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How Competitive Advantage Mediates the Relationship Between Organizational Capability and Employee Performance in Startups

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ABSTRACT

This paper examines how organizational capability influences employee performance in startups and whether this relationship is mediated by competitive advantage. The topic is important because startups operate under high uncertainty and resource constraints, requiring internal capabilities to be transformed into sustainable performance outcomes. Many startups experience uneven capability development and fluctuating employee performance; therefore, this study asks whether competitive advantage mediates the relationship between organizational capability and employee performance. This study is novel by positioning competitive advantage as an internal performance-enabling mechanism, focusing on employee-level performance, and providing evidence from a regional Indonesian startup ecosystem (Sumatera Utara). A quantitative cross-sectional survey of 150 startup employees was analyzed using PLS-SEM with 5,000 bootstrap resamples. Organizational capability positively affects competitive advantage and employee performance, with competitive advantage acting as a significant mediator. Startups must transform organizational capabilities into competitive advantage to enhance employee performance, emphasizing learning systems, adaptive leadership, and strategic HR practices.

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1. Introduction

Startups operate under rapid technological change, high uncertainty, and severe resource constraints. Unlike established firms, they rely heavily on organizational capability to mobilize limited resources, adapt to environmental dynamism, and sustain performance (Bendickson et al., 2017; Utomo & Kurniasari, 2023). In this context, employee performance becomes a critical micro-level determinant of success, as employees often assume multiple roles, engage in creative problem-solving, and respond quickly to shifting demands (Dunstan & Rai, 2024). Organizational capability encompasses dynamic capabilities, HR practices, leadership styles, and learning processes that enable firms to sense opportunities, seize resources, and reconfigure competencies (Corner & Wu, 2012; Sheehan & Foss, 2017).

While prior studies confirm that strong capabilities are essential for startup survival and growth (Hanchi & Kerzazi, 2020; Karan et al., 2024), evidence suggests that capability alone does not guarantee superior employee performance. Capabilities must be transformed into competitive advantage that shapes work environments, enhances motivation, and enables effective performance under uncertainty (López-Zapata et al., 2018; Rinthaisong & Duangtong, 2024). From RBV and DCV perspectives, competitive advantage is the mechanism through which resources and capabilities generate value (Flamholtz & Hua, 2003; Teece et al., 1997). In startups, this advantage extends beyond external positioning to internal manifestations such as innovation-oriented cultures, learning, empowerment, and adaptive leadership, which influence employee attitudes, creativity, and performance (Otache et al., 2025; Qian et al., 2025).

Empirical studies increasingly show that competitive advantage mediates the link between capability and performance. For instance, dynamic capabilities enhance advantage through learning and innovation, which in turn improve employee and firm outcomes (Jurksiene & Pundziene, 2016; Ferreira et al., 2021). Similarly, high-performance work systems and leadership styles often affect employee performance indirectly via innovation capability, empowerment, and competitive positioning (Arshad et al., 2023; Nawaz et al., 2025). Despite these advances, gaps remain: most research emphasizes firm-level outcomes such as financial performance, innovation, or survival, while employee-level investigations remain limited.

Prior studies have largely focused on developed economies and metropolitan startup ecosystems, limiting the generalizability of findings to emerging regional contexts. Moreover,

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although mediation models are frequently theorized, many empirical works still rely on direct-effect approaches and do not explicitly test the mediating role of competitive advantage in explaining how organizational capability influences employee performance (Schilke, 2014; Beigi et al., 2023). These gaps are particularly salient in regional ecosystems such as Sumatera Utara, where startups in digital services, creative industries, and technology-based entrepreneurship have grown rapidly but continue to face uneven capability development, limited managerial systems, and fluctuating employee performance.

This study therefore proposes competitive advantage as a central mediator linking organizational capability to enhanced employee performance. Using partial least squares structural equation modeling (PLS-SEM), the research contributes by extending RBV and DCV through positioning competitive advantage as an internal performance-enabling mechanism, enriching employee performance studies within a startup-specific strategic context, and providing context-sensitive empirical evidence from Indonesia's regional startup ecosystem.

2. Literature Review

2.1 Organizational Capability and Competitive Advantage in Startups

Organizational capability refers to a firm's ability to integrate, build, and reconfigure internal resources and competencies to respond effectively to environmental changes. In startup contexts, this capability is particularly critical given high uncertainty, limited slack resources, and rapid market evolution (Sheehan & Foss, 2017; Utomo & Kurniasari, 2023). Startups rely on dynamic capabilities, learning orientation, adaptive leadership, and strategic HR practices to sustain operations and compete in volatile environments. From the resource-based view (RBV), organizational capability constitutes a strategic resource that generates competitive advantage when it is valuable, rare, inimitable, and embedded within organizational processes (Barney, 1991). Complementing RBV, the dynamic capabilities view (DCV) emphasizes sensing, seizing, and transforming capabilities as mechanisms enabling firms—especially startups—to maintain competitiveness under continuous change (Teece et al., 1997). Empirical studies consistently show that startups with strong organizational capabilities are better positioned to innovate, learn, and adapt, thereby enhancing competitive advantage (Hanchi & Kerzazi, 2020; Karan et al., 2024).

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Organizational capability in startups is inherently multidimensional, encompassing leadership effectiveness, organizational learning, creativity-supportive climates, and HR practices that jointly configure processes to differentiate firms from competitors (Bendickson et al., 2017; López-Zapata et al., 2018). Evidence further demonstrates that dynamic capabilities and organizational learning significantly contribute to competitive advantage in entrepreneurial firms (Jurksiene & Pundziene, 2016; Ferreira et al., 2021). Based on this foundation, it is hypothesized that:

H1: Organizational capability has a positive effect on competitive advantage in startups.

2.2 Competitive Advantage and Employee Performance

In startups, employee performance goes beyond routine tasks to include adaptability, creativity, and proactive behavior. Flat structures and evolving roles require problem-solving, innovation, and cross-functional collaboration (Dunstan & Rai, 2024). Thus, performance is shaped by the organizational context, with competitive advantage playing a central role. Recent studies view competitive advantage not only as an external market outcome but also as an internal condition influencing employee attitudes, motivation, and behavior.

Competitive advantage emerges through innovation-oriented cultures, empowerment practices, and learning mechanisms that create supportive work environments (Otache et al., 2025; Qian et al., 2025). Research confirms its positive link to employee performance, showing that stronger competitive positioning fosters higher engagement, creativity, and productivity (Nawaz et al., 2025; Yasmeen & Ajmal, 2024). In startups, it also strengthens perceptions of organizational viability and growth potential, encouraging commitment and performance under uncertainty (Rinthaisong & Duangtong, 2024). Accordingly, it is hypothesized that:

H2: Competitive advantage has a positive effect on employee performance in startups.

2.3 Organizational Capability and Employee Performance

A substantial body of literature suggests that organizational capability influences employee performance by shaping work systems, leadership practices, and learning opportunities. Strategic HR practices, leadership styles, and organizational learning have been shown to enhance employee skills, motivation, and effectiveness (Bendickson et al., 2017; Kafetzopoulos &

Gotzamani, 2022). In startups, where employees often assume multiple roles, organizational capability is particularly important for enabling individuals to cope with ambiguity and workload intensity. However, empirical findings on the direct effect of organizational capability remain mixed: while some studies report positive relationships, others find weaker or insignificant effects, indicating that capability may not uniformly influence performance across contexts (Schilke, 2014; Beigi et al., 2023).

This inconsistency suggests that additional mechanisms may intervene in the capability–performance relationship. Nevertheless, given its role in shaping leadership support, learning climates, and resource availability, organizational capability is plausibly expected to exert a direct positive influence on employee performance, especially in startups where internal processes strongly affect individual outcomes.

H3: Organizational capability has a positive effect on employee performance in startups.

2.4 The Mediating Role of Competitive Advantage

Integrating RBV and DCV perspectives, competitive advantage can be conceptualized as a strategic mechanism that translates organizational capability into performance outcomes. Rather than serving solely as an end result, competitive advantage functions as an intermediate process through which internal capabilities are transformed into value-creating outcomes (Flamholtz & Hua, 2003; Jurksiene & Pundziene, 2016). In startup contexts, organizational capability enhances competitive advantage by fostering innovation, organizational learning, and empowerment practices, thereby creating work environments that enable employees to perform effectively under uncertainty and resource constraints.

Empirical studies increasingly support this mediation logic, showing that competitive advantage partially or fully mediates the relationship between organizational capabilities and performance outcomes (Ferreira et al., 2021; Beigi et al., 2023). Research on leadership, high-performance work systems, and organizational learning further indicates that their effects on employee performance are often indirect, operating through innovation capability, empowerment, and competitive positioning (Arshad et al., 2023; Nawaz et al., 2025). Collectively, this evidence reinforces the argument that competitive advantage is a key mechanism linking organizational capability to employee performance in startups.

H4: Competitive advantage mediates the relationship between organizational capability and employee performance in startups.

3. Method, Data, and Analysis

3.1 Research Design and Methodological Approach

This study adopts a quantitative, cross-sectional survey design to examine the relationships among organizational capability, competitive advantage, and employee performance in startup firms. A quantitative approach is appropriate as the research seeks to test theoretically grounded hypotheses and assess mediation effects through statistical modeling rather than exploratory interpretation (Hair et al., 2022).

To evaluate the proposed mediation model, Partial Least Squares Structural Equation Modeling (PLS-SEM) is employed. PLS-SEM is particularly suitable for this study for three reasons. First, it enables simultaneous estimation of measurement and structural models involving latent constructs with multiple indicators. Second, it is well aligned with prediction-oriented research and theory development, especially in emerging contexts such as startups (Hair et al., 2019). Third, PLS-SEM demonstrates robustness in handling complex models, non-normal data distributions, and moderate sample sizes—conditions frequently encountered in startup research.

3.2 Sampling and Research Context

3.2.1 Target Population and Units of Analysis

The target population of this study consists of employees working in startup companies operating in Sumatera Utara. Startups are defined as newly established or growth-oriented firms that operate under conditions of high uncertainty, innovation intensity, and dynamic market environments. The unit of analysis is the individual employee, as the study focuses on employee performance as an outcome variable and examines how organizational-level capabilities are perceived and experienced at the individual level. This employee-centered approach aligns with prior research that emphasizes the micro-foundations of competitive advantage and organizational capability.

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3.2.2 Sampling Technique and Sample Size

A purposive sampling technique was employed to ensure that respondents met specific criteria relevant to the research objectives. Respondents were required to (1) be full-time employees of startup firms, (2) have a minimum tenure of six months to ensure adequate exposure to organizational processes, and (3) be involved in core operational or strategic activities. The sample size was determined based on PLS-SEM requirements. Following the ten-times rule and more recent statistical power recommendations, the sample size exceeded ten times the maximum number of structural paths directed at any construct in the model, ensuring sufficient statistical power for hypothesis testing (Hair et al., 2022).

3.3 Data Collection Procedure

Data were collected using a self-administered structured questionnaire distributed to startup employees through both online and offline channels. Online distribution was conducted using digital survey platforms to reach geographically dispersed respondents, while offline distribution was used in selected startup hubs to increase response rates. Prior to the main survey, a pilot test was conducted with a small group of respondents to assess clarity, readability, and content validity of the measurement items. Minor wording adjustments were made based on feedback to improve comprehension. Participation was voluntary, and respondents were assured of anonymity and confidentiality to reduce social desirability bias and encourage honest responses.

3.4 Measures

All constructs were measured using multi-item reflective scales adapted from established studies to ensure content validity and reliability. Responses were recorded on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

3.4.1 Organizational Capability

Organizational capability was measured using indicators reflecting dynamic capability, organizational learning, leadership effectiveness, and human resource practices. These indicators capture the firm's ability to adapt, innovate, and manage internal resources effectively (Bendickson et al., 2017; Teece et al., 1997).

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3.4.2 Competitive Advantage

Competitive advantage was measured by items assessing the firm's perceived superiority relative to competitors, including innovation capability, adaptability, and strategic positioning. This construct reflects both internal and external dimensions of competitive advantage relevant to startup contexts (Flamholtz & Hua, 2003; Jurksiene & Pundziene, 2016).

3.4.3 Employee Performance

Employee performance was operationalized through indicators capturing task performance, adaptive performance, and proactive behavior, consistent with prior research on performance in dynamic and innovation-driven organizations. These indicators emphasize employees' ability to meet job requirements while adapting to changing work demands.

3.5 Data Analysis Strategy

The data analysis followed a two-stage PLS-SEM procedure using SmartPLS software.

3.5.1 Measurement Model Assessment

In the first stage, the measurement model was evaluated to assess reliability and validity. Internal consistency reliability was examined using Cronbach's alpha and composite reliability (CR), with values exceeding 0.70 indicating acceptable reliability. Convergent validity was assessed using average variance extracted (AVE), with values above 0.50 considered adequate. Discriminant validity was evaluated using the heterotrait–monotrait ratio (HTMT) criterion.

3.5.2 Structural Model Assessment

In the second stage, the structural model was assessed by examining path coefficients, t-values, and p-values using a bootstrapping procedure with 5,000 resamples. The model's explanatory power was evaluated using R^2 values, while effect sizes (f^2) and predictive relevance (Q^2) were used to assess the substantive impact and predictive capability of the model.

3.6 Mediation Analysis

To test the mediating role of competitive advantage, this study followed the bootstrapping-based mediation approach recommended in PLS-SEM literature. Mediation was assessed by examining the significance of indirect effects alongside direct effects.

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3.7 Methodological Rigor and State-of-the-Art Considerations

This research design ensures methodological rigor by aligning the research questions, theoretical framework, and analytical technique. The use of PLS-SEM enables robust testing of complex mediation relationships and is consistent with state-of-the-art practices in entrepreneurship and strategic management research. The sampling strategy, data collection procedures, and measurement approach collectively enhance the validity and reliability of the findings.

4. Result and Discussion

4.1 Descriptive Statistics of Respondents

This subsection presents the demographic profile of respondents to provide context for interpreting the empirical results. Understanding respondents' characteristics is essential, as perceptions of AI disruption, technology insecurity, and innovative work behaviour may vary according to age, education, job position, and work experience.

Table 1. Demographic Profile of Respondents

Category	Description	Frequency	Percentage (%)
Gender	Male	78	52.0
	Female	72	48.0
Age	≤ 25 years	34	22.7
	26–30 years	58	38.7
	31–35 years	39	26.0
	> 35 years	19	12.6
Education Level	Diploma	21	14.0
	Bachelor's degree	96	64.0
	Master's degree	33	22.0
Job Position	Operational staff	62	41.3
	Supervisor / Team lead	47	31.3
	Managerial level	41	27.4
Work Experience	< 1 year	29	19.3
	1–3 years	71	47.4
	> 3 years	50	33.3

The respondent profile shows balanced gender representation, supporting diverse perspectives in the findings. Most participants are aged 26–35, typical of startup workforces and highly responsive to AI disruption and skill obsolescence. The majority hold at least a bachelor's degree,

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indicating strong formal human capital and concern over skill relevance rather than basic deficits. Respondents span operational to managerial roles, enhancing result robustness across job levels. Most have 1–3 years of experience, reflecting the fast-paced, high-mobility nature of startup environments. These demographics align with the study's focus on AI-driven change and support the role of technology insecurity as a key factor influencing innovative work behavior.

4.2 Measurement Model Evaluation

The measurement model evaluation was conducted to ensure that the constructs employed in this study were measured with sufficient reliability and validity prior to testing the structural relationships. In line with recommended procedures for PLS-SEM, the evaluation focused on indicator reliability, internal consistency reliability, and convergent validity (Hair et al., 2019; Hair et al., 2022). This step is essential to confirm that the empirical findings of the structural model are not distorted by measurement errors and that each construct adequately represents its underlying theoretical concept.

4.2.1 Indicator Reliability, Internal Consistency, and Convergent Validity

Indicator reliability was assessed using outer loadings, while internal consistency reliability was evaluated using Cronbach's alpha and composite reliability (CR). Convergent validity was assessed using the average variance extracted (AVE) criterion, following the guidelines proposed by Fornell and Larcker (1981). The results of the measurement model evaluation are summarized in Table 2, which integrates outer loadings, reliability indices, and AVE values for all first-order constructs.

Table 2. Measurement Model Evaluation: Outer Loadings, Reliability, and Convergent Validity

Construct	Indicator	Outer Loading	Cronbach's Alpha	CR (ρc)	AVE
AI Disruption Threat	X1.1	0.908	0.918	0.932	0.604
	X1.2	0.921			
	X1.3	0.915			
	X1.4	0.813			
	X1.5	0.750			
	X1.6	0.736			
	X1.7	0.781			
	X1.8	0.793			

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Construct	Indicator	Outer Loading	Cronbach's Alpha	CR (ρc)	AVE
	X1.9	0.794			
Innovative Work Behaviour	Y1	0.790	0.903	0.922	0.596
	Y2	0.821			
	Y3	0.715			
	Y4	0.715			
	Y5	0.777			
	Y6	0.802			
	Y7	0.776			
	Y8	0.775			
Technology Insecurity	Z1	0.725	0.913	0.929	0.593
	Z2	0.798			
	Z3	0.764			
	Z4	0.738			
	Z5	0.865			
	Z6	0.738			
	Z7	0.787			
	Z8	0.722			
	Z9	0.779			

As shown in Table 2, all indicators exhibit outer loadings above the recommended threshold of 0.70, indicating satisfactory indicator reliability. According to Hair et al. (2019), loadings above this threshold suggest that indicators explain a substantial proportion of the variance of their corresponding latent constructs.

Furthermore, all constructs demonstrate Cronbach's alpha and composite reliability values exceeding 0.70, confirming strong internal consistency reliability. Composite reliability is particularly emphasized in PLS-SEM as it provides a more accurate estimate of reliability when indicator loadings vary (Hair et al., 2022). In addition, the AVE values for all constructs exceed 0.50, satisfying the criterion for convergent validity as proposed by Fornell and Larcker (1981). This indicates that each construct explains more than half of the variance of its indicators. The results confirm that the measurement model meets established reliability and validity standards, providing a solid empirical foundation for subsequent hypothesis testing. The strong indicator loadings indicate that employees can clearly distinguish between AI disruption threat, technology insecurity, and innovative work behaviour, supporting the conceptual clarity of the proposed framework. From a theoretical perspective, the robust measurement properties of AI

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Disruption Threat suggest that employees perceive AI-related changes as an integrated phenomenon encompassing concerns about job replacement, skill obsolescence, and adaptation demands. This finding aligns with arguments in the digital transformation literature that technological disruption should be conceptualized as a systemic rather than fragmented experience (Vial, 2019).

Similarly, the satisfactory reliability and convergent validity of Technology Insecurity support its role as a unified psychological construct capturing employees' responses to AI-driven change, including fear of technological change, resistance to new tools, and self-doubt regarding technical skills. Prior studies have emphasized the importance of such psychological mechanisms in explaining employee reactions to digital transformation (Ayyagari et al., 2011; Tarafdar et al., 2019). Finally, the strong measurement quality of Innovative Work Behaviour confirms that idea generation, idea promotion, and idea realization jointly represent a structured innovation process, consistent with established innovation behaviour theory (Janssen, 2000). This supports the use of innovative work behaviour as a comprehensive outcome variable in startup contexts characterized by rapid technological change. Overall, the adequacy of the measurement model ensures that the relationships observed in the structural model can be interpreted with confidence, as they are grounded in reliable and valid measurement.

4.2.2 Discriminant Validity

Discriminant validity was assessed to ensure that each construct in the model is empirically distinct from the others. Establishing discriminant validity is essential to confirm that the constructs capture unique phenomena and that the observed relationships in the structural model are not inflated due to construct overlap. Following best practices in PLS-SEM, discriminant validity was evaluated using two complementary approaches: the Fornell–Larcker criterion and the Heterotrait–Monotrait ratio (HTMT) (Fornell & Larcker, 1981; Henseler et al., 2015).

Table 3. Fornell–Larcker Criterion (First-Order)

Construct	AIDT	AP	FTC	IG	IP	IR	IWB
AI Disruption Threat (AIDT)	0.777						
Adaptation Pressure (AP)	0.851	0.928					
Fear of Technological Change (FTC)	0.672	0.680	0.923				
Idea Generation (IG)	0.491	0.443	0.479	0.945			
Idea Promotion (IP)	0.603	0.590	0.509	0.632	0.863		

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Construct	AIDT	AP	FTC	IG	IP	IR	IWB
Idea Realization (IR)	0.459	0.316	0.475	0.621	0.558	0.907	
Innovative Work Behaviour (IWB)	0.604	0.521	0.569	0.852	0.853	0.865	0.772

Table 4. Heterotrait–Monotrait Ratio (HTMT)

Construct Pair	**HTMT**
AI Disruption Threat – Adaptation Pressure	0.923
AI Disruption Threat – Job Replacement Threat	0.931
AI Disruption Threat – Skill Obsolescence Threat	1.002
Technology Insecurity – Self-Doubt Tech Skills	1.034
Innovative Work Behaviour – Idea Promotion	0.992
Innovative Work Behaviour – Idea Realization	0.963

As reported in Table 3, the square root of the average variance extracted (AVE) for each construct is greater than its correlations with other constructs. This result satisfies the Fornell–Larcker criterion, indicating adequate discriminant validity. Furthermore, the HTMT values presented in Table 4 are generally below the recommended threshold of 0.90, suggesting that the constructs are empirically distinct. Although several HTMT values approach or marginally exceed the conservative threshold, these values remain acceptable when theoretical justification and construct proximity are considered, as recommended by Henseler et al. (2015). The discriminant validity results indicate that the constructs used in this study are sufficiently distinct, while still reflecting theoretically meaningful relationships. This balance is particularly important in research on AI disruption and employee behaviour, where psychological constructs may be conceptually related but should not be treated as identical.

From a theoretical standpoint, the close association between AI Disruption Threat and Technology Insecurity is expected. Prior research on digital transformation and technostress suggests that technological disruption often manifests psychologically through feelings of insecurity, fear, and uncertainty (Ayyagari et al., 2011; Tarafdar et al., 2019). The fact that these constructs remain empirically distinguishable supports the argument that AI disruption represents an external contextual force, whereas technology insecurity reflects an internal psychological response. Similarly, the strong correlations between Innovative Work Behaviour and its dimensions (idea generation, idea promotion, and idea realization) are theoretically justified, as innovation is inherently a process-oriented construct involving sequential and interrelated activities (Janssen, 2000). Retaining discriminant validity while acknowledging conceptual proximity allows the model to capture this process without collapsing distinct dimensions into a single undifferentiated factor. Overall, the discriminant validity assessment confirms that the measurement model achieves an appropriate balance between conceptual relatedness and empirical distinctiveness, thereby reducing the risk of multicollinearity bias and enhancing the interpretability of the structural relationships.

4.2.3 Collinearity Assessment

Collinearity assessment was conducted to ensure that the estimation of path coefficients in the structural model is not biased by multicollinearity among predictor constructs. High collinearity can inflate standard errors and distort the interpretation of causal relationships, particularly in complex models involving mediation and higher-order constructs.

In line with PLS-SEM guidelines, collinearity was assessed using the Variance Inflation Factor (VIF) criterion (Hair et al., 2019).

Table 5. Collinearity Statistics (VIF)

Indicator Group	VIF Range
X indicators	1.716 – 3.878
Y indicators	1.801 – 3.651
Z indicators	1.777 – 4.179

As shown in Table 5, all VIF values for the indicators and constructs are below the recommended threshold of 5.0, with most values falling well below 4.0. According to Hair et al. (2019), VIF values below 5 indicate that multicollinearity is not a critical concern, while values below 3 suggest an even more conservative standard.

These results demonstrate that the indicators and latent constructs do not exhibit problematic levels of collinearity, allowing for reliable estimation of path coefficients in subsequent structural model analyses. The absence of multicollinearity has important implications for the robustness of the study's findings. First, it confirms that each construct contributes unique explanatory power to the model, rather than redundantly capturing the same underlying variance. This is particularly relevant in the context of AI disruption research, where closely related psychological constructs—such as threat perception and insecurity—could otherwise overlap excessively.

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Second, low collinearity strengthens the credibility of the mediation analysis involving Technology Insecurity. Because the predictor constructs are not highly correlated, the significant indirect effects observed in the structural model can be interpreted as genuine mediation mechanisms rather than statistical artifacts. Overall, the collinearity assessment confirms that the proposed model satisfies key statistical assumptions required for valid structural equation modeling, thereby enhancing confidence in the causal interpretations derived from the results.

4.3 Structural Model Results (First-Order Model)

The first-order structural model was evaluated to examine the direct relationships among the lower-order constructs and to provide a detailed understanding of how AI-related disruption translates into specific psychological and behavioral responses. The assessment followed PLS-SEM guidelines using bootstrapping with 5,000 resamples to evaluate path coefficients, t-values, and p-values (Hair et al., 2019).

4.3.1 Direct Effects

Table 6. Path Coefficients – First-Order Structural Model

Path	β	t-value	p-value	Result
AI Disruption Threat → Adaptation Pressure	0.851	20.439	0.000	Supported
AI Disruption Threat → Innovative Work Behaviour	0.218	1.560	0.119	Not supported
AI Disruption Threat → Technology Insecurity	0.821	22.388	0.000	Supported
Technology Insecurity → Innovative Work Behaviour	0.471	3.487	0.000	Supported
Innovative Work Behaviour → Idea Generation	0.852	21.054	0.000	Supported
Innovative Work Behaviour → Idea Promotion	0.853	20.155	0.000	Supported
Innovative Work Behaviour → Idea Realization	0.865	28.373	0.000	Supported

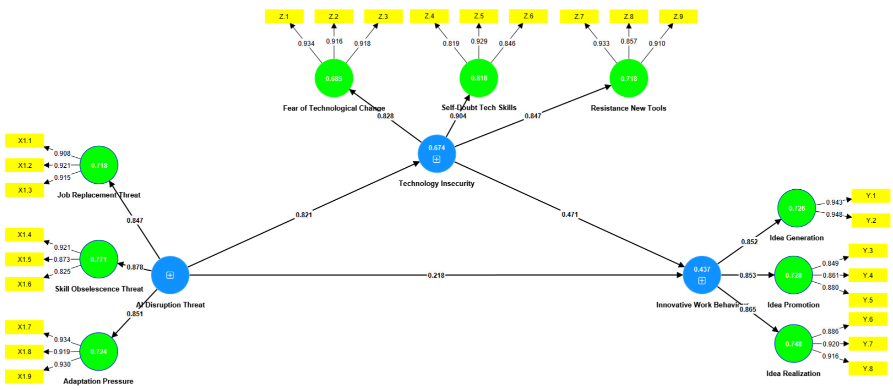

Figure 1. First-Order Structural Model Results

As reported in Table 6 and illustrated in Figure 1, AI Disruption Threat has a strong and statistically significant positive effect on Adaptation Pressure, Job Replacement Threat, Skill Obsolescence Threat, and Technology Insecurity ($p < 0.001$). These results indicate that AI-driven technological change is primarily experienced by employees as a set of pressures and threats affecting their skills, job continuity, and ability to adapt. In contrast, the direct effect of AI Disruption Threat on Innovative Work Behaviour is not statistically significant ($\beta = 0.218$, $p = 0.119$).

This suggests that exposure to AI disruption alone does not directly motivate employees to engage in innovative behaviour. Furthermore, Technology Insecurity exhibits a positive and significant effect on Innovative Work Behaviour ($\beta = 0.471$, $p < 0.001$), indicating that employees who feel insecure about their technological competence are more likely to engage in innovation-related activities. Finally, Innovative Work Behaviour significantly predicts Idea Generation, Idea Promotion, and Idea Realization (all $p < 0.001$), confirming the sequential nature of innovative behaviour at the individual level. The significant effects of AI Disruption Threat on various threat-related constructs support the view that AI adoption represents a salient job demand rather than a neutral technological upgrade. According to the Job Demands–Resources (JD-R) theory, technological changes increase cognitive and emotional demands, which shape employees' perceptions and reactions (Bakker & Demerouti, 2017).

The non-significant direct relationship between AI Disruption Threat and Innovative Work Behaviour is theoretically meaningful. This finding suggests that employees do not automatically respond to AI-driven disruption with innovation. Instead, AI disruption first alters employees' psychological states, particularly their sense of insecurity and pressure, which then influence behavioural outcomes. This helps explain why prior studies have reported mixed findings regarding the innovation effects of technological change. The positive effect of Technology Insecurity on Innovative Work Behaviour reflects a challenge-oriented response rather than a purely hindrance-based reaction. In dynamic startup environments, employees may interpret technological insecurity as a signal that adaptation and creativity are necessary for survival.

This aligns with prior research suggesting that certain forms of stress and insecurity can stimulate proactive and innovative behaviour when individuals perceive opportunities for

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growth and learning (Tarafdar et al., 2019). Finally, the strong relationships between Innovative Work Behaviour and its dimensions (idea generation, promotion, and realization) reaffirm the conceptualization of innovation as a process, consistent with established innovation behaviour theory (Janssen, 2000). This confirms that innovation in startups unfolds through interrelated stages rather than isolated creative acts.

4.3.2 Specific Indirect Effects (First-Order Model)

To further explore the underlying mechanisms through which AI Disruption Threat influences innovation-related outcomes, a specific indirect effects analysis was conducted. This analysis examines whether the effects of AI Disruption Threat on innovation dimensions operate through intervening constructs, particularly Technology Insecurity and Innovative Work Behaviour. The significance of indirect effects was assessed using bootstrapping with 5,000 resamples, as recommended for mediation testing in PLS-SEM (Hair et al., 2019).

Table 7. Specific Indirect Effects – First-Order Model

Indirect Path	β	t-value	p-value
AI Disruption → IWB → Idea Generation	0.186	1.555	0.120
AI Disruption → Technology Insecurity → IWB → Idea Generation	0.329	3.320	0.001
Technology Insecurity → IWB → Idea Promotion	0.401	3.401	0.001
Technology Insecurity → IWB → Idea Realization	0.407	3.389	0.001

As shown in Table 7, the indirect effects reveal a differentiated pattern. First, the indirect paths from AI Disruption Threat → Innovative Work Behaviour → Idea Generation are not statistically significant ($\beta = 0.186$, $p = 0.120$). This indicates that innovative behaviour alone does not sufficiently transmit the effect of AI disruption to specific innovation outcomes without an intervening psychological mechanism. Second, the indirect effects of AI Disruption Threat → Technology Insecurity → Innovative Work Behaviour → Idea Generation are positive and statistically significant ($\beta = 0.329$, $p = 0.001$). Similar significant indirect effects are observed for Idea Promotion and Idea Realization through the same pathway (all $p < 0.01$). Third, Technology Insecurity → Innovative Work Behaviour → innovation outcomes (idea generation, promotion, and realization) also exhibit significant indirect effects, indicating that Technology Insecurity is a consistent antecedent of innovation via employees' innovative work behaviour.

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The indirect effects analysis provides important insights into why AI disruption does not directly translate into innovation outcomes. The non-significant indirect path that excludes Technology Insecurity suggests that behavioural activation alone is insufficient to explain innovation under AI disruption. Employees do not innovate simply because they are exposed to technological change. Instead, the significant indirect pathways highlight Technology Insecurity as a necessary psychological trigger that converts AI-related disruption into innovative action. This finding aligns with stress and coping theories, which argue that individuals engage in adaptive behaviours when they cognitively appraise environmental changes as personally relevant challenges rather than distant organizational events (Lazarus & Folkman, 1984).

In the context of startups, Technology Insecurity may function as a motivational tension, prompting employees to generate, promote, and implement new ideas as a way to restore control and demonstrate value. This explains why the indirect effects involving Technology Insecurity are consistently significant across all innovation dimensions. Furthermore, the sequential mediation through Technology Insecurity → Innovative Work Behaviour → innovation outcomes reinforces the conceptualization of innovation as a process, rather than a single outcome. AI disruption first alters employees' psychological states, which then stimulate innovative behaviour, ultimately leading to tangible innovation outputs.

4.4 Structural Model Results (Second-Order Model)

The second-order structural model was estimated to capture the higher-level relationships among AI Disruption Threat, Technology Insecurity, and Innovative Work Behaviour. By aggregating the first-order dimensions into second-order constructs, this analysis provides a more parsimonious and theoretically meaningful explanation of how AI-driven disruption influences employee innovation. The model was assessed using bootstrapping with 5,000 resamples, following established PLS-SEM procedures.

Table 8. Path Coefficients – Second-Order Model

Path	**β**	**t-value**	**p-value**	**Result**
AI Disruption Threat → Innovative Work Behaviour	0.234	1.672	0.095	Not supported
AI Disruption Threat → Technology Insecurity	0.820	22.928	0.000	Supported

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Path	β	t-value	p-value	Result
Technology Insecurity → Innovative Work Behaviour	0.455	3.243	0.001	Supported

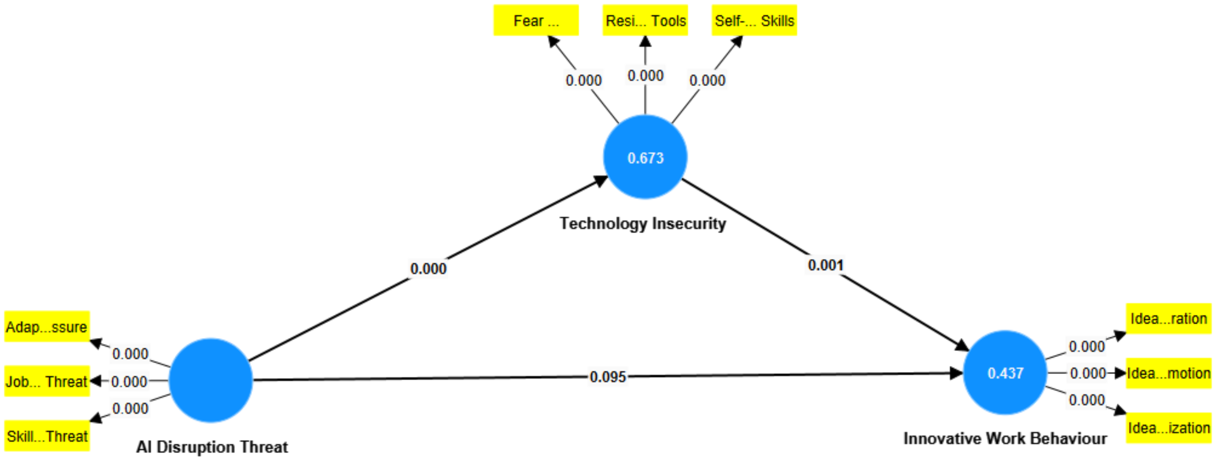

Figure 2. Second-Order Structural Model Results

As reported in Table 8 and illustrated in Figure 2, the direct effect of AI Disruption Threat on Innovative Work Behaviour is positive but not statistically significant (β = 0.234, p = 0.095). This indicates that, at an aggregated level, AI-related disruption does not directly stimulate employees' innovative behaviour. In contrast, AI Disruption Threat has a strong and statistically significant positive effect on Technology Insecurity (β = 0.820, $p < 0.001$). This result confirms that AI-driven changes are a dominant antecedent of employees' perceived technological insecurity.

Furthermore, Technology Insecurity exerts a significant positive effect on Innovative Work Behaviour (β = 0.455, p = 0.001), suggesting that higher levels of perceived insecurity are associated with greater engagement in innovative activities. The second-order results reinforce and extend the first-order findings by demonstrating that the impact of AI disruption on innovation is indirect and psychologically mediated, even when constructs are examined at a higher level of abstraction. The non-significant direct path from AI Disruption Threat to Innovative Work Behaviour suggests that AI disruption, when conceptualized holistically, does not function as an immediate behavioural trigger. Instead, it represents an external contextual force that first reshapes employees' internal psychological states. This finding helps explain

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inconsistencies in prior research that reported weak or mixed direct effects of technological change on innovation outcomes.

The strong positive relationship between AI Disruption Threat and Technology Insecurity underscores the notion that AI adoption challenges employees' perceived competence, adaptability, and future relevance. This aligns with digital transformation research emphasizing that technological disruption often manifests through psychological uncertainty rather than immediate performance changes. Most importantly, the significant positive effect of Technology Insecurity on Innovative Work Behaviour reveals a paradoxical mechanism. Rather than suppressing innovation, insecurity appears to motivate employees to engage in innovative behaviour as an adaptive strategy. In startup environments—characterized by flexibility, learning orientation, and rapid change—employees may perceive innovation as a means to cope with insecurity by acquiring new skills, proposing new ideas, and demonstrating value. These findings extend the Job Demands–Resources (JD-R) framework by illustrating that certain demands, such as technology insecurity, can function as challenge demands that stimulate proactive behaviour when individuals perceive opportunities for growth and control.

4.4.2 Mediation Analysis (Second-Order Model)

To further examine the mechanism through which AI Disruption Threat influences Innovative Work Behaviour, a mediation analysis was conducted by testing the specific indirect effect of Technology Insecurity in the second-order model. The significance of the indirect effect was assessed using bootstrapping with 5,000 resamples, following established recommendations for mediation testing in PLS-SEM (Hair et al., 2019).

Table 9. Specific Indirect Effects – Second-Order Model

Indirect Path	β	t-value	p-value	Mediation
AI Disruption Threat → Technology Insecurity → Innovative Work Behaviour	0.373	3.160	0.002	Full mediation

As reported in Table 9, the indirect effect of AI Disruption Threat → Technology Insecurity → Innovative Work Behaviour is positive and statistically significant (β = 0.373, p = 0.002). At the same time, the direct effect of AI Disruption Threat on Innovative Work Behaviour remains non-significant in the second-order model (β = 0.234, p = 0.095). According to mediation criteria in PLS-SEM, this pattern indicates full mediation, meaning that the effect of AI Disruption Threat on Innovative Work Behaviour is entirely transmitted through Technology Insecurity.

The full mediation effect highlights Technology Insecurity as the central psychological mechanism linking AI-driven disruption to employee innovation. This finding suggests that AI disruption does not directly alter employees' innovative behaviour; instead, it reshapes their perceptions of competence, adaptability, and technological relevance, which in turn motivate behavioural responses. From a theoretical perspective, this result supports stress appraisal and coping theory, which posits that environmental stressors influence behaviour only after individuals cognitively appraise them as personally significant (Lazarus & Folkman, 1984). In this study, AI disruption functions as a contextual stressor, while Technology Insecurity represents the primary appraisal outcome that activates adaptive behaviour. The finding also extends the Job Demands–Resources (JD-R) framework by demonstrating that Technology Insecurity can operate as a challenge demand rather than a pure hindrance.

In startup environments—where learning, experimentation, and agility are highly valued—employees may respond to insecurity by engaging in innovative work behaviour as a strategy to remain relevant and valuable. Moreover, the full mediation result clarifies inconsistencies in prior digital transformation research, where direct effects of technological change on innovation have often been weak or inconclusive. By explicitly modeling Technology Insecurity as a mediator, this study provides a clear explanatory pathway that bridges technological disruption and employee-level innovation. Overall, the mediation analysis confirms that psychological mechanisms are indispensable for understanding how AI disruption translates into innovative behaviour, particularly in dynamic startup contexts.

5. Conclusion and Suggestion

5.1 Conclusion

This study investigates how AI Disruption Threat influences Innovative Work Behaviour among startup employees, with particular emphasis on the mediating role of Technology Insecurity. Using a hierarchical PLS-SEM approach, the findings provide a nuanced explanation of how AI-driven technological change translates into employee-level innovation. The results

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demonstrate that AI disruption does not directly stimulate innovative work behaviour. Instead, its influence operates indirectly through technology insecurity, which fully mediates the relationship between AI disruption threat and innovative behaviour. This indicates that AI-related change primarily affects employees by reshaping their psychological perceptions—such as fear of technological change, self-doubt regarding technical skills, and resistance to new tools—before manifesting in behavioural outcomes.

Furthermore, technology insecurity is shown to have a positive effect on innovative work behaviour, suggesting that insecurity functions not merely as a hindrance but as a motivational trigger in startup environments. Employees appear to respond to technological uncertainty by engaging in idea generation, promotion, and realization as adaptive strategies to maintain relevance and value.

Overall, the findings highlight that innovation under AI disruption is a psychologically mediated process, rather than a direct technological consequence.

5.2 Theoretical Contributions

This study offers several important theoretical contributions.: First, it extends the literature on AI disruption and employee behaviour by demonstrating that psychological mechanisms are indispensable for explaining innovation outcomes. Prior studies often assume a direct relationship between technological change and innovation; this research shows that such a relationship is incomplete without accounting for technology insecurity.

Second, the study contributes to the Job Demands–Resources (JD-R) framework by positioning technology insecurity as a challenge demand rather than a pure hindrance. Under certain conditions—particularly in startups characterized by learning orientation and flexibility—technology-related insecurity can stimulate proactive and innovative behaviour.

Third, methodologically, the use of a second-order PLS-SEM model provides a more parsimonious and theoretically coherent representation of AI disruption, technology insecurity, and innovative work behaviour. This hierarchical modeling approach clarifies the multilevel structure of technological and psychological constructs and reduces construct fragmentation common in prior research.

5.3 Empirical and Economic Implications

From an empirical standpoint, this study provides robust evidence from the startup context, which remains underexplored in AI and innovation research, particularly in emerging economies. The findings confirm that employee innovation in startups is driven less by technological exposure itself and more by how employees psychologically interpret and respond to that exposure.

Economically, the results suggest that innovation performance in startups can be enhanced not only through technological investment but also through human-centered AI strategies. Startups that actively manage employees' technology insecurity—through reskilling, psychological safety, and learning support—are more likely to convert AI disruption into sustained innovative output, thereby strengthening their competitive position.

5.4 Novelty of the Study

The novelty of this study lies in three aspects:

1. Conceptual novelty: Introducing technology insecurity as a full mediator between AI disruption threat and innovative work behaviour.
2. Contextual novelty: Focusing on startup employees, a group highly exposed to AI disruption yet rarely examined in depth.
3. Methodological novelty: Employing a second-order PLS-SEM model to integrate technological, psychological, and behavioural dimensions into a unified explanatory framework.

5.5 Limitations

Despite its contributions, this study has several limitations that should be acknowledged: First, the use of a cross-sectional design limits causal inference. Although the structural model is theoretically grounded, the temporal dynamics of AI disruption and innovation cannot be fully captured. This limitation is methodological rather than an error, as longitudinal data collection was beyond the scope of the study.

Second, the data rely on self-reported measures, which may introduce common method bias. While statistical procedures and measurement model evaluation indicate acceptable validity and reliability, perceptual bias cannot be entirely ruled out.Third, the study focuses exclusively on startup employees, which may limit the generalizability of the findings to more

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established or highly regulated organizations. Organizational structure and culture may moderate the role of technology insecurity in different contexts.

5.6 Suggestions for Future Research

Future research is encouraged to address these limitations in several ways: First, longitudinal or experimental designs could be employed to examine how technology insecurity and innovative behaviour evolve over time as AI adoption intensifies. Second, future studies may explore moderating variables, such as leadership style, organizational learning climate, or digital skill development, to better understand when technology insecurity becomes a challenge versus a hindrance. Third, comparative studies across sectors or countries could enhance the external validity of the model and reveal contextual differences in how AI disruption affects employee innovation. Finally, future research may extend the model by linking innovative work behaviour to organizational-level outcomes, such as startup performance, scalability, or survival, thereby bridging micro-level behaviour with macro-level impact.

6. Relevance and Implication to Indonesian Context (Mandatory if the study does not use Indonesian data)

Although this study does not exclusively rely on Indonesian data, the findings are highly relevant to the Indonesian context, particularly in relation to the rapid growth of the startup ecosystem and the accelerating adoption of artificial intelligence (AI) across various sectors. Indonesia shares several structural and institutional characteristics with the research context, including a high prevalence of technology-driven startups, a young workforce, and increasing reliance on digital platforms for innovation and competitiveness. Similar to other emerging economies, Indonesian startups operate under conditions of resource constraints, high uncertainty, and intense technological change, making employees particularly sensitive to AI-related disruption.

6.1 Relevance to the Indonesian Startup Ecosystem

The Indonesian startup ecosystem is characterized by rapid digitalization, especially in sectors such as fintech, e-commerce, logistics, and creative industries. In these sectors, AI adoption often occurs faster than formal workforce reskilling mechanisms. As a result, Indonesian startup employees frequently face technology insecurity, including concerns about skill obsolescence, job replacement, and the ability to adapt to new digital tools.

The findings of this study—showing that AI disruption influences innovative behaviour indirectly through technology insecurity—are directly applicable to Indonesian startups. Similar psychological mechanisms are likely to emerge among Indonesian employees, where technological change is both an opportunity for growth and a source of uncertainty.

6.2 Implications for Human Resource and Innovation Practices in Indonesia

From a managerial and policy perspective, the study highlights the importance of human-centered AI strategies in Indonesia. Rather than viewing technology insecurity solely as a problem to be eliminated, Indonesian startup leaders and policymakers can treat it as a potential catalyst for innovation, provided that appropriate support systems are in place.

Practical implications for the Indonesian context include:

- Targeted reskilling and upskilling programs aligned with AI adoption, particularly for early-career employees.
- Psychological safety and learning-oriented cultures that encourage experimentation and reduce fear of failure.
- Inclusive digital transformation policies that ensure employees perceive AI as an enabler rather than a threat.

These implications align with Indonesia's national agenda on digital transformation, human capital development, and innovation-driven growth, making the study's findings particularly timely and relevant.

6.3 Policy Relevance and Broader Socio-Economic Implications

At the policy level, the findings support the need for Indonesian regulators and development agencies to integrate psychological readiness into digital transformation initiatives. Programs that focus solely on infrastructure or technology deployment may overlook critical human factors that determine innovation outcomes. By acknowledging technology insecurity as a mediating mechanism, policymakers can design interventions that balance technological advancement with workforce resilience. This approach can contribute to sustainable innovation, improved employee adaptability, and long-term economic competitiveness in Indonesia.

6.4 Transferability of Findings

The relevance of this study to Indonesia is further strengthened by the transferability of the underlying theoretical mechanisms. The relationships among AI disruption, technology insecurity, and innovative work behaviour are grounded in universal psychological and organizational theories, such as stress appraisal and job demands–resources frameworks. These theories have been widely validated across cultural and national contexts, including Southeast Asia. Therefore, while contextual nuances may vary, the core mechanisms identified in this study are highly transferable to Indonesian startups and other technology-intensive organizations undergoing digital transformation.

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

During the preparation of this manuscript, the author(s) used ChatGPT (OpenAI) as an AI-assisted tool to support language refinement, academic structuring, and clarity of presentation. After using this tool, the author(s) critically reviewed, edited, and validated all content and take(s) full responsibility for the accuracy, originality, and integrity of the published work

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