HOCs, and out-of-sample prediction, identification remains observational; future work can add designs with shocks (policy changes) or instruments. Third, industry heterogeneity is statistically significant but modest (χ^2 $p < .05$; small–moderate Cramér's V); richer sectoral covariates and longitudinal data may surface stronger contingencies.

Future research should (i) test governance conditions (owner dominance, external influence) as moderators within archetypes, (ii) examine digital-channel maturity as a lever interacting with RC, and (iii) evaluate policy pilots (e.g., brokerage vouchers) via randomized rollout.

Conclusion

By contrasting rival capability logics on a validated measurement architecture—and mapping each firm to the model that best predicts its performance—we deliver a decision-ready lens for MSMEs and policymakers. The core message is simple: relationships are the engine; scope is the gearbox; and speed delivers when those two are meshed (as in Model E). Aligning investments and public programs to that reality is more reliable than generic "move faster" prescriptions.

This study not only complements the existing literature but also actively challenges several fundamental assumptions in strategic management and MSME studies. Here are four key challenges these findings pose to scholars in the field. Dynamic Capabilities Are Not Monolithic Concepts, But Rather Archetypal Configurations. Many studies on dynamic capabilities, such as those by Bitencourt et al. (2020) and Weaven et al. (2021), tend to treat capabilities (such as sensing, seizing, and reconfiguring) as a series of independent variables that generally have a positive impact on performance.

This study challenges these parallel and additive views. The findings suggest that the interaction and sequence of capabilities are far more important than the presence of each capability in isolation. Model A (Agility-led), which most closely approximates the conventional view that capabilities operate independently, fails to significantly explain the path to performance, except for Relational Capital. In contrast, the Dual-lever (Model E) archetype suggests that the value of new capabilities emerges when they are properly configured: a relationship that simultaneously enables scope and speed.

Is the common dynamic capabilities framework outdated for the MSME context? Should the theory shift from "what capabilities matter?" to "which capability configurations work, and in what order?"

The "Faster is Better" Assumption is a Dangerous Myth for MSMEs. The literature often links speed and agility directly to better performance. For example, Wang et al. (2018) found that innovation speed mediates the relationship between intellectual capital and performance, while Troise et al. (2022) highlighted the role of agility in the digital age.

This study fundamentally challenges the linear assumption that "faster is always better." Evidence from research in West Java suggests that Speed of Adaptation is a double-edged sword. Without a clear relational foundation and direction for diversification, speed does not lead to better performance and can even be negatively correlated, as implied by the Model D analysis. Speed only becomes valuable when it is part of a dual-lever archetype, where it serves as an accelerator for an already solid strategy, rather than as a strategy in itself.

Should we stop examining speed as a direct antecedent of performance? Instead, should theory begin modeling speed as a dependent variable (the outcome of other capabilities) or as a moderator that is only active under certain conditions (e.g., high levels of Relational Capital)? Relational Capital Is Not Just an 'Asset,' But an Enabling Meta-Capability. Scholars such as Yi et al. (2016) and Long & Zhao (2022) have made important contributions by demonstrating that relational capital supports capability development and performance. However, they often position it as one of several important factors.

This research challenges the position of Relational Capital (RC) as equivalent to other capabilities. The findings suggest that RC should be viewed as a higher-order enabler or "meta-capability." RC is not an option, but rather a prerequisite. Models B and E explicitly show that RC is the starting point that activates diversification and speed. Without RC, the other capability "engines" cannot be effectively ignited.

Are current theoretical models of MSME performance inadequate because they fail to capture the hierarchical nature of capabilities? Should future models explicitly position RC as a causal antecedent of other dynamic capabilities, rather than as a parallel predictor?

Statistical Significance Alone Is Not Enough; Theory Must Have Predictive Validity. Standard research practice in the social sciences and management often stops at testing the significance of hypotheses in samples (in-sample fit), as seen in many of the referenced studies. This study challenges this entire paradigm by integrating rival model testing and out-of-sample predictive validation (PLSpredict) as the core of its analysis. Its findings suggest that a model may be statistically significant, but lack meaningful predictive power in the real world. By mapping each company to the archetype that most accurately predicts its performance, this study sets a new standard:

Are we as an academic community focusing too much on explanatory power (explaining variance in existing data) and neglecting predictive power (the ability to predict new outcomes)? Should journals and doctoral programs require researchers to test their theories against plausible rival models and report predictive validation metrics as a condition of publication?

Conflict of interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

Declaration of sponsorship

We declare that we have no sponsorship or funding to finance the completion of our research.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Ethics clarification

This study did not involve any experimental manipulation or intervention; it relied solely on a voluntary questionnaire completed by adult MSME owners/managers about their business practices. The survey contained no clinical procedures, deception, or sensitive personal data collection, and participation was anonymous, with the option to skip items or withdraw at any time. Consistent with common human-subjects guidance for minimal-risk, non-interventional survey research, the project was treated as exempt from full ethics committee review; accordingly, no protocol number was issued. Nevertheless, we adhered to core ethical principles: written informed consent was obtained before participation and data were analyzed in de-identified, aggregate form (see §3.1 Data Sampling).

References

[1] Rupeika-Apoga, R., & Petrovska, K. (2022). Barriers to Sustainable Digital Transformation in Micro-, Small-, and Medium-Sized Enterprises. Sustainability. https://doi.org/10.3390/su142013558.

[2] Arisena, S., Hendrawan1, Chatra, A., Iman, N., Hidayatullah, S., & Suprayitno, D. (2024). Digital Transformation in MSMEs: Challenges and Opportunities in Technology Management. Jurnal Informasi dan Teknologi. https://doi.org/10.60083/jidt.v6i2.551.

[3] Lei, J., Indıran, L., & Kohar, U. (2023). Barriers to Digital Transformation among MSMEs in the Tourism Industry: Case Studies from Bali. International Journal of Academic Research in Business and Social Sciences. https://doi.org/10.6007/ijarbss/v13-i3/16575.

[4] Purnomo, S., Nurmalitasari, N., & Nurchim, N. Digital transformation of MSMEs in Indonesia: A systematic literature review. Journal of Management and Digital Business. 2024 https://doi.org/10.53088/jmdb.v4i2.1121.

[5] Yogatama, A. H., Hermawan, A., Handayati, P., & Malang, U. Gender and Intersectionality in the Digital Transformation of MSMEs in Indonesia: Enablers and Challenges from a Scoping Review Perspective. International Journal of Integrative Sciences. 2025 https://doi.org/10.55927/ijis.v4i4.152.

[6] Setini, M., Yasa, P., & Sitiari, N. MSME digitalization: How are social capital factors in encouraging the use of digital applications?. International Journal of Data and Network Science. 2025 https://doi.org/10.5267/j.ijdns.2024.10.007.

[7] Qu, C., & Kim, E. Investigating AI Adoption, Knowledge Absorptive Capacity, and Open Innovation in Chinese Apparel MSMEs: An Extended TAM-TOE Model with PLS-SEM Analysis. Sustainability. 2025 https://doi.org/10.3390/su17051873.

[8] Putritamara, J., Hartono, B., Toiba, H., Utami, H., Rahman, M., & Masyithoh, D. Do Dynamic Capabilities and Digital Transformation Improve Business Resilience during the COVID-19 Pandemic? Insights from Beekeeping MSMEs in Indonesia. Sustainability. 2023 https://doi.org/10.3390/su15031760.
[9] Yi, Y., Li, Y., Hitt, M., Liu, Y., & Wei, Z. The influence of resource bundling on the speed of strategic change: Moderating effects of relational capital. Asia Pacific Journal of Management. 2016; 33. https://doi.org/10.1007/S10490-016-9458-Z.
[10] Susiang, M. Dynamic Capabilities, Resources, and Social Capital in Creating Sustainable Competitive Strategies in Indonesian MSME. International Journal of Business, Law, and Education. 2024 https://doi.org/10.56442/ijble.v5i1.499.
[11] Ghobakhloo, M., Iranmanesh, M., Vilkas, M., Grybauskas, A., & Amran, A. Drivers and barriers of Industry 4.0 technology adoption among manufacturing SMEs: a systematic review and transformation roadmap. Journal of Manufacturing Technology Management. 2022 https://doi.org/10.1108/jmtm-12-2021-0505.
[12] Herceg, I., Kuč, V., Mijušković, V., & Herceg, T. Challenges and Driving Forces for Industry 4.0 Implementation. Sustainability. 2020 https://doi.org/10.3390/su12104208.
[13] Kumar, S., Raut, R., Aktas, E., Narkhede, B., & Gedam, V. Barriers to adoption of Industry 4.0 and sustainability: a case study with SMEs. International Journal of Computer Integrated Manufacturing. 2022; 36. https://doi.org/10.1080/0951192X.2022.2128217.
[14] Hariyono, A., Narsa, I., & McMillan, D. The value of intellectual capital in improving MSMEs' competitiveness, financial performance, and business sustainability. Cogent Economics & Finance. 2024; 12. https://doi.org/10.1080/23322039.2024.2325834.
[15] Susiang, M. Dynamic Capabilities, Resources, and Social Capital in Creating Sustainable Competitive Strategies in Indonesian MSME. International Journal of Business, Law, and Education. 2024 https://doi.org/10.56442/ijble.v5i1.499.
[16] Bhadra, K., Kamalanabhan, T., & Singh, S. Evolution of dynamic capabilities for business sustainability performance: Evidence from the Indian manufacturing sector. Business Strategy and the Environment. 2024 https://doi.org/10.1002/bse.3767.
[17] Widagdo, B., & Sa'diyah, C. Business sustainability: Functions of financial behavior, technology, and knowledge. Problems and Perspectives in Management. 2023 https://doi.org/10.21511/ppm.21(1).2023.11.
[18] Nurjannah, D., Wardhana, E., Handayati, P., Winarno, A., & Jihadi, M. The Influence of Managerial Capabilities, Financial Literacy, and Risk Mitigation On SMEs Business Sustainability. Journal of Law and Sustainable Development. 2023 https://doi.org/10.55908/sdgs.v11i4.520.
[19] Hariyono, A., Narsa, I., & McMillan, D. The value of intellectual capital in improving MSMEs' competitiveness, financial performance, and business sustainability. Cogent Economics & Finance. 2024; 12. https://doi.org/10.1080/23322039.2024.2325834.
[20] Susiang, M. Dynamic Capabilities, Resources, and Social Capital in Creating Sustainable Competitive Strategies in Indonesian MSME. International Journal of Business, Law, and Education. 2024 https://doi.org/10.56442/ijble.v5i1.499.
[21] Bhadra, K., Kamalanabhan, T., & Singh, S. Evolution of dynamic capabilities for business sustainability performance: Evidence from the Indian manufacturing sector. Business Strategy and the Environment. 2024 https://doi.org/10.1002/bse.3767.
[22] Widagdo, B., & Sa'diyah, C. Business sustainability: Functions of financial behavior, technology, and knowledge. Problems and Perspectives in Management. 2023 https://doi.org/10.21511/ppm.21(1).2023.11.

[23] Nurjannah, D., Wardhana, E., Handayati, P., Winarno, A., & Jihadi, M. The Influence of Managerial Capabilities, Financial Literacy, and Risk Mitigation On SMEs Business Sustainability. Journal of Law and Sustainable Development. 2023 https://doi.org/10.55908/sdgs.v11i4.520.
[24] Miocevic, D. Dynamic exporting capabilities and SME's profitability: Conditional effects of market and product diversification. Journal of Business Research. 2021; 136. https://doi.org/10.1016/J.JBUSRES.2021.07.025.
[25] Pandey, A. Assessing the Role of International Diversification in Enhancing SME Resilience: A Comparative Analysis. International Journal for Research in Applied Science and Engineering Technology. 2025 https://doi.org/10.22214/ijraset.2025.66873.
[26] Miocevic, D. Dynamic exporting capabilities and SME's profitability: Conditional effects of market and product diversification. Journal of Business Research. 2021; 136. https://doi.org/10.1016/J.JBUSRES.2021.07.025.
[27] Sarwar, Z., Khan, M., Yang, Z., Khan, A., Haseeb, M., & Sarwar, A. An Investigation of Entrepreneurial SMEs' Network Capability and Social Capital to Accomplish Innovativeness: A Dynamic Capability Perspective. SAGE Open. 2021; 11. https://doi.org/10.1177/21582440211036089.
[28] Weaven, S., Quach, S., Thaichon, P., Frazer, L., Billot, K., & Grace, D. Surviving an economic downturn: Dynamic capabilities of SMEs. Journal of Business Research. 2021; 128. https://doi.org/10.1016/J.JBUSRES.2021.02.009.
[29] Wu, H., Chen, J., & Jiao, H. Dynamic capabilities as a mediator linking international diversification and innovation performance of firms in an emerging economy. Journal of Business Research. 2016; 69. https://doi.org/10.1016/J.JBUSRES.2015.11.003.
[30] Bitencourt, C., De Oliveira Santini, F., Ladeira, W., Santos, A., & Teixeira, E. The extended dynamic capabilities model: A meta-analysis. European Management Journal. 2020 https://doi.org/10.1016/J.EMJ.2019.04.007.
[31] Weaven, S., Quach, S., Thaichon, P., Frazer, L., Billot, K., & Grace, D. Surviving an economic downturn: Dynamic capabilities of SMEs. Journal of Business Research. 2021; 128. https://doi.org/10.1016/J.JBUSRES.2021.02.009.
[32] Dejardin, M., Raposo, M., Ferreira, J., Fernandes, C., Veiga, P., & Farinha, L. The impact of dynamic capabilities on SME performance during COVID-19. Review of Managerial Science. 2022; 17. https://doi.org/10.1007/s11846-022-00569-x.
[33] Troise, C., Corvello, V., Ghobadian, A., & O'Regan, N. How can SMEs successfully navigate a VUCA environment: The role of agility in the digital transformation era. Technological Forecasting and Social Change. 2022 https://doi.org/10.1016/j.techfore.2021.121227.
[34] , H., Budhwar, P., Shipton, H., Nguyen, H., & Nguyen, B. Building organizational resilience, innovation through resource-based management initiatives, organizational learning, and environmental dynamism. Journal of Business Research. 2021 https://doi.org/10.1016/j.jbusres.2021.11.090.
[35] Karna, A., Richter, A., & Riesenkampff, E. Revisiting the role of the environment in the capabilities–financial performance relationship: A meta-analysis. Strategic Management Journal. 2016; 37. https://doi.org/10.1002/SMJ.2379.
[36] Ozanne, L., Chowdhury, M., Prayag, G., & Mollenkopf, D. SMEs navigating COVID-19: The influence of social capital and dynamic capabilities on organizational resilience. Industrial Marketing Management. 2022; 104. https://doi.org/10.1016/j.indmarman.2022.04.009.

[37] Parente, R., Murray, J., Zhao, Y., Kotabe, M., & Dias, R. Relational resources, tacit knowledge integration capability, and business performance. J. Knowl. Manag. 2020; 26. https://doi.org/10.1108/jkm-07-2020-0501.
[38] Long, J., & Zhao, W. Building dynamic capabilities of small and medium-sized enterprises through relational embeddedness: evidence from China. Electronic Commerce Research. 2022; 23. https://doi.org/10.1007/s10660-022-09579-z.
[39] Kim, Y., & Park, J. A Study on the Structural Relationship Between Social Capital, Dynamic Capability, and Business Performance in the Supply Chain Environment. Software Engineering, Artificial Intelligence, Networking, and Parallel/Distributed Computing. 2021 https://doi.org/10.1007/978-3-030-67008-5_4.
[40] Holzmayer, F., & Schmidt, S. Dynamic managerial capabilities, firm resources, and related business diversification – Evidence from the English Premier League. Journal of Business Research. 2020; 117. https://doi.org/10.1016/j.jbusres.2020.05.044.
[41] Heaton, S., Teece, D., & Agronin, E. Dynamic capabilities and governance: An empirical investigation of financial performance of the higher education sector. Strategic Management Journal. 2022 https://doi.org/10.1002/smj.3444.
[42] Lin, H., Hsu, I., Hsu, A., & Chung, H. Creating competitive advantages: Interactions between ambidextrous diversification strategy and contextual factors from a dynamic capability perspective. Technological Forecasting and Social Change. 2020 https://doi.org/10.1016/j.techfore.2020.119952.
[43] Xie, Z., Wang, J., & Miao, L. Big data and emerging market firms' innovation in an open economy: The diversification strategy perspective. Technological Forecasting and Social Change. 2021; 173. https://doi.org/10.1016/J.TECHFORE.2021.121091.
[44] Mangifera, L., Perwithosuci, W., Aisyah, S., & Widawati, M. Does Financial Resource Development Effort Affect the Dynamic Entrepreneurial Capability and Performance of SMEs?. Jurnal Manajemen Universitas Bung Hatta. 2024 https://doi.org/10.37301/jmubh.v19i1.24553.
[45] Menne, F., Surya, B., Yusuf, M., Suriani, S., Ruslan, M., & Iskandar, I. Optimizing the Financial Performance of SMEs Based on Sharia Economy: Perspective of Economic Business Sustainability and Open Innovation. Journal of Open Innovation: Technology, Market, and Complexity. 2022 https://doi.org/10.3390/joitmc8010018.
[46] Hernita, H., Surya, B., Perwira, I., Abubakar, H., & Idris, M. Economic Business Sustainability and Strengthening Human Resource Capacity Based on Increasing the Productivity of Small and Medium Enterprises (SMEs) in Makassar City, Indonesia. Sustainability. 2021 https://doi.org/10.3390/SU13063177.
[47] Trieu, H., Nguyen, P., Nguyen, T., Vu, H., & Tran, K. Information technology capabilities and organizational ambidexterity facilitating organizational resilience and firm performance of SMEs. Asia Pacific Management Review. 2023 https://doi.org/10.1016/j.apmrv.2023.03.004.
[48] Oladimeji, M., & Udosen, I. The Effect of Diversification Strategy on Organizational Performance. Journal of Competitiveness. 2019 https://doi.org/10.7441/joc.2019.04.08.
[49] Wang, Z., Cai, S., Liang, H., Wang, N., & Xiang, E. Intellectual capital and firm performance: the mediating role of innovation speed and quality. The International Journal of Human Resource Management. 2018; 32. https://doi.org/10.1080/09585192.2018.1511611.
[50] Arte, P., & Larimo, J. Moderating influence of product diversification on the international diversification-performance relationship: A meta-analysis. Journal of Business Research. 2021 https://doi.org/10.1016/j.jbusres.2021.10.037.

[51] Chu, S., Gong, X., Fang, Z., Lan, H., & Gou, H. Diversification, Relational Capital and Bank Performance: Evidence from Commercial Banks in China. 2020 https://doi.org/10.2991/MSIE-19.2020.60.
[52] Oladimeji, M., & Udosen, I. The Effect of Diversification Strategy on Organizational Performance. Journal of Competitiveness. 2019 https://doi.org/10.7441/joc.2019.04.08.
[53] Corvino, A., Caputo, F., Pironti, M., Doni, F., & Martini, S. The moderating effect of firm size on relational capital and firm performance. Journal of Intellectual Capital. 2019 https://doi.org/10.1108/jic-03-2019-0044.
[54] Kurniawati, A., Wahyuni, S., Fitriati, A., & Inayati, N. The Effect of Capital Structure, Institutional Ownership, Liquidity, and Diversification Strategy on Financial Performance. Indonesian Journal of Business Analytics. 2022 https://doi.org/10.55927/ijba.v2i2.1602.
[55] Szudrowicz, I. Research on the connection between relational capital and company performance. Prace Naukowe Uniwersytetu Ekonomicznego we Wrocławiu. 2020 https://doi.org/10.15611/PN.2020.12.10.
[56] Ghofur, M., N., & Rosini, I. ANALYSIS OF THE EFFECT OF DIVERSIFICATION AND INTELLECTUAL CAPITAL ON CORPORATE FINANCIAL PERFORMANCE WITH GOOD CORPORATE GOVERNANCE AS A MODERATOR. International Journal of Accounting, Management, Economics and Social Sciences (IJAMESC). 2024 https://doi.org/10.61990/ijamesc.v2i6.351.
[57] Chu, S., Gong, X., Fang, Z., Lan, H., & Gou, H. Diversification, Relational Capital and Bank Performance: Evidence from Commercial Banks in China. 2020 https://doi.org/10.2991/MSIE-19.2020.60.
[58] Kamukama, N., Ahiauzu, A., & Ntayi, J. Intellectual capital and performance: testing interaction effects. Journal of Intellectual Capital. 2010; 11. https://doi.org/10.1108/14691931011085687.
[59] Wahyuningtias, E., & Kusumawardhani, R. The moderating effect of income diversification on intellectual capital and company performance: Case study of banking in Indonesia. Jurnal Siasat Bisnis. 2024 https://doi.org/10.20885/jsb.vol28.iss1.art7.
[60] Blouch, R., & Khan, M. Giving a little to many or a lot to a few? Examining the role of firms' strategy and capital in the industrial era 4.0. The Bottom Line. 2025 https://doi.org/10.1108/bl-01-2023-0023.
[61] Massaro, M., Dumay, J., & Bagnoli, C. Where there is a will, there is a way: IC, strategic intent, diversification, and firm performance. Journal of Intellectual Capital. 2015; 16. https://doi.org/10.1108/JIC-07-2014-0091.
[62] Chu, S., Gong, X., Fang, Z., Lan, H., & Gou, H. Diversification, Relational Capital and Bank Performance: Evidence from Commercial Banks in China. 2020 https://doi.org/10.2991/MSIE-19.2020.60.
[63] Githaiga, P. Human capital, income diversification and bank performance–an empirical study of East African banks. Asian Journal of Accounting Research. 2020 https://doi.org/10.1108/ajar-06-2020-0041.
[64] Park, K., & Jang, S. Capital structure, free cash flow, diversification, and firm performance: a holistic analysis.. International Journal of Hospitality Management. 2013; 33. https://doi.org/10.1016/J.IJHM.2013.01.007.