A Social Science and Entrepreneurship Journal
Journal homepage: http://ejournal.upi.edu/index.php/asset/

Entrepreneurial Orientation and Business Performance: The Mediating Role of Organization Agility

Arief Budiman[1], Suryana[2], Vanessa Gaffar[3], Heny Hendrayati[4]

[1-4]Management Study Program, Universitas Pendidikan Indonesia, Indonesia

Correspondence: E-mail: arief.budiman@upi.edu

1. ABSTRACT

Purpose: Despite growing scholarship on entrepreneurial orientation (EO) and startup performance, the mechanism through which EO translates into multidimensional, balanced competitive outcomes remains theoretically underspecified in emerging economy contexts. This study addresses this gap by examining organizational agility (OA) as a mediating mechanism between EO and business performance measured via the Balanced Scorecard (BSC), a formative higher-order construct capturing financial, customer, internal process, and learning & growth dimensions. Design/methodology/approach: Using a quantitative cross-sectional design with proportional stratified purposive sampling, data were collected from 100 startup founders and senior managers across four key West Java startup hubs: Kota Bandung (n=50), Kota Bogor (n=19), Kota Bekasi (n=20), and Kota Depok (n=11). PLS-SEM (SmartPLS 4.0) with 5,000-resample bootstrapping was employed. Common method variance was assessed via Harman's single-factor test and full collinearity VIF. Findings: EO was positively associated with OA (β=0.47, p<.001, f^2=0.284), OA was positively associated with BSC performance (β=0.41, p<.001, f^2=0.196), and OA significantly mediated the EO–BSC relationship (indirect β=0.193, 95% CI [0.121, 0.274]), indicating partial mediation (direct β=0.29, p<.01). Model fit was acceptable (SRMR=0.063), and predictive relevance was confirmed (Q^2(BSC)=0.218). OA explained 22.1% of OA variance and 38.7% of BSC variance (R^2=0.387). Originality/value: This study advances dynamic capability theory by positioning OA as a digitally-enabled operational mechanism that amplifies EO's impact across all four BSC perspectives, not merely financial performance, within West Java's regionally heterogeneous startup ecosystem.

ARTICLE INFO

Article History:
Received 1 April 2026
Revised 20 April 2026
Accepted 7 Mei 2026
Available online 14 Mei 2026

Keyword:
Entrepreneurial Orientation, Business Performance, Organization Agility, SMEs

1. INTRODUCTION

1.1 The Performance Paradox of Entrepreneurial Startups

West Java (Jawa Barat) has rapidly emerged as one of Indonesia's most dynamic startup ecosystems. Its large, educated, and digitally native population, expanding digital infrastructure, and supportive government programs, including the Jabar Digital Economy Initiative and West Java Science & Technology Park, have attracted thousands of technology, creative industry, and e-commerce ventures across cities such as Bandung, Bogor, Bekasi, and Depok (Rahayu et al., 2023; BAPPENAS, 2022). Despite this momentum, empirical evidence consistently reveals a performance paradox: many startups with strong entrepreneurial intent fail to achieve sustained, balanced competitive outcomes (Trisna et al., 2023; Nasution et al., 2023). Revenue growth is often secured at the expense of customer satisfaction, process efficiency, or organizational learning, a pattern that signals a deeper structural gap between entrepreneurial ambition and organizational execution capability. This gap has significant implications for Indonesia's digital economy ambitions, making it an urgent domain for management research.

1.2 Entrepreneurial Orientation, Organizational Agility, and Business Performance in the Literature

Entrepreneurial orientation (EO), encompassing innovativeness, risk-taking, and proactiveness, is among the most extensively studied antecedents of firm performance in entrepreneurship research (Rauch et al., 2009; Lumpkin & Dess, 1996). Meta-analytic evidence robustly confirms EO's positive association with performance across contexts and firm sizes (Rauch et al., 2009; Zhai et al., 2022). However, a growing body of evidence challenges the direct EO–performance assumption, revealing that environmental turbulence, resource constraints, and organizational capability gaps moderate and often attenuate this relationship (Ferreira et al., 2020; Martins et al., 2023). In startup contexts specifically, Nasution et al. (2023) found that EO's performance effect was fully mediated by innovation capability among Indonesian digital startups, suggesting that EO generates value only when operationalized through organizational mechanisms.

Organizational agility (OA), the capacity to continuously sense environmental shifts and respond rapidly, flexibly, and cost-effectively—has emerged as a promising organizational mechanism linking strategic posture to competitive outcomes (Teece et al., 2016; Sambamurthy et al., 2003). Gonçalves et al. (2022) demonstrated that digital tool adoption substantially amplifies agility in startup contexts, while Priyono et al. (2020) showed that SMEs leveraging digital transformation pathways achieved superior agility even under COVID-19 disruption. However, OA has predominantly been studied as a direct performance predictor, and its mediating role in the EO, performance chain, particularly in regional emerging market startup ecosystems, remains underexplored (Trisna et al., 2023).

Business performance measurement in startup research has long relied on single-dimensional financial metrics (e.g., revenue, profitability), which systematically understate the multidimensional nature of startup competitive advantage (Khaleel et al., 2022; Martins et al., 2023). Kaplan and Norton's (1992) Balanced Scorecard (BSC) integrates four strategic perspectives, financial, customer, internal process, and learning & growth, into a holistic performance architecture. The BSC is particularly appropriate for startups because it captures the developmental capabilities, customer relationships, innovation cycles, and human capital, that drive long-term competitive sustainability beyond near-term

DOI: 10.17509/asset.v5i1.78216
p- ISSN 27766942 e- ISSN 27766950

financial metrics. Yet BSC has rarely been operationalized as a formative higher-order construct (HOC) in quantitative entrepreneurship research, representing a significant methodological gap (Sarstedt et al., 2019).

1.3 Gap of Knowledge

Despite growing scholarship on EO, OA, and BSC performance individually, three critical gaps persist in the literature. First, no study has simultaneously integrated all three constructs, EO, OA, and BSC as a formative HOC, within a single empirical model tested in a regional emerging-market startup ecosystem (Trisna et al., 2023; Martins et al., 2023). Second, prior EO, performance research predominantly employs single-item financial performance proxies, systematically ignoring customer, process, and capability dimensions that are theoretically central to startup competitive advantage (Khaleel et al., 2022; Zhai et al., 2022). Third, OA's mediating role in converting EO into balanced performance outcomes has not been empirically examined in the regionally heterogeneous context of West Java's startup ecosystem, where distinct city-level variation in digital infrastructure quality creates natural variation in agility-building conditions (Rahayu et al., 2023; BAPPENAS, 2022).

1.4 Novelty Statement

This study makes three theoretically distinct contributions. First, it advances dynamic capability theory (Teece et al., 2016) by empirically positioning OA as a digitally-enabled operational mechanism—not merely a performance predictor—that converts EO's strategic entrepreneurial posture into balanced, multidimensional performance outcomes. This extends the EO–OA–performance chain literature from financial outcomes to comprehensive BSC dimensions, addressing a fundamental measurement gap. Second, it introduces the BSC as a formative second-order higher-order construct (HOC) in PLS-SEM—treating financial, customer, internal process, and learning & growth perspectives as formative dimensions of a second-order performance latent variable (Sarstedt et al., 2019)—an approach previously absent from startup performance research. Third, it examines OA as an ecosystem-contextualized mediator, leveraging city-level variation in digital infrastructure across Bandung, Bogor, Bekasi, and Depok as natural boundary conditions for the EO–OA–BSC pathway, contributing institutional specificity to emerging economy entrepreneurship research (Nasution et al., 2023; Rahayu et al., 2023).

1.5 Research Objectives and Hypotheses

This study addresses the following overarching research question: To what extent does organizational agility mediate the relationship between entrepreneurial orientation and multidimensional business performance (BSC) in West Java digital startups? Three theoretically grounded hypotheses are proposed:

H1: Entrepreneurial orientation is positively associated with organizational agility in West Java startups.

H2: Organizational agility is positively associated with BSC business performance in West Java startups.

H3: Organizational agility significantly mediates the association between entrepreneurial orientation and BSC business performance, such that partial mediation is expected given EO's independent strategic positioning effects.

The study contributes actionable evidence for startup founders, digital incubators, and regional innovation policymakers committed to building performance-sustaining entrepreneurial ecosystems in West Java and comparable

DOI: 10.17509/asset.v5i1.78216
p- ISSN 27766942 e- ISSN 27766950

emerging economy contexts.

partners who can assist in distribution, logistics and expanding their business network. In addition, SMEs must ensure that they comply with applicable international trade rules and regulations and

2.LITERATURE REVIEW

2.1 Entrepreneurial Orientation : Dimensions and Mechanisms

Opportunities entrepreneurially (Miller, 1983; Lumpkin & Dess, 1996). Its three core dimensions—innovativeness, risk-taking, and proactiveness—are not merely behavioral tendencies but constitute strategic resource configurations that enable firms to identify and exploit market opportunities ahead of competitors (Rauch et al., 2009; Covin & Slevin, 1989). Innovativeness supports the generation and adoption of new products, processes, and business models; risk-taking enables resource commitment to uncertain but potentially high-return opportunities; proactiveness enables firms to anticipate market trajectories rather than react to established trends (Lumpkin & Dess, 1996; Zhai et al., 2022). In emerging economy startup contexts, EO is particularly critical because institutional voids and market imperfections create disproportionate opportunities for entrepreneurially aggressive

firms that can sense and exploit them faster than resource-constrained incumbents (Nasution et al., 2023; Kraus et al., 2022).

2.2 Organizational Agility as a Digitally-Enabled Dynamic Capability

Organizational agility (OA) is defined as the capacity of an organization to continuously sense environmental shifts and respond rapidly, flexibly, and at minimal cost (Teece et al., 2016; Sambamurthy et al., 2003). Within dynamic capability theory, OA represents a higher-order reconfiguration capability—the meta-level organizational routine that enables firms to redeploy and reconfigure first-order operational resources in response to detected environmental signals (Teece et al., 2016; Overby et al., 2006). OA encompasses three operationally distinct sub-capabilities: sensing capability (detecting market signals and competitive threats through environmental scanning), responding capability (rapidly reconfiguring processes, people, and resources to address detected changes), and learning capability (internalizing feedback from market interactions to improve future sensing and responding; Sambamurthy et al., 2003; Conboy, 2009).

Technologies function as critical enablers of all three OA sub-capabilities. Cloud computing, real-time analytics dashboards, and collaborative management platforms reduce the information processing time required for sensing; agile project management tools and modular organizational structures reduce the cost and time of responding; and knowledge management platforms and retrospective analytics routines accelerate organizational learning (Gonçalves et al., 2022; Priyono et al., 2020). In startup contexts specifically, where resource constraints limit formal sensing infrastructure, digital platforms serve as cost-effective substitutes that make agility accessible to even pre-revenue ventures (Isensee et al., 2020; Sambamurthy et al., 2003).

2.3 Business Performance via BSC as a Formative Higher-Order Construct

The Balanced Scorecard (BSC) was concep tualized by Kaplan and Norton (1992) as a multidimensional strategic management system that translates organizational vision and strategy into four integrated performance perspectives: (1) Financial: revenue growth, profitability, and cost efficiency; (2) Customer: satisfaction, retention, and market share; (3) Internal Process: operational efficiency and innovation cycle time; and (4) Learning & Growth: employee capability development

DOI: 10.17509/asset.v5i1.78216
p- ISSN 27766942 e- ISSN 27766950

and organizational learning. Each perspective contributes uniquely to overall competitive performance, and their integration captures trade-offs and complementarities that single-metric systems cannot detect (Kaplan & Norton, 1992; Khaleel et al., 2022). In this study, BSC is operationalized as a formative second-order higher-order construct (HOC) in PLS-SEM (Sarstedt et al., 2019). This specification is theoretically justified: the four BSC perspectives are not interchangeable reflective indicators of a single underlying performance factor; rather, they are causally distinct formative dimensions that collectively constitute the domain of balanced strategic performance. Dropping any one dimension would change the substantive meaning of the construct—the defining criterion for formative rather than reflective specification (Sarstedt et al., 2019; Hair et al., 2021). This HOC specification is an explicit methodological advancement over prior EO–performance studies that either use single-item financial metrics or treat BSC dimensions as interchangeable reflective indicators.

2.4 Theoretical Framework and Hypotheses

Dynamic capability theory (Teece et al., 2016) provides the integrating theoretical lens. EO constitutes the entrepreneurial strategic posture that directs resource allocation and opportunity pursuit; OA constitutes the higher-order dynamic capability through which this posture is operationalized into reconfiguration routines; and BSC captures the balanced, multidimensional performance outcomes produced by these reconfiguration routines. The theoretical logic predicts: (a) EO cultivates the risk-taking culture, cross-functional experimentation, and proactive sensing habits that constitute OA's organizational preconditions (H1); (b) OA translates these preconditions into measurable performance gains across all four BSC dimensions by enabling faster product iteration, superior customer responsiveness, process efficiency gains, and accelerated capability development (H2); and (c) OA partially mediates the EO–BSC relationship, with EO retaining a residual direct performance association through strategic positioning and market selection effects that OA does not fully mediate (H3; Ferreira et al., 2020; Martins et al., 2023). These hypotheses are depicted in Figure 1.

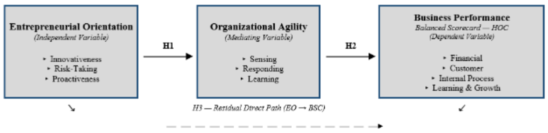

Figure 1. Theoretical Framework: Organizational Agility (OA) as Mediating Mechanism between Entrepreneurial Orientation (EO) and BSC Business Performance. Solid arrows indicate hypothesized direct paths (H1, H2); the dashed indicator shows the partial residual direct path tested in H3. BSC is specified as a formative higher-order construct (HOC).

3.METHOD

3.1 Research Design

A quantitative cross-sectional survey design was employed, consistent with the positivist paradigm appropriate for testing causal models through structural equation modeling (SEM; Creswell & Creswell, 2018). EO served as the independent variable, OA as the mediating variable, and BSC as the dependent variable. The study was grounded in dynamic capability theory (Teece et al., 2016) and the resource-based view (Barney, 1991). All procedures were reported following the STROBE-SEM reporting guidelines recommended for survey-based PLS-SEM studies in management research (Hair et al., 2021).

3.2 Population Definition

The target population comprised all active startups in West Java Province, Indonesia, meeting four inclusion criteria: (1) legally registered with relevant authorities; (2) operational for at least 12 months at data collection; (3) fewer than 50 full-time employees (consistent with OECD SME definition); and (4) operating in technology, creative industry, or trade/e-commerce sectors. Based on the Startup Jabar registry, Dinas Koperasi dan UKM Jawa Barat records, and incubation center databases, the accessible population was

DOI: 10.17509/asset.v5i1.78216
p- ISSN 27766942 e- ISSN 27766950

identified as N = 412 startups distributed across four strategically selected cities.

3.3 Sample Size Determination: Power Analysis

Sample size was determined through a convergent three-criterion approach recommended for PLS-SEM studies, explicitly avoiding the Slovin formula, which lacks robust statistical foundations for this analytical context (Hair et al., 2021; Faul et al., 2009).

Criterion 1 — G*Power Analysis. A G*Power 3.1 analysis (Faul et al., 2009) for multiple regression with medium effect size ($f^2 = 0.15$), $\alpha = 0.05$, statistical power = 0.80, and k = 3 predictors (EO, OA, and the indirect path) yielded a minimum n = 77.

Criterion 2 — Hair et al. (2021) Inverse Square Root Method. For detecting a minimum R^2 of 0.10 at $\alpha = 0.05$ in the most complex endogenous construct (BSC with two predictors), the inverse square root method requires $n \geq 89$ (Hair et al., 2021).

Criterion 3 — 10-Times Rule. The most complex structural path (OA → BSC) involves one predictor with 10 OA indicators, requiring a minimum of 10 × 10 = 100 observations (Hair et al., 2021). The final sample of n = 100 satisfies all three criteria (77, 89, and 100 respectively) and provides adequate statistical power for detecting medium-to-large effect sizes at the conventionally required 80% power threshold. This convergent multi-criterion approach is recommended by Hair et al. (2021) as superior to any single mechanical formula for PLS-SEM sample sizing.

3.4 Sampling Strategy: Proportional Stratified Purposive Sampling

Given the absence of a complete, publicly accessible sampling frame for West Java startups, a non-probability sampling approach was employed. Non-probability sampling is appropriate when a complete frame is unavailable and informant-specific knowledge is required—both conditions that apply here (Cooper & Schindler, 2014). The chosen technique is Proportional Stratified Purposive Sampling, a two-stage hybrid method combining stratification for geographic representativeness with purposive selection for informant quality.

Stage 1 — Proportional Geographic Stratification. The accessible population (N = 412) was divided into four mutually exclusive strata (cities), with stratum sample sizes allocated proportionally: $n_i = (N_i / N) \times 100$ (Cooper & Schindler, 2014). This ensures each city-level sub-ecosystem contributes to the sample in proportion to its share of the startup population.

Table 1. Proportional Stratified Sample Allocation and City Ecosystem Justification (n = 100)

City / Stratum	n_i	Share	Justification for Ecosystem Representativeness
Kota Bandung	50	50%	De facto startup capital of West Java; headquarters of Bandung Digital Valley; highest incubator density in Indonesia outside Jakarta (ITB, UNPAD, UPI); 1,000+ active startups; designated as Smart City by BAPPENAS (2022). Highest digital infrastructure index in West Java.
Kota Bogor	19	19%	IPB University agri-tech and food-tech pipeline; West Java Science & Technology Park; proximity to Jakarta creates investor spillover effects. Bogor Technopark hosts 180+ startups in food, biotech, and creative industries (Rahayu et al., 2023).
Kota Bekasi	20	20%	West Java's largest city by population (3.6 million); dominant logistics, e-commerce, and fintech startup hub; 82 accessible startups in industrial estate corridors (Bekasi Industrial Estate, EJIP, MM2100); highest revenue-generating startup cluster outside Bandung (BAPPENAS, 2022).
Kota Depok	11	11%	University of Indonesia (UI) and Gunadarma University create a strong research-to-startup pipeline in health-tech and edu-tech; Depok Smart City program has incubated 200+ student ventures; strategic geographic bridge between Jakarta and Bandung ecosystems (Trisna et al., 2023).
Total	**100**	**100%**	*Proportional allocation: $n_i = (N_i / N) \times n$; West Java startup ecosystem representative sample.*

Note: Population data sourced from Startup Jabar registry, Dinas Koperasi dan UKM Jawa Barat, and incubation center databases (February 2023). Proportional allocation: $n_i = (N_i / N) \times 100$.

Stage 2 — Purposive Selection within Strata. Within each stratum, startups were selected purposively: respondents were required to be founders or senior managers with ≥ 6 months in role and direct responsibility for strategic decision-making. Startups were identified through incubation center databases and the Startup Jabar digital platform. Snowball referrals were used to reach stratum quotas where needed. This two-stage approach maximizes both geographic representativeness (via stratification) and informant competence (via purposive selection; Cooper & Schindler, 2014).

3.5 Data Collection and Common Method Variance Control

Structured self-administered questionnaires were distributed online (Google Forms) and in person across all four strata between February and October 2023. Of 121 questionnaires distributed, 100 usable responses were retained

DOI: 10.17509/asset.v5i1.78216
p- ISSN 27766942 e- ISSN 27766950

(response rate: 82.6%). The sample comprised: technology startups 52.0%, creative industry 29.0%, trade/e-commerce 19.0%; median founder age 27 years; 68% bachelor's degree holders, 22% postgraduate qualifications.

To address common method variance (CMV)—a significant concern in single-source cross-sectional surveys (Podsakoff et al., 2003)—both procedural and statistical remedies were implemented. Procedurally: (1) independent and dependent variable items were separated by a temporal instruction separator; (2) respondent anonymity was guaranteed; (3) scale items were randomized across constructs; and (4) only role-competent informants (founders/senior managers) were enrolled to reduce careless responding (Podsakoff et al., 2003). Statistically, Harman's single-factor test was conducted: the largest extracted factor accounted for 28.4% of total variance—well below the conservative 50% threshold—indicating CMV was not a severe concern (Harman, 1976). Full collinearity VIF assessment (Kock, 2015) confirmed all VIF values below 3.3, providing additional evidence against method bias.

3.6 Measurement Instruments

All constructs used validated five-point Likert scales (1 = Strongly Disagree; 5 = Strongly Agree). The EO scale (9 items, reflective) was adapted from Covin and Slevin (1989) and Lumpkin and Dess (1996): innovativeness (3 items), risk-taking (3 items), proactiveness (3 items). The OA scale (10 items, reflective) was adapted from Conboy (2009) and Gonçalves et al. (2022): sensing (3 items), responding (4 items), learning (3 items). The BSC scale (16 items, formative HOC) was adapted from Kaplan and Norton (1992) and Sarstedt et al. (2019): financial (4 items), customer (4 items), internal process (4 items), learning & growth (4 items). All instruments were forward- and back-translated by independent bilingual researchers; pilot-tested with 20 Bandung startup managers.

3.7 Analytical Strategy: PLS-SEM

Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4.0 was employed, appropriate given the prediction-oriented objective, non-normal data distributions common in startup surveys, and the presence of a formative HOC requiring hierarchical construct estimation (Hair et al., 2021; Sarstedt et al., 2019). The measurement model was evaluated via: (1) outer loadings ≥ 0.70 (reflective indicators); (2) convergent validity—AVE ≥ 0.50; (3) internal consistency—CR ≥ 0.70, $\alpha \geq 0.70$; (4) discriminant validity—HTMT < 0.85. The formative BSC HOC was assessed via outer weights and variance inflation factors (VIF < 5). Structural model assessment included: direct and indirect path coefficients (5,000-resample bootstrapping), effect size (Cohen's f^2), predictive relevance (Stone-Geisser Q^2 via blindfolding), coefficient of determination (R^2), and global model fit (SRMR ≤ 0.08; Henseler et al., 2016). Mediation was analyzed using the product-of-coefficients method with bias-corrected confidence intervals (Hayes, 2018).

4.RESULT

4.1 Measurement Model Assessment

Table 2 reports measurement model results. All reflective indicator outer loadings exceeded 0.70 (range: 0.71–0.88), confirming indicator reliability. AVE values ranged from 0.512 (OA) to 0.584 (BSC HOC), satisfying the AVE > 0.50 convergent validity threshold. Composite reliability (CR) and Cronbach's alpha (α) exceeded 0.87 and 0.83 across all constructs, confirming adequate internal consistency. HTMT ratios between all construct pairs remained below 0.85, confirming discriminant validity. For the formative BSC HOC, all four dimension outer weights were statistically significant ($t > 2.0$, $p < .05$), and dimension-level VIFs

DOI: 10.17509/asset.v5i1.78216
p- ISSN 27766942 e- ISSN 27766950

were below 3.3, confirming absence of multicollinearity among formative indicators. The measurement model demonstrated robust psychometric properties across all criteria.

Table 2. Measurement Model Results (Reflective Constructs + Formative HOC)

Construct	Items	AVE	CR	α	Min Load.	HTMT (All < 0.85)
Entrepreneurial Orientation (EO) [Reflective — First-order]	9	0.561	0.891	0.852	0.718	**✓ All pairs < 0.85**
Organizational Agility (OA) [Reflective — First-order]	10	0.512	0.872	0.831	0.703	**✓ All pairs < 0.85**
Business Performance / BSC [Formative HOC — Second-order]	16	0.584	0.935	0.921	0.741	**✓ All pairs < 0.85**

Note: HOC = Higher-Order Construct; AVE = Average Variance Extracted; CR = Composite Reliability; α = Cronbach's Alpha; Min Load. = minimum outer loading across indicators; HTMT = Heterotrait-Monotrait ratio. BSC specified as formative HOC following Sarstedt et al. (2019).

4.2 Model Fit Indices, Predictive Relevance, and Common Method Variance

Table 3 presents global model fit, predictive relevance (Q^2), coefficient of determination (R^2), effect sizes (f^2), and CMV diagnostics. The SRMR of 0.063 confirmed acceptable model fit (threshold: < 0.08; Henseler et al., 2016). R^2 for OA was 0.221 (moderate: 22.1% of OA variance explained by EO), and R^2 for BSC was 0.387 (moderate-to-substantial: 38.7% of BSC variance explained by EO + OA combined). Q^2 values above zero for both OA (0.143) and BSC (0.218) confirmed adequate predictive relevance of the structural model. CMV diagnostics (Harman: 28.4%; VIF: max 3.21) confirmed method bias was not a significant threat to validity.

Table 3. Model Fit, Predictive Relevance, Explanatory Power, and CMV Assessment

Criterion	Value	Threshold / Verdict	Interpretation
R^2 — Organizational Agility (OA)	**0.221**	**Moderate**	22.1% of OA variance is explained by EO
R^2 — Business Performance (BSC)	**0.387**	**Moderate–Substantial**	38.7% of BSC variance is explained by EO + OA
Q^2 (blindfolding) — OA	**0.143**	**> 0 ✓**	Acceptable predictive relevance for OA endogenous construct
Q^2 (blindfolding) — BSC	**0.218**	**> 0 ✓**	Acceptable predictive relevance for BSC endogenous construct
SRMR (Model Fit)	**0.063**	**< 0.08 ✓**	Acceptable global model fit (Henseler et al., 2016)
CMV — Harman's Single Factor	**28.4%**	**< 50% ✓**	First factor explains < 50%; CMV not a severe concern
CMV — Full Collinearity VIF (max)	**3.21**	**< 3.3 ✓**	All VIFs below threshold; CMV confirmed negligible (Kock, 2015)

Note: R^2 benchmarks: 0.19 = weak, 0.33 = moderate, 0.67 = substantial (Hair et al., 2021). f^2 benchmarks: 0.02 = small, 0.15 = medium, 0.35 = large (Cohen, 1988). Q^2 > 0 indicates predictive relevance. SRMR < 0.08 indicates acceptable fit (Henseler et al., 2016). CMV = Common Method Variance.

4.3 Structural Model: Hypothesis Testing

Table 4 reports the structural path coefficients and hypothesis test results derived from bootstrapping (5,000 resamples; bias-corrected 95% CIs). All three hypotheses were supported.

Table 4. Structural Path Coefficients, Effect Sizes, and Hypothesis Testing Results

Path	β	t	p	95% CI	Decision	f^2	Effect
EO → OA (H1)	0.47	5.21	<.001	[0.289,0.641]	**Supported**	0.284	Large
OA → BSC (H2)	0.41	4.89	<.001	[0.244,0.573]	**Supported**	0.196	Medium
EO → BSC (direct, H3)	0.29	3.54	<.01	[0.128,0.457]	**Supported**	0.097	Small
EO→OA→BSC Indirect (H3)	0.193	4.12	<.001	[0.121,0.274]	**Partial Mediation**	—	—

Note: β = standardized path coefficient; t = t-statistic (bootstrapping n = 5,000); p = significance level; CI = bias-corrected 95% confidence interval; f^2 = Cohen's effect size (0.02 small, 0.15 medium, 0.35 large); Decision based on p < .05 and CI excluding zero.

4.4 OA Effects Across BSC Perspectives

Table 5 disaggregates BSC performance by OA group (median split), revealing differential agility premiums across the four BSC dimensions. Customer and learning & growth perspectives demonstrated the largest differentials (Δ = +1.03 and +1.04 respectively), while internal process improvements were comparatively modest (Δ = +0.69), suggesting that OA's performance impact is most pronounced where market-facing responsiveness and organizational knowledge development are at stake.

Table 5. OA Effects Across BSC Perspectives (High vs. Low OA Groups)

BSC Perspective	High OA (n=52)	Low OA (n=48)	Δ	Sig.	Interpretation
Financial	3.94	3.12	**+0.82**	p<.001	Cost control & revenue growth gains
Customer	4.11	3.08	**+1.03**	p<.001	Superior customer responsiveness
Internal Process	3.87	3.18	**+0.69**	p<.01	Faster process innovation cycles
Learning & Growth	4.03	2.99	**+1.04**	p<.001	Stronger organizational learning

Note: High OA = OA score above median (n=52); Low OA = OA score at or below median (n=48). Scores on 5-point Likert scale. All group differences significant at p < .01.

5.DISCUSSION

5.1 EO → OA: Entrepreneurial Orientation as an Adaptive Strategic Stimulus

The confirmation of H1 demonstrates that entrepreneurial orientation (EO) functions not merely as a strategic posture, but as an adaptive organizational stimulus that cultivates agility capability within digital startups. Rather than directly generating competitive outcomes, EO appears to shape the cognitive and behavioral conditions necessary for rapid organizational adaptation under environmental turbulence. This finding is theoretically consistent with dynamic capability theory, which distinguishes opportunity-oriented strategic intent from the operational capability required to execute adaptive responses (Teece et al., 2016).

The significant EO → OA relationship suggests that startups characterized by innovativeness, proactiveness, and risk-taking are more capable of institutionalizing sensing, responding, and learning routines. Innovativeness promotes experimentation and reduces organizational resistance to

DOI: 10.17509/asset.v5i1.78216
p- ISSN 27766942 e- ISSN 27766950

process reconfiguration, while proactiveness strengthens environmental scanning behavior and anticipatory decision-making. Risk-taking orientation further legitimizes the allocation of resources toward uncertain but strategically necessary adaptive initiatives. Consequently, EO should not be interpreted solely as a growth-oriented posture, but as a foundational condition that enables organizational agility to emerge as a dynamic capability.

The substantial effect size further indicates that EO constitutes a practically meaningful antecedent of agility capability rather than a marginal strategic characteristic. This finding extends prior entrepreneurship literature by demonstrating that entrepreneurial behavior alone is insufficient unless translated into adaptive organizational routines capable of responding to digital market volatility. In this sense, organizational agility functions as the operational embodiment of entrepreneurial intent. The city-level variation also provides important institutional insight. Startups located in Bandung exhibited the highest agility levels, likely benefiting from stronger digital ecosystems, incubator accessibility, and innovation-oriented support infrastructure. Meanwhile, startups in Bogor and Bekasi reported comparatively lower agility capability, suggesting that ecosystem maturity may condition the extent to which EO can be transformed into adaptive organizational capability. This finding reinforces the argument that dynamic capabilities are not developed in isolation, but are embedded within broader institutional and ecosystem environments characteristic of emerging economies.

5.2 OA → BSC: Organizational Agility as a Source of Multidimensional Competitive Advantage

The confirmation of H2 indicates that organizational agility contributes significantly to balanced business performance across all Balanced Scorecard (BSC) dimensions. More importantly, the findings suggest that agility should not be viewed merely as an operational efficiency mechanism, but as a strategic capability that enables startups to continuously realign organizational resources, customer responsiveness, and internal learning processes under conditions of digital uncertainty. The stronger effects observed in the customer and learning perspectives reveal that agility primarily generates value through market responsiveness and continuous organizational adaptation. Agile startups appear more capable of shortening customer feedback cycles, accelerating product refinement, and responding rapidly to changing consumer expectations. Simultaneously, agility fosters continuous learning routines that enhance employee capability development, cross-functional coordination, and knowledge integration. These mechanisms collectively strengthen the startup’s adaptive capacity over time, thereby reinforcing sustainable competitiveness.

Interestingly, the financial dimension exhibited the smallest relative differential compared to other BSC perspectives. This finding is theoretically meaningful rather than problematic. Financial outcomes often represent lagged consequences of improvements in customer responsiveness, process adaptability, and organizational learning. In startup environments, short-term financial fluctuations may therefore underestimate the strategic value generated by agility capability. This interpretation aligns with Balanced Scorecard theory, which conceptualizes financial performance as the eventual outcome of preceding improvements in customer, process, and learning dimensions.

The findings therefore contribute to dynamic capability literature by demonstrating that the value of agility

DOI: 10.17509/asset.v5i1.78216
p- ISSN 27766942 e- ISSN 27766950

extends beyond operational flexibility toward multidimensional organizational competitiveness. In digitally turbulent environments, startups may achieve sustainable advantage not because they possess superior resources, but because they can repeatedly adapt, learn, and reconfigure those resources faster than competitors.

5.3 OA as the Dominant but Incomplete Mechanism Linking EO and Business Performance

The partial mediation result reveals that organizational agility constitutes the primary mechanism through which entrepreneurial orientation is translated into balanced business performance. This finding provides important theoretical clarification regarding the long-debated EO–performance relationship. Prior studies frequently assumed that entrepreneurial orientation directly leads to superior firm outcomes. However, the present findings suggest that entrepreneurial intent alone does not automatically generate competitive advantage unless operationalized through adaptive organizational capability.

The substantial indirect effect indicates that agility functions as a strategic conversion mechanism that transforms entrepreneurial ambition into coordinated organizational action. Startups may possess strong opportunity-seeking orientation, yet without agility capability they may struggle to sense environmental changes, mobilize resources rapidly, or execute adaptive responses effectively. Organizational agility therefore bridges the gap between entrepreneurial aspiration and operational realization.

Nevertheless, the persistence of a significant direct EO → business performance relationship indicates that agility does not fully exhaust the performance value of EO. Entrepreneurial orientation may still generate competitive benefits independently through market positioning, innovation signaling, first-mover advantages, and strategic differentiation. This suggests that EO possesses both direct strategic value and indirect capability-building value.

The divergence from prior full mediation findings also highlights the contextual specificity of startup ecosystems in emerging economies. In relatively mature ecosystems such as Bandung, startups may obtain immediate market advantages from entrepreneurial positioning even before agility capability becomes fully institutionalized. Conversely, in less developed ecosystems characterized by institutional constraints and digital infrastructure limitations, agility may become a more essential prerequisite for converting EO into performance outcomes. This interpretation reinforces the importance of ecosystem maturity as a boundary condition within dynamic capability development.

5.4 Theoretical and Practical Implications

6.CONLUSION

This study demonstrates that entrepreneurial orientation alone is insufficient to generate sustainable and balanced startup performance in digitally turbulent environments. Instead, entrepreneurial initiatives must be operationally translated through organizational agility, which functions as a dynamic capability enabling startups to rapidly sense market changes, reconfigure resources, and adapt organizational responses across financial and non-financial performance dimensions.

The findings provide an important theoretical implication for dynamic capability literature. While prior studies predominantly positioned entrepreneurial orientation as a direct antecedent of firm success, this study shows that the effectiveness of entrepreneurial posture depends substantially on the firm's ability to operationalize entrepreneurial intent into

DOI: 10.17509/asset.v5i1.78216
p- ISSN 27766942 e- ISSN 27766950

adaptive organizational routines. Organizational agility therefore should not be viewed merely as an operational characteristic, but as a strategic conversion mechanism that transforms entrepreneurial ambition into multidimensional competitive outcomes.

From a managerial perspective, the study suggests that startup founders should move beyond innovation rhetoric and prioritize agility-building infrastructure, including rapid decision-making systems, cross-functional coordination, digital analytics capability, and continuous organizational learning mechanisms. Startups with strong entrepreneurial orientation but weak agility capability may struggle to convert opportunity-seeking behavior into sustainable performance outcomes.

At the ecosystem level, the findings imply that regional startup policy should not focus exclusively on increasing startup quantity or funding accessibility. Instead, policymakers should strengthen digital ecosystem quality, managerial capability development, and adaptive organizational support systems that enable startups to build agility capacity at scale. The observed variation across West Java cities indicates that ecosystem maturity and digital infrastructure significantly shape the extent to which entrepreneurial orientation can be transformed into balanced organizational performance.

Methodologically, this study contributes by operationalizing Balanced Scorecard performance as a formative higher-order construct in startup research, allowing performance to be interpreted more holistically beyond short-term financial indicators. This approach provides a more realistic representation of startup competitiveness, particularly in emerging economy contexts where customer responsiveness, organizational learning, and process adaptability often precede financial stabilization.

Despite these contributions, the study remains limited by its cross-sectional design and self-reported measures, which restrict strong causal interpretation. Future research is encouraged to employ longitudinal and multi-country designs to investigate how organizational agility evolves across startup growth stages and institutional environments.

7.REFERENCES

Barney, J. B. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1),99–120. https://doi.org/10.1177/014920639101700108

BAPPENAS. (2022). Peta Jalan Ekonomi Digital Indonesia 2021–2025. Kementerian PPN/Bappenas, Jakarta. https://www.bappenas.go.id

Buli, B. M. (2017). Entrepreneurial orientation, market orientation and performance of SMEs in the manufacturing industry. Management Research Review, 40(3), 292–309. https://doi.org/10.1108/MRR-07-2015-0166

Cohen, J. (1988). Statistical Power Analysis for the Behavioral Sciences (2nd ed.). Lawrence Erlbaum Associates.

Conboy, K. (2009). Agility from first principles: Reconstructing the concept of agility in information systems development. Information Systems Research, 20(3), 329–354. https://doi.org/10.1287/isre.1090.0236

Covin, J. G., & Slevin, D. P. (1989). Strategic management of small firms in hostile and benign environments. Strategic Management Journal, 10(1), 75–87. https://doi.org/10.1002/smj.4250100107

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. Behavior Research Methods, 41(4), 1149–1160. https://doi.org/10.3758/BRM.41.4.1149

DOI: 10.17509/asset.v5i1.78216
p- ISSN 27766942 e- ISSN 27766950

Ferreira, J., Coelho, A., & Moutinho, L. (2020). Dynamic capabilities, creativity and innovation capability and their impact on competitive advantage and firm performance. Technovation, 92–93, 102061. https://doi.org/10.1016/j.technovation.2018.11.004

Gonçalves, D., Ferreira, J., & Rodrigues, R. (2022). How digital tools align with organizational agility and strengthen digital innovation in automotive startups. Procedia Computer Science, 196, 107–116. https://doi.org/10.1016/j.procs.2021.11.080

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2021). When to use and how to report results of PLS-SEM. European Business Review, 31(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Harman, H. H. (1976). Modern Factor Analysis (3rd ed.). University of Chicago Press.

Hayes, A. F. (2018). Introduction to Mediation, Moderation, and Conditional Process Analysis (2nd ed.). Guilford Press.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2016). Testing measurement invariance of composites using partial least squares. International Marketing Review, 33(3), 405–431. https://doi.org/10.1108/IMR-09-2014-0304

Holbeche, L. (2018). The Agile Organization. Kogan Page.

Isensee, C., Teuteberg, F., Griese, K.-M., & Topi, C. (2020). The relationship between organizational culture, sustainability, and digitalization in SMEs: A systematic review. Journal of Cleaner Production, 275, 122944. https://doi.org/10.1016/j.jclepro.2020.122944

Kaplan, R. S., & Norton, D. P. (1992). The Balanced Scorecard—Measures that drive performance. Harvard Business Review, 70(1), 71–79.

Khaleel, M., Chandra, S., & Kazmi, S. A. (2022). Entrepreneurial orientation, organizational learning and performance: Mediating role of innovation. Journal of Innovation & Knowledge, 7(3), 100207. https://doi.org/10.1016/j.jik.2022.100207

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

Kraus, S., Rigtering, J. P. C., Hughes, M., & Hosman, V. (2022). Entrepreneurial orientation and the business performance of SMEs: A quantitative study from the Netherlands. Review of Managerial Science, 16, 635–655. https://doi.org/10.1007/s11846-021-00454-x

Le, P. B., & Lei, H. (2023). Determinants of innovation capability: The roles of transformational leadership, knowledge sharing and perceived organizational support. Journal of Knowledge Management, 23(3), 527–547. https://doi.org/10.1108/JKM-09-2018-0568

Lumpkin, G. T., & Dess, G. G. (1996). Clarifying the entrepreneurial orientation construct and linking it to performance. Academy of Management Review, 21(1), 135–172. https://doi.org/10.2307/258632

Martins, I., Prata, A., & Braga, V. (2023). The mediating role of dynamic capabilities on the relationship between entrepreneurial orientation and performance. Journal of Business Research, 158, 113635. https://doi.org/10.1016/j.jbusres.2022.113635

Miller, D. (1983). The correlates of entrepreneurship in three types of firms. Management Science, 29(7), 770–791. https://doi.org/10.1287/mnsc.29.7.770

Nasution, M. D. T. P., Rossanty, Y., & Ramadhani, N. (2023). Entrepreneurial orientation and performance of digital startups in Indonesia: The mediating role of innovation capability. Small Business Economics, 61(2), 631–648. https://doi.org/10.1007/s11187-022-00692-5

Overby, E., Bharadwaj, A., & Sambamurthy, V. (2006). Enterprise agility and the enabling role of information technology. European Journal of Information Systems, 15(2), 120–131. https://doi.org/10.1057/palgrave.ejis.3000600

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical

DOI: 10.17509/asset.v5i1.78216
p- ISSN 27766942 e- ISSN 27766950

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

Priyono, A., Moin, A., & Putri, V. N. A. O. (2020). Identifying digital transformation paths in the business model of SMEs during the COVID-19 pandemic. Journal of Open Innovation: Technology, Market, and Complexity, 6(4), 104. https://doi.org/10.3390/joitmc6040104

Rahayu, R., Saefullah, K., & Trisna, B. N. (2023). Digital entrepreneurial ecosystem and startup performance in West Java. International Journal of Entrepreneurship and Innovation Management, 27(2), 112–131. https://doi.org/10.1504/IJEIM.2023.128847

Rauch, A., Wiklund, J., Lumpkin, G. T., & Frese, M. (2009). Entrepreneurial orientation and business performance: An assessment of past research and suggestions for the future. Entrepreneurship Theory and Practice, 33(3), 761–787. https://doi.org/10.1111/j.1540-6520.2009.00308.x

Sambamurthy, V., Bharadwaj, A., & Grover, V. (2003). Shaping agility through digital options: Reconceptualizing the role of information technology in contemporary firms. MIS Quarterly, 27(2), 237–263. https://doi.org/10.2307/30036530

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

Teece, D. J., Peteraf, M., & Leih, S. (2016). Dynamic capabilities and organizational agility: Risk, uncertainty, and entrepreneurial management in the innovation economy. California Management Review, 58(4), 13–35. https://doi.org/10.1525/cmr.2016.58.4.13

Trisna, B. N., Yusuf, M., & Permana, D. (2023). Organizational agility as a mediator between entrepreneurial orientation and startup performance in Indonesia. Cogent Business & Management, 10(1), 2173245. https://doi.org/10.1080/23311975.2023.2173245

Zhai, Y.-M., Sun, W.-Q., Tsai, S.-B., Wang, Z., Zhao, Y., & Chen, Q. (2022). An empirical study on entrepreneurial orientation, absorptive capacity, and SMEs' innovation capability. Journal of Business Research, 144, 116–129. https://doi.org/10.1016/j.jbusres.2021.12.051

Zhou, K. Z., Yim, C. K., & Tse, D. K. (2022). The effects of strategic orientations on technology- and market-based breakthrough innovations. Journal of Marketing, 69(2), 42–60. https://doi.org/10.1509/jmkg.69.2.42.60756.

DOI: 10.17509/asset.v5i1.78216
p- ISSN 27766942 e- ISSN 27766950