

# The Innovation Performance in Digital Ecosystems: The Roles of Platform Openness, Strategic Collaboration, Knowledge Sharing, and Absorptive Capacity

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## ABSTRACT

**Purpose** – This study examines how innovation performance is generated within digital ecosystems by investigating the roles of platform openness, strategic collaboration, knowledge sharing, and absorptive capacity. It focuses on whether platform openness and strategic collaboration directly enhance innovation performance or operate through knowledge sharing, and whether absorptive capacity strengthens these relationships.

**Design/methodology/approach** – A quantitative research design was employed using survey data collected from 218 firms operating within digitally embedded ecosystems across Jakarta, Surabaya, Bandung, and Makassar, Indonesia. Respondents were selected through purposive sampling, and the data were analyzed using Structural Equation Modeling with Partial Least Squares (SEM-PLS).

**Finding/Results** – The findings indicate that platform openness positively influences innovation performance, with knowledge sharing partially mediating this relationship. Strategic collaboration does not directly influence innovation performance but has a significant indirect effect through knowledge sharing, indicating full mediation. Absorptive capacity does not significantly moderate the proposed relationships.

**Originality/Value** – The study demonstrates that innovation performance in digital ecosystems is driven primarily by knowledge-sharing processes rather than platform openness or strategic collaboration alone. These findings highlight the importance of developing mechanisms that facilitate knowledge exchange to convert ecosystem participation and inter-organizational collaboration into innovation outcomes.

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## **1. Introduction**

Digital transformation has fundamentally reshaped how firms create and capture value, shifting innovation processes from firm-centric activities toward ecosystem-based collaboration. In contemporary digital ecosystems, firms operate through interconnected digital platforms that enable resource integration, complementarities, and distributed innovation (Xing et al., 2024). Rather than relying solely on internal R&D, organizations increasingly leverage platform-based interactions to orchestrate knowledge flows across organizational boundaries.

Platform openness plays a central strategic role in this transformation. Digital platform capabilities—particularly openness in terms of accessibility, modularity, and interoperability—have been empirically linked to enhanced innovation outcomes through open innovation mechanisms (Wang et al., 2023). Open platforms facilitate inbound and outbound knowledge flows, allowing firms to integrate external ideas and technologies into their innovation processes. However, openness is not inherently beneficial; its impact depends on how effectively firms manage collaborative relationships and internal knowledge integration.

Strategic collaboration within digital ecosystems further amplifies innovation potential. Firms embedded in collaborative networks gain access to complementary assets and specialized expertise, which enhances innovation performance when properly managed (Xing et al., 2024). Nevertheless, collaboration alone does not automatically generate innovation advantages. The transformation of shared knowledge into valuable innovation outcomes requires structured knowledge-sharing mechanisms and internal absorptive capabilities.

Knowledge sharing represents a critical mediating mechanism in ecosystem-based innovation. Empirical evidence indicates that digital capacity improves innovation performance primarily through enhanced absorptive capacity and knowledge integration processes (Halik & Halik, 2024; Kastelli et al., 2024). In digital environments characterized by rapid technological change, knowledge sharing enables firms to recombine dispersed information resources into novel products and services.

Absorptive capacity functions as a crucial boundary condition in this relationship. Firms with strong absorptive capacity are more capable of recognizing valuable external knowledge, assimilating it, and transforming it into commercially viable innovation (Abourobah et al., 2023). Recent research confirms that absorptive capacity significantly strengthens the relationship between digital capability and innovation performance, particularly in technology-intensive contexts (Kastelli et al., 2024). Conversely, firms with limited absorptive capacity may struggle to convert ecosystem knowledge flows into innovation outcomes, resulting in underperformance despite high levels of collaboration (Galib et al., 2022).

Despite the growing body of literature on digital platforms and open innovation, several theoretical gaps remain. First, prior studies tend to examine digital platform capability or absorptive capacity independently rather than integrating them within an ecosystem-enabled innovation framework (HALIK et al., 2023; Wang et al., 2023). Second, empirical research rarely models knowledge sharing as an explicit mediating mechanism linking platform openness and strategic collaboration to innovation performance. Third, while absorptive capacity has been widely studied, its moderating role as a boundary condition in digital ecosystem contexts remains insufficiently explored, particularly in emerging economies (Halik et al., 2026; Xing et al., 2024).

Recent empirical findings reinforce the urgency of examining ecosystem-based innovation mechanisms:

**Table 1.** Empirical Phenomenon Supporting the Study

| Study                                                      | Key Finding                                                                                                | Relevance                                     |
|------------------------------------------------------------|------------------------------------------------------------------------------------------------------------|-----------------------------------------------|
| (Wang et al. 2023) & (Halik and Halik 2024)                | Digital platform capability enhances sustainable innovation performance through open innovation mechanisms | Highlights importance of platform openness    |
| (Kastelli et al. 2024)                                     | Absorptive capacity mediates the relationship between digital capacity and innovation performance          | Demonstrates role of knowledge integration    |
| (Abourokbah, Mashat, and Salam 2023) & (Halik et al. 2026) | Absorptive capacity significantly strengthens innovation performance in digital supply chains              | Confirms boundary condition effect            |
| (Xing et al. 2024)                                         | Digital platforms enable open innovation within ecosystem structures                                       | Supports ecosystem - enabled innovation logic |

Source: Adapted from previous research (2026)

Based on the theoretical gaps identified above, this study seeks to address the following research questions:

- Does platform openness significantly influence innovation performance within digital ecosystems?
- Does strategic collaboration significantly influence innovation performance?
- Does platform openness enhance knowledge sharing among ecosystem actors?
- Does strategic collaboration facilitate knowledge sharing within digital ecosystems?
- Does knowledge sharing significantly influence innovation performance?
- Does knowledge sharing mediate the relationship between platform openness and innovation performance?
- Does knowledge sharing mediate the relationship between strategic collaboration and innovation performance?
- Does absorptive capacity moderate the relationship between platform openness and innovation performance?
- Does absorptive capacity moderate the relationship between knowledge sharing and innovation performance?
- Does absorptive capacity moderate the relationship between strategic collaboration and innovation performance?

## **2. Literature Review & Hypothesis Development**

Digital ecosystems enable firms to collaborate, exchange knowledge, and co-create innovation through digitally mediated platforms. Prior studies emphasize that ecosystem participation alone does not automatically generate innovation outcomes; instead, innovation emerges from the interaction between structural openness, collaborative engagement, and knowledge integration processes (Lin, 2007; Teece, 2010).

The theoretical backbone of this study is grounded in Dynamic Capabilities Theory and the Knowledge-Based View (KBV) of the firm. Dynamic capabilities explain how firms adapt,

integrate, and reconfigure internal and external resources to respond to rapidly changing environments (Teece, 2010). In digital ecosystems, dynamic capabilities facilitate superior innovation performance by enabling firms to continuously sense, seize, and transform opportunities arising from digital platforms and collaborative networks (Chatterjee et al., 2023; Halik et al., 2026). At the same time, KBV posits that knowledge is the most strategically vital resource for innovation, and organizational performance depends on the firm's ability to effectively acquire, integrate, and apply both internal and external knowledge sources (Grant, 1996; Kogut & Zander, 1992).

In digital ecosystems, these theories converge to explain how platform openness and strategic collaboration provide access to distributed knowledge and complementary assets, but how internal organizational capabilities determine whether this knowledge leads to actual innovation performance. This foundational logic supports the investigation of mediated and moderated mechanisms in the current study.

### **2.1 Platform Openness and Innovation Performance**

Within digital ecosystems, platform openness enables external actors to access technological infrastructure, share complementary resources, and co-create value. From a Dynamic Capabilities perspective, openness expands a firm's sensing and seizing capacity by exposing it to diverse external knowledge pools (Teece, 2010). The Knowledge-Based View further suggests that increased access to heterogeneous knowledge sources enhances recombination opportunities, which are essential for innovation (Grant, 1996; Kogut & Zander, 1992). Recent empirical research demonstrates that digital platform capability positively influences sustainable innovation performance by facilitating open innovation mechanisms (Halik & Halik, 2024; Wang et al., 2023). Open platform architectures also stimulate complementor-driven innovation and accelerate new product development (Cenamor et al., 2019). Therefore:

**H1: Platform openness positively influences innovation performance.**

### **2.2 Strategic Collaboration and Innovation Performance**

Strategic collaboration reflects structured partnerships that enable joint problem-solving and coordinated innovation. According to open innovation theory, collaboration enhances access to complementary knowledge and reduces uncertainty in innovation activities. Empirical studies indicate that inter-organizational collaboration significantly improves innovation outcomes, particularly in digitally connected ecosystems where coordination costs are lower and knowledge exchange is more fluid (Xing et al., 2024). From a KBV perspective, collaboration increases the diversity and depth of accessible knowledge resources, strengthening innovation capacity. Thus:

**H2: Strategic collaboration positively influences innovation performance.**

### **2.3 Platform Openness and Knowledge Sharing**

Platform openness structurally facilitates knowledge exchange by lowering entry barriers and enabling transparent communication among ecosystem participants. Dynamic ecosystem theory posits that open architectures enhance multidirectional information flows and foster collaborative learning. Empirical findings suggest that open digital platforms stimulate inbound and outbound knowledge exchange, strengthening inter-organizational knowledge-sharing mechanisms (Cenamor et al., 2019). Accordingly:

**H3: Platform openness positively influences knowledge sharing.**

### **2.4 Strategic Collaboration and Knowledge Sharing**

Collaboration establishes relational trust, shared norms, and joint governance mechanisms that support knowledge exchange. Social exchange and KBV arguments indicate that

collaborative partnerships create formal and informal channels for sharing tacit and explicit knowledge. Recent systematic reviews confirm that collaborative open innovation significantly enhances knowledge-sharing intensity among participating firms (Meireles et al., 2022). Hence:

**H4: Strategic collaboration positively influences knowledge sharing.**

## **2.5 Knowledge Sharing and Innovation Performance**

Knowledge sharing is widely recognized as a direct enabler of innovation. Through shared learning and knowledge recombination, firms can develop new products, services, and processes more effectively (Fleming, 2001). Empirical evidence indicates that firms with higher levels of digital-enabled knowledge exchange demonstrate superior innovation performance (Xing et al., 2024). KBV argues that performance differences arise from a firm's ability to integrate distributed knowledge into new value-creating activities. Thus:

**H5: Knowledge sharing positively influences innovation performance.**

**Knowledge Sharing as a Mediator between Platform Openness and Innovation Performance**

Although platform openness provides access to external knowledge, its benefits materialize only when such knowledge is effectively exchanged and utilized. In dynamic ecosystems, openness alone does not guarantee innovation outcomes unless supported by active knowledge-sharing processes (Boudreau, 2010; Gunawan et al., 2024). Prior research shows that digital capabilities improve innovation performance primarily through open knowledge mechanisms rather than through structural openness alone (Wang et al., 2023). Therefore:

**H6: Knowledge sharing mediates the relationship between platform openness and innovation performance.**

## **2.6 Knowledge Sharing as a Mediator between Strategic Collaboration and Innovation Performance**

Strategic collaboration enhances innovation performance by fostering coordinated knowledge exchange. However, collaboration without active knowledge sharing may fail to produce innovation outcomes (Dyer & Singh, 1998). Empirical evidence suggests that collaborative innovation processes achieve superior results when knowledge-sharing intensity is high (Xie & Yu, 2025). Hence:

**H7: Knowledge sharing mediates the relationship between strategic collaboration and innovation performance.**

## **2.7 Moderating Effect of Absorptive Capacity between Platform Openness and Innovation Performance**

Absorptive capacity determines how effectively firms recognize and exploit external knowledge obtained through platform openness. According to Dynamic Capabilities Theory, absorptive capacity strengthens a firm's ability to transform accessible knowledge into innovative outputs (Galib et al., 2025). Recent studies confirm that absorptive capacity significantly enhances the impact of digital capabilities on innovation performance (Kastelli et al., 2024). Thus:

**H8: Absorptive capacity positively moderates the relationship between platform openness and innovation performance, such that the relationship is stronger when absorptive capacity is high.**

## **2.8 Moderating Effect of Absorptive Capacity between Knowledge Sharing and Innovation Performance**

Knowledge sharing provides access to external insights, but firms must possess absorptive capacity to internalize and apply shared knowledge effectively. Without this capability, knowledge exchange may not translate into performance gains. Empirical findings show that absorptive capacity strengthens the link between knowledge processes and innovation outcomes (Abourokbah et al., 2023). Therefore:

**H9: Absorptive capacity positively moderates the relationship between knowledge sharing and innovation performance.**

## **2.9 Moderating Effect of Absorptive Capacity between Strategic Collaboration and Innovation Performance**

Strategic collaboration generates potential innovation value through shared resources and joint initiatives. However, firms must absorb and integrate collaborative knowledge to realize performance benefits. Dynamic capability research suggests that absorptive capacity enhances the effectiveness of collaborative innovation strategies (Kastelli et al., 2024). Thus:

**H10: Absorptive capacity positively moderates the relationship between strategic collaboration and innovation performance.**

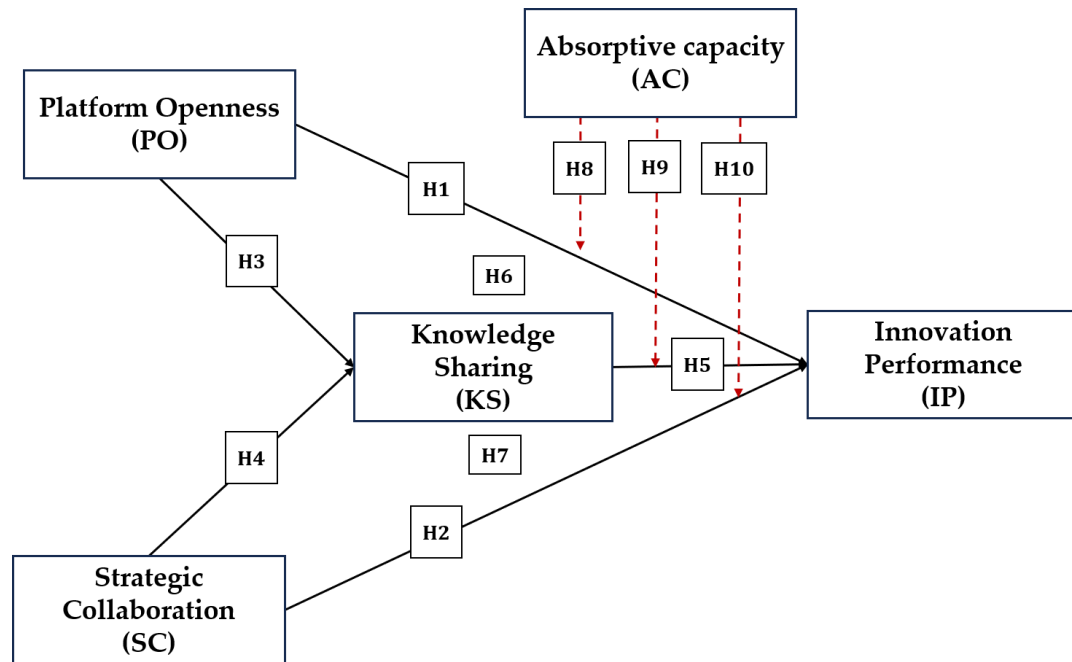
Building upon the theoretical foundations of the Dynamic Capabilities Theory and the Knowledge-Based View, this study develops a conceptual framework that explains how innovation performance is facilitated through within digital ecosystems. Specifically, the framework proposes that ecosystem-level strategies namely platform openness and strategic collaboration, serve as primary drivers of innovation outcomes. However, consistent with process-oriented innovation perspectives, the model assumes that the effects of these strategic mechanisms do not occur in isolation.

Instead, the framework posits that knowledge sharing functions as a central explanatory mechanism through which ecosystem strategies are translated into innovation performance. In digitally connected environments, openness and collaboration expand access to distributed knowledge resources, yet the transformation of such resources into innovative outputs depends on active knowledge exchange processes among ecosystem participants.

Furthermore, recognizing that access to external knowledge does not automatically ensure its effective utilization, this study introduces absorptive capacity as a critical boundary condition. Firms differ in their ability to recognize, assimilate, and apply externally acquired knowledge. Therefore, absorptive capacity is proposed to strengthen the direct and indirect relationships between ecosystem strategy, knowledge sharing, and innovation performance.

Taken together, the proposed framework integrates structural ecosystem characteristics, relational collaboration mechanisms, and internal organizational capabilities into a unified model of digital innovation mechanisms. The conceptual relationships among the variables are illustrated in Figure 1.

**Figure 1.** Conceptual Framework



### 3. Methodology

#### 3.1 Research Design

This study adopts a quantitative research approach using a cross-sectional survey design to examine the relationships among platform openness, strategic collaboration, knowledge sharing, absorptive capacity, and innovation performance within digital ecosystems. Quantitative survey designs are widely employed in innovation and digital ecosystem research because they allow researchers to test theoretical relationships and evaluate causal patterns across organizational contexts (Hair, Page, and Brunsveld 2022).

The unit of analysis in this study is the firm, while the unit of observation consists of key informants representing each organization. Key informants include individuals holding managerial or strategic positions such as founders, innovation managers, research and development (R&D) managers, or business development managers. These individuals are considered appropriate respondents because they possess sufficient knowledge regarding their firm's innovation activities, collaboration practices, and digital ecosystem participation (Memon et al. 2025; Podsakoff, MacKenzie, and Podsakoff 2016).

The conceptual framework of this research proposes that platform openness and strategic collaboration influence innovation performance directly and indirectly through knowledge sharing, while absorptive capacity functions as a moderating capability that may strengthen the effectiveness of knowledge exchange within digital ecosystems.

#### 3.2 Population, Sample, and Sampling Technique

The population of this research consists of firms operating within digital ecosystem environments, particularly organizations that rely on digital platforms, technology-based services, or digitally mediated collaboration networks.

These firms include:

- digital platform-based businesses,
- technology startups,

- software and IT solution providers,
- digital creative industry firms,
- companies integrating digital platforms into their business models.

Given the difficulty of obtaining a complete sampling frame of ecosystem participants, this study employs a purposive sampling technique. Purposive sampling allows the researcher to select respondents who meet specific criteria relevant to the research objectives (Sugiyono 2020).

Firms included in the sample must satisfy the following criteria:

- a. The firm actively participates in a digital platform ecosystem.
- b. The firm engages in inter-organizational collaboration with external partners.
- c. The firm has been operating for at least three years, ensuring adequate experience with ecosystem participation.
- d. The respondent occupies a managerial or strategic role with knowledge of innovation and collaboration processes.

In structural equation modeling research, an adequate sample size is essential to ensure statistical power and reliable parameter estimation. Previous methodological studies recommend a minimum sample size of 150–200 observations for models involving mediation and moderation relationships (Hair, Howard, and Nitzl 2021).

Accordingly, this study collected 218 valid responses, which exceeds the recommended threshold for PLS-SEM analysis, ensuring sufficient statistical robustness for hypothesis testing.

### **3.3 Research Location and Time**

The research was conducted among firms participating in digital ecosystems in Indonesia, particularly organizations involved in technology-driven industries and platform-based business environments. These firms are embedded in collaborative digital networks that facilitate knowledge exchange and innovation activities.

Data collection was carried out using an online survey questionnaire, which allowed efficient access to geographically dispersed respondents and ensured consistency in the data collection process (Sugiyono 2020).

The survey was conducted during the 2025–2026 research period, during which respondents completed structured questionnaires measuring their firm's collaboration practices, knowledge-sharing activities, absorptive capacity, and innovation outcomes.

### **3.4 Data Analysis Technique**

The data analysis in this study uses Partial Least Squares Structural Equation Modeling (PLS-SEM). This technique is suitable for research models that involve complex relationships, mediation mechanisms, and moderating effects among latent constructs (Hair et al. 2019). The moderating effects were estimated using the product indicator approach implemented in Smart-PLS 4 because all latent constructs in this study were operationalized as reflective measurement models.

PLS-SEM is particularly appropriate for innovation and digital ecosystem studies because it:

- supports exploratory and predictive research models,
- accommodates relatively complex structural relationships,
- works effectively with non-normal data distributions.

The analysis procedure consists of two main stages:

#### **a. Measurement Model Evaluation (Outer Model)**

The measurement model is assessed to ensure the reliability and validity of the constructs. The following criteria are applied:

- Indicator reliability (factor loadings > 0.70)
- Internal consistency reliability using Composite Reliability
- Convergent validity using Average Variance Extracted (AVE > 0.50)
- Discriminant validity using the Heterotrait-Monotrait Ratio (HTMT)

These procedures follow the methodological recommendations proposed by (Hair et al. 2019).

#### **b. Structural Model Evaluation (Inner Model)**

The structural model is assessed through:

- Coefficient of determination ( $R^2$ )
- Effect size ( $f^2$ )
- Model Fit
- Bootstrapping analysis to test the significance of path coefficients.

Bootstrapping with 5,000 resamples is applied to examine the significance of direct effects, indirect effects (mediation), and moderating effects in the research model (Hair et al. 2021).

### **3.5 Measurement Indicators**

All constructs in this study are measured using multi-item Likert-scale indicators, where respondents indicate their level of agreement on a five-point scale (1 = strongly disagree, 5 = strongly agree).

The measurement items are adapted from established scales in prior international studies to ensure reliability and validity. See Table 2.

**Table 2.** Measurement Items

| Construct                    | Code | Measurement Items                                                          | Source                                                                                                                                                     |
|------------------------------|------|----------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Platform Openness (PO)       | PO1  | The platform supports external partner contribution.                       | (Jung and Lyytinen 2014)<br>(Sahetapy et al. 2025)<br>(Haleem et al. 2022)<br>(HALIK et al. 2023)                                                          |
|                              | PO2  | The platform provides external developers with clear access to APIs/tools. |                                                                                                                                                            |
|                              | PO3  | The platform enables integration of external services.                     |                                                                                                                                                            |
|                              | PO4  | Platform governance encourages third-party innovation.                     |                                                                                                                                                            |
| Strategic Collaboration (SC) | SC1  | We engage in long-term strategic alliances with partners.                  | (Xing et al. 2024)<br>(Nahapiet and Ghoshal 1998)<br>(Halik and Halik 2024)<br>(Strutzenberger and Ambos 2014)<br>(Meireles, Azevedo, and Boaventura 2022) |
|                              | SC2  | Our strategic partners share resources relevant to innovation.             |                                                                                                                                                            |
|                              | SC3  | Joint development activities are regularly conducted.                      |                                                                                                                                                            |
|                              | SC4  | Collaboration partners co-create innovation outcomes.                      |                                                                                                                                                            |
| Knowledge Sharing (KS)       | KS1  | We frequently share technical knowledge with partners.                     | (Lin 2007)<br>(Singh et al. 2021)                                                                                                                          |

| Construct                   | Code | Measurement Items                                            | Source                                             |
|-----------------------------|------|--------------------------------------------------------------|----------------------------------------------------|
| Absorptive Capacity (AC)    | KS2  | Partners willingly exchange valuable information.            | (Halik and Halik 2024)<br>(Kastelli et al. 2024)   |
|                             | KS3  | Knowledge shared enhances mutual learning.                   |                                                    |
|                             | KS4  | There are structured routines for knowledge exchange.        |                                                    |
|                             | KS5  | Knowledge sharing improves organizational problem solving.   |                                                    |
|                             | AC1  | We can recognize valuable external knowledge.                |                                                    |
|                             | AC2  | We are able to assimilate external knowledge.                | (M'Chirgui and Pénard 2011)                        |
|                             | AC3  | We transform knowledge into useful concepts.                 | (Abourokbah et al. 2023)<br>(Kastelli et al. 2024) |
|                             | AC4  | We exploit external knowledge for innovation outcomes.       |                                                    |
| Innovation Performance (IP) | IP1  | We frequently introduce new products.                        |                                                    |
|                             | IP2  | Our new products achieve strong market success.              |                                                    |
|                             | IP3  | Our firm is faster than competitors in product development.  | (Halik et al. 2026)<br>(Wang et al. 2023)          |
|                             | IP4  | Our innovation activities improve internal processes.        | (Kastelli et al. 2024)                             |
|                             | IP5  | Our innovation results in enhanced competitive advantage.    |                                                    |
|                             | IP6  | Overall, our innovation outcomes exceed industry benchmarks. |                                                    |

Source: Authors' compilation based on previous studies. (2026)

## 4. Result and Discussion

### 4.1 Result

#### 4.1.1 Respondent Demographics

A total of 247 questionnaires were collected during the data collection period. After screening for completeness and response consistency, 218 valid responses were retained for further analysis, resulting in a usable response rate of 88.26%. This sample size exceeds the minimum requirement for PLS-SEM models involving mediation and moderation, thereby providing sufficient statistical power for the analysis (Hair et al., 2022).

The respondents were drawn from four major Indonesian cities such as Jakarta, Surabaya, Bandung, and Makassar, representing key digital innovation hubs in the country.

Firms were identified through regional business directories, industrial associations, and local business networks. To avoid duplicate responses, only one senior manager or owner from each firm was invited to participate. Responses were screened for completeness, response consistency, and missing values. Twenty-nine questionnaires were excluded because they contained substantial missing data, inconsistent response patterns, or failed the data quality screening criteria. Consequently, 218 valid responses were retained for the final analysis.

Regarding respondents' positions, most participants held managerial or strategic roles within their organisations. Specifically, 32.1% were founders or co-founders, 27.5% served as innovation or R&D managers, 21.6% were business development managers, and 18.8% occupied senior operational or digital transformation roles. This distribution indicates that respondents were directly involved in strategic decision-making and innovation activities, supporting the suitability of the key-informant approach adopted in this study.

In terms of firm characteristics, 41.3% of firms were small enterprises, 38.5% were medium-sized, and 20.2% were large organisations. Furthermore, 67.4% of firms had operated for more than five years, indicating that most respondents represented organisations with a relatively mature operational background.

With respect to industry sectors, 46.8% of firms operated in digital platform-based services, 28.4% in technology development and IT solutions, 14.7% in creative digital industries, and 10.1% in other digitally integrated sectors such as fintech and logistics technology. These sectors reflect the digital ecosystem context targeted in this study.

In addition, 72.9% of firms reported collaborating with at least three strategic partners, 64.2% were actively involved in joint innovation projects, and 78.0% indicated a strong reliance on external knowledge sources for innovation development. These characteristics are consistent with the collaborative and knowledge-driven nature of innovation within digital ecosystems. The demographic profile of the respondents is summarised in Table 3.

**Table 3.** Respondent Demographics (N = 218)

| Category      | Classification                             | Frequency | Percentage (%) |
|---------------|--------------------------------------------|-----------|----------------|
| Region (City) | Jakarta                                    | 60        | 27.5           |
|               | Surabaya                                   | 54        | 24.8           |
|               | Bandung                                    | 52        | 23.9           |
|               | Makassar                                   | 52        | 23.9           |
| Position      | Founder / Co-Founder                       | 70        | 32.1           |
|               | Innovation / R&D Manager                   | 60        | 27.5           |
|               | Business Development Manager               | 47        | 21.6           |
|               | Senior Operations / Digital Transformation | 41        | 18.8           |
| Firm Size     | Small (< 50 employees)                     | 90        | 41.3           |
|               | Medium (50–249 employees)                  | 84        | 38.5           |
|               | Large ( $\geq$ 250 employees)              | 44        | 20.2           |
| Firm Age      | $\leq$ 5 years                             | 71        | 32.6           |
|               | > 5 years                                  | 147       | 67.4           |
| Industry Type | Digital Platform Services                  | 102       | 46.8           |

| Category                       | Classification                          | Frequency | Percentage (%) |
|--------------------------------|-----------------------------------------|-----------|----------------|
| Collaboration Intensity        | Technology Development / IT Solutions   | 62        | 28.4           |
|                                | Creative Digital Industry               | 32        | 14.7           |
|                                | Fintech / Logistics Technology / Others | 22        | 10.1           |
|                                | ≥ 3 Strategic Partners                  | 159       | 72.9           |
|                                | < 3 Strategic Partners                  | 59        | 27.1           |
|                                |                                         |           |                |
| Joint Innovation Participation | Actively Involved                       | 140       | 64.2           |
|                                | Not Actively Involved                   | 78        | 35.8           |
| External Knowledge Dependence  | High Dependence                         | 170       | 78.0           |
|                                | Low–Moderate Dependence                 | 48        | 22.0           |

Source: Processed primary data (2026)

To assess the potential for non-response bias, an early–late response comparison was conducted following the procedure recommended by (Armstrong and Overton 1977). Responses received during the initial phase of data collection were compared with those obtained in the later stage, based on key constructs used in the study. Independent sample t-tests revealed no statistically significant differences between early and late respondents across the main variables ( $p > 0.05$ ). These results suggest that non-response bias is unlikely to be a serious concern in this study.

#### 4.1.2 Measurement Model Evaluation

The measurement model was assessed prior to evaluating the structural relationships to ensure that all constructs satisfied the required reliability and validity criteria. Following established PLS-SEM guidelines, the evaluation covered indicator reliability, internal consistency reliability, convergent validity, and discriminant validity (Ghozali, 2021; Hair et al., 2019, 2021).

**Table 4.** Measurement Model Evaluation Results

| Construct                    | Indicator | Outer Loading | Cronbach's Alpha | Composite Reliability (rho_a) | Composite Reliability (rho_c) | Average Variance Extracted (AVE) |
|------------------------------|-----------|---------------|------------------|-------------------------------|-------------------------------|----------------------------------|
| Platform Openness (PO)       | PO1       | 0.911         | 0.910            | 0.917                         | 0.937                         | 0.789                            |
|                              | PO2       | 0.900         |                  |                               |                               |                                  |
|                              | PO3       | 0.919         |                  |                               |                               |                                  |
|                              | PO4       | 0.820         |                  |                               |                               |                                  |
| Strategic Collaboration (SC) | SC1       | 0.909         | 0.902            | 0.913                         | 0.932                         | 0.774                            |
|                              | SC2       | 0.918         |                  |                               |                               |                                  |
|                              | SC3       | 0.876         |                  |                               |                               |                                  |
|                              | SC4       | 0.812         |                  |                               |                               |                                  |
| Knowledge Sharing (KS)       | KS1       | 0.814         | 0.874            | 0.887                         | 0.909                         | 0.667                            |
|                              | KS2       | 0.792         |                  |                               |                               |                                  |

| Construct                   | Indicator | Outer Loading | Cronbach's Alpha | Composite Reliability (rho_a) | Composite Reliability (rho_c) | Average Variance Extracted (AVE) |
|-----------------------------|-----------|---------------|------------------|-------------------------------|-------------------------------|----------------------------------|
| Innovation Performance (IP) | KS3       | 0.894         | 0.905            | 0.911                         | 0.927                         | 0.678                            |
|                             | KS4       | 0.862         |                  |                               |                               |                                  |
|                             | KS5       | 0.710         |                  |                               |                               |                                  |
|                             | IP1       | 0.836         |                  |                               |                               |                                  |
|                             | IP2       | 0.885         |                  |                               |                               |                                  |
|                             | IP3       | 0.814         |                  |                               |                               |                                  |
|                             | IP4       | 0.838         |                  |                               |                               |                                  |
|                             | IP5       | 0.802         |                  |                               |                               |                                  |
| Absorptive Capacity (AC)    | IP6       | 0.762         | 0.854            | 0.871                         | 0.901                         | 0.694                            |
|                             | AC1       | 0.847         |                  |                               |                               |                                  |
|                             | AC2       | 0.771         |                  |                               |                               |                                  |
|                             | AC3       | 0.874         |                  |                               |                               |                                  |
|                             | AC4       | 0.838         |                  |                               |                               |                                  |

Source: Smart-PLS 4 Output (2026)

Indicator reliability was first examined using outer loadings. All indicators exceeded the recommended threshold of 0.70, indicating adequate item reliability. Although KS5 (0.710) displayed a relatively lower loading, it remained above the acceptable level and was therefore retained (Hair et al., 2019; Santosa, 2018).

Internal consistency reliability was assessed using Cronbach's Alpha and Composite Reliability (CR). All constructs reported values well above the recommended threshold of 0.70, confirming strong internal consistency among the measurement items.

Convergent validity was evaluated using the Average Variance Extracted (AVE). All constructs achieved AVE values greater than 0.50, indicating that the constructs explained more than half of the variance of their respective indicators (Hair et al., 2021; Henseler et al., 2015).

**Table 5.** Discriminant Validity – Heterotrait-Monotrait Ratio (HTMT)

| Construct                    | AC    | IP    | KS    | PO    | SC |
|------------------------------|-------|-------|-------|-------|----|
| Absorptive Capacity (AC)     | –     |       |       |       |    |
| Innovation Performance (IP)  | 0.198 | –     |       |       |    |
| Knowledge Sharing (KS)       | 0.108 | 0.674 | –     |       |    |
| Platform Openness (PO)       | 0.136 | 0.406 | 0.323 | –     |    |
| Strategic Collaboration (SC) | 0.078 | 0.484 | 0.669 | 0.341 | –  |

Source: Smart-PLS 4 Output (2026)

Discriminant validity was assessed using the Heterotrait-Monotrait Ratio (HTMT) criterion. Following the recommendations of Henseler et al. (2015), HTMT values below 0.85 indicate that the constructs are empirically distinct and possess adequate discriminant validity, while values below 0.90 are also considered acceptable in less conservative assessments.

As presented in Table 5, all pairwise HTMT values range from 0.078 to 0.674, which are well below the conservative threshold of 0.85. The highest HTMT value is observed between

Knowledge Sharing and Innovation Performance (HTMT = 0.674), followed by Knowledge Sharing and Strategic Collaboration (HTMT = 0.669). Although these constructs exhibit relatively stronger conceptual associations, their HTMT values remain substantially below the recommended cut-off, confirming that they measure distinct latent constructs.

Furthermore, the remaining construct pairs demonstrate relatively low HTMT values, such as Absorptive Capacity–Strategic Collaboration (0.078), Absorptive Capacity–Knowledge Sharing (0.108), and Platform Openness–Strategic Collaboration (0.341), indicating clear empirical separation among the constructs.

Overall, these findings confirm that the measurement model satisfies the discriminant validity criterion, demonstrating that Platform Openness, Strategic Collaboration, Knowledge Sharing, Absorptive Capacity, and Innovation Performance represent conceptually and empirically distinct constructs. Therefore, the constructs are appropriate for subsequent structural model evaluation and hypothesis testing.

Overall, the measurement model satisfies the recommended reliability and validity criteria for PLS-SEM analysis. These results indicate that the constructs—Platform Openness, Strategic Collaboration, Knowledge Sharing, Innovation Performance, and Absorptive Capacity—are measured reliably and can therefore be used for subsequent structural model evaluation.

#### **4.1.3 Structural Model Evaluation**

The structural model was assessed to evaluate the predictive capability of the proposed framework and to examine the relationships among the latent constructs. Following the recommended procedures in PLS-SEM, the assessment included collinearity diagnostics, explanatory power ( $R^2$ ), effect size ( $f^2$ ), model fit, and hypothesis testing using the bootstrapping procedure (Hair et al., 2021).

Collinearity Assessment (VIF). Collinearity among predictor constructs was examined using the Variance Inflation Factor (VIF). In PLS-SEM, VIF values should remain below 5.0 (Ghozali, 2021; Hair et al., 2019).

**Table 6.** Inner Model Collinearity Assessment (Inner VIF Values)

| <b>Structural Path</b>                                                 | <b>Inner VIF</b> |
|------------------------------------------------------------------------|------------------|
| Absorptive Capacity → Innovation Performance                           | <b>1.054</b>     |
| Absorptive Capacity × Knowledge Sharing → Innovation Performance       | <b>1.861</b>     |
| Absorptive Capacity × Platform Openness → Innovation Performance       | <b>1.194</b>     |
| Absorptive Capacity × Strategic Collaboration → Innovation Performance | <b>1.687</b>     |
| Knowledge Sharing → Innovation Performance                             | <b>1.762</b>     |
| Platform Openness → Innovation Performance                             | <b>1.155</b>     |
| Platform Openness → Knowledge Sharing                                  | <b>1.052</b>     |
| Strategic Collaboration → Innovation Performance                       | <b>1.653</b>     |
| Strategic Collaboration → Knowledge Sharing                            | <b>1.052</b>     |

Source: SmartPLS 4 Output (2026)

To assess structural collinearity, the inner variance inflation factor (Inner VIF) values were examined for all predictor constructs in the structural model. As shown in Table 6, all Inner VIF values range from 1.052 to 1.861, which are substantially below the recommended threshold of 5.0 (Hair et al., 2021). These findings indicate that multicollinearity among the

predictor constructs is not a concern and that the estimated structural relationships are not adversely affected by collinearity.

Coefficient of Determination ( $R^2$ ). The coefficient of determination ( $R^2$ ) indicates the extent to which endogenous constructs are explained by their predictor variables. In PLS-SEM,  $R^2$  values of 0.75, 0.50, and 0.25 are generally interpreted as substantial, moderate, and weak, respectively (Hair et al., 2019; Haryono, 2017). However, in behavioural and organisational research contexts,  $R^2$  values between 0.30 and 0.50 are commonly regarded as acceptable due to the complexity of social phenomena.

**Table 7.** Coefficient of Determination (R-Square Results)

| Endogenous Construct        | R-Square ( $R^2$ ) | R-Square Adjusted | Interpretation |
|-----------------------------|--------------------|-------------------|----------------|
| Knowledge Sharing (KS)      | 0.392              | 0.386             | Moderate       |
| Innovation Performance (IP) | 0.437              | 0.418             | Moderate       |

Source: SmartPLS 4 Output (2026)

The results show that Knowledge Sharing (KS) records an  $R^2$  value of 0.392 (Adjusted  $R^2$  = 0.386), indicating that Platform Openness and Strategic Collaboration explain approximately 39.2% of the variance in knowledge-sharing activities. This level of explanatory power can be considered moderate, suggesting that openness and collaborative strategies play an important role in facilitating knowledge exchange, although additional organisational or environmental factors may also contribute.

For Innovation Performance (IP), the model produces an  $R^2$  value of 0.437 (Adjusted  $R^2$  = 0.418). This implies that 43.7% of the variance in innovation performance is explained by Platform Openness, Strategic Collaboration, Knowledge Sharing, Absorptive Capacity, and their interaction effects. The result indicates a moderate yet meaningful predictive capability of the model in explaining innovation outcomes within the studied ecosystem context.

The minimal difference between  $R^2$  and Adjusted  $R^2$  across constructs further indicates model stability and the absence of overfitting. Overall, these findings suggest that the proposed framework provides a satisfactory level of explanatory power in capturing the mechanisms through which collaborative ecosystem structures and knowledge processes contribute to organisational innovation performance.

Effect Size ( $f^2$ ). The effect size ( $f^2$ ) evaluates the individual contribution of each exogenous construct to an endogenous variable by examining the change in  $R^2$  when a predictor is removed from the model. Following Cohen (1992),  $f^2$  values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively (Hair et al., 2021).

**Table 8.** Effect Size ( $f^2$ )

| Structural Path                                  | $f^2$ Value | Effect Size Interpretation |
|--------------------------------------------------|-------------|----------------------------|
| Knowledge Sharing → Innovation Performance       | 0.241       | Medium                     |
| Platform Openness → Innovation Performance       | 0.066       | Small                      |
| Platform Openness → Knowledge Sharing            | 0.039       | Small                      |
| Strategic Collaboration → Innovation Performance | 0.008       | Negligible                 |
| Strategic Collaboration → Knowledge Sharing      | 0.512       | Large                      |

| Structural Path                                                        | f <sup>2</sup><br>Value | Effect Size<br>Interpretation |
|------------------------------------------------------------------------|-------------------------|-------------------------------|
| Absorptive Capacity × Platform Openness → Innovation Performance       | 0.001                   | Negligible                    |
| Absorptive Capacity × Knowledge Sharing → Innovation Performance       | 0.004                   | Negligible                    |
| Absorptive Capacity × Strategic Collaboration → Innovation Performance | 0.006                   | Negligible                    |

Source: Smart-PLS 4 Output (2026)

The effect size analysis provides further insight into the relative importance of each structural relationship. The results indicate that Strategic Collaboration has a large effect on Knowledge Sharing ( $f^2 = 0.512$ ), suggesting that collaborative partnerships play a dominant role in facilitating knowledge exchange within digital ecosystems. This highlights the importance of structured inter-organisational interactions in enabling knowledge flows among firms.

Knowledge Sharing demonstrates a medium effect on Innovation Performance ( $f^2 = 0.241$ ), confirming its central role in translating ecosystem interactions into innovation outcomes. This finding reinforces the mediating logic of the model, indicating that innovation benefits emerge primarily when collaborative knowledge exchange occurs.

By contrast, Platform Openness shows small effects on both Knowledge Sharing ( $f^2 = 0.039$ ) and Innovation Performance ( $f^2 = 0.066$ ). While openness contributes to innovation dynamics, its independent influence appears more limited compared to active collaboration. This suggests that open digital infrastructures alone are insufficient to generate strong innovation outcomes without accompanying collaborative mechanisms.

Interestingly, the direct effect of Strategic Collaboration on Innovation Performance is negligible ( $f^2 = 0.008$ ). This implies that collaboration does not directly translate into innovation outcomes but instead operates largely through knowledge-sharing processes, thereby strengthening the theoretical argument for a mediating mechanism.

#### 4.1.4 Predictive Performance (PLSpredict).

In addition to assessing the explanatory power of the structural model through the coefficient of determination ( $R^2$ ), this study evaluated the model's out-of-sample predictive performance using the PLS-predict procedure implemented in Smart-PLS 4. Unlike  $R^2$ , which reflects the model's in-sample explanatory capability, PLS-predict assesses the model's ability to accurately predict observations that were not used during model estimation. Following the recommendations of Shmueli et al. (2019) and Hair et al. (2022), predictive performance is evaluated by examining the  $Q^2_{\text{predict}}$  values and comparing the prediction errors of the PLS-SEM model with those of the benchmark linear model (LM). Positive  $Q^2_{\text{predict}}$  values indicate that the model possesses predictive relevance, while lower RMSE values for the PLS-SEM model relative to the LM suggest superior predictive performance.

**Table 9.** PLS-predict Results

| Indicator | $Q^2_{\text{predict}}$ | PLS-SEM<br>RMSE | LM RMSE | Predictive Assessment   |
|-----------|------------------------|-----------------|---------|-------------------------|
| IP1       | 0.166                  | 0.859           | 0.873   | PLS-SEM performs better |
| IP2       | 0.219                  | 1.009           | 1.027   | PLS-SEM performs better |

| Indicator | Q <sup>2</sup> <sub>predict</sub> | PLS-SEM<br>RMSE | LM RMSE | Predictive Assessment   |
|-----------|-----------------------------------|-----------------|---------|-------------------------|
| IP3       | 0.155                             | 0.900           | 0.925   | PLS-SEM performs better |
| IP4       | 0.183                             | 0.843           | 0.864   | PLS-SEM performs better |
| IP5       | 0.133                             | 0.897           | 0.904   | PLS-SEM performs better |
| IP6       | 0.119                             | 0.961           | 0.991   | PLS-SEM performs better |
| KS1       | 0.226                             | 0.801           | 0.822   | PLS-SEM performs better |
| KS2       | 0.219                             | 0.869           | 0.900   | PLS-SEM performs better |
| KS3       | 0.382                             | 0.862           | 0.831   | LM performs better      |
| KS4       | 0.300                             | 0.883           | 0.915   | PLS-SEM performs better |
| KS5       | 0.122                             | 0.918           | 0.946   | PLS-SEM performs better |

Source: Smart-PLS 4 Output (2026)

Table 9 presents the PLS-predict results used to evaluate the model's out-of-sample predictive performance. First, all indicators exhibit positive Q<sup>2</sup><sub>predict</sub> values, ranging from 0.119 to 0.382. According to Shmueli et al. (2019), positive Q<sup>2</sup><sub>predict</sub> values indicate that the structural model possesses predictive relevance and is capable of generating predictions beyond the estimation sample.

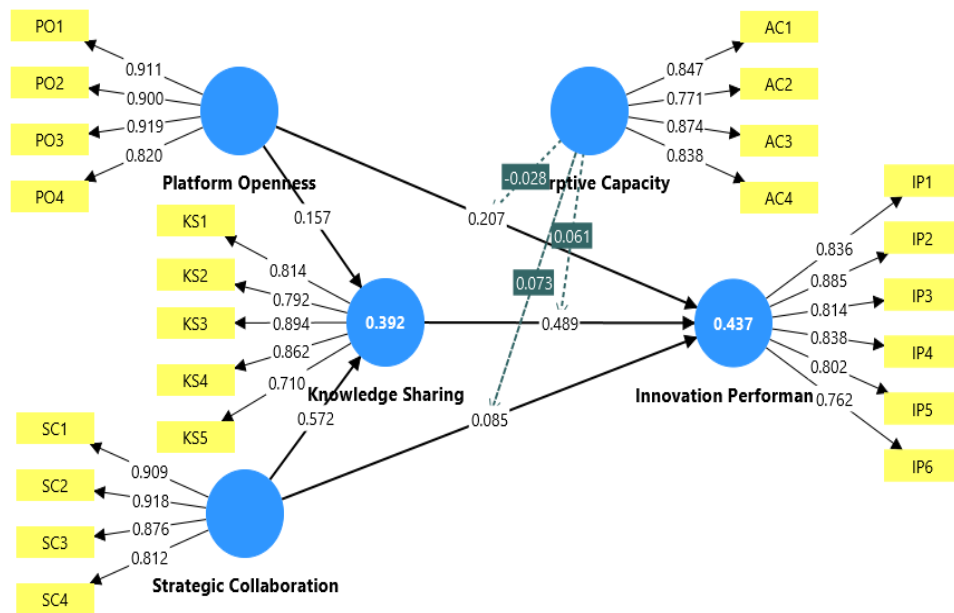
Furthermore, the comparison between the prediction errors of the PLS-SEM model and the benchmark linear model (LM) demonstrates that the PLS-SEM model performs better for 10 of the 11 indicators, as evidenced by lower RMSE values. Only one indicator (KS3) records a slightly lower RMSE under the linear model (0.831) than under the PLS-SEM model (0.862). Nevertheless, the overwhelming majority of indicators show superior predictive accuracy for the PLS-SEM model.

Overall, these findings indicate that the proposed structural model demonstrates moderate predictive power. The consistently positive Q<sup>2</sup><sub>predict</sub> values, together with the lower prediction errors for nearly all indicators, suggest that the model not only explains the observed relationships but also possesses satisfactory capability to predict future observations. These results provide additional support for the robustness of the proposed PLS-SEM model.

#### **4.1.5 Model Fit Assessment.**

Although PLS-SEM primarily emphasises predictive capability rather than global goodness-of-fit, model fit was assessed using the Standardised Root Mean Square Residual (SRMR) as recommended in recent methodological literature (Hair et al., 2019; Henseler et al., 2015). The SRMR value obtained from the Smart-PLS output was 0.061, which is below the recommended threshold of 0.08. This result indicates that the proposed model demonstrates an acceptable level of overall fit and that the discrepancy between the observed and model-implied correlation matrices is sufficiently small.

The estimated structural equation model is presented in Figure 2.

**Figure 2.** Structure Equation Model

#### 4.1.6 Hypothesis Testing

Hypothesis testing was performed using a bootstrapping procedure with 5,000 resamples to assess the significance of the structural paths. Following the guidelines of (Hair et al. 2021), a path coefficient is considered statistically significant when the t-value exceeds 1.96 at the 5% significance level (two-tailed), corresponding to  $p < 0.05$ .

**Table 10.** Path Coefficients and Hypothesis Testing

| Hypothesis | Structural Path                                                    | $\beta$<br>(Original Sample) | t-value | p-value | 95% CI<br>Lower | 95% CI<br>Upper | Decision /<br>Mediation Type           |
|------------|--------------------------------------------------------------------|------------------------------|---------|---------|-----------------|-----------------|----------------------------------------|
| H1         | Platform Openness → Innovation Performance                         | 0.207                        | 3.285   | 0.001   | 0.083           | 0.331           | Supported                              |
| H2         | Strategic Collaboration → Innovation Performance                   | 0.085                        | 1.101   | 0.271   | -0.068          | 0.234           | Not Supported                          |
| H3         | Platform Openness → Knowledge Sharing                              | 0.157                        | 2.583   | 0.010   | 0.040           | 0.282           | Supported                              |
| H4         | Strategic Collaboration → Knowledge Sharing                        | 0.572                        | 10.211  | <0.001  | 0.456           | 0.677           | Supported                              |
| H5         | Knowledge Sharing → Innovation Performance                         | 0.489                        | 6.608   | <0.001  | 0.347           | 0.640           | Supported                              |
| H6         | Platform Openness → Innovation Performance (via Knowledge Sharing) | 0.077                        | 2.322   | 0.020   | 0.018           | 0.148           | Supported<br>(Complementary Mediation) |

| Hypothesis | Structural Path                                                                   | $\beta$<br>(Original Sample) | t-value | p-value | 95% CI<br>Lower | 95% CI<br>Upper | Decision /<br>Mediation Type              |
|------------|-----------------------------------------------------------------------------------|------------------------------|---------|---------|-----------------|-----------------|-------------------------------------------|
| H7         | Strategic Collaboration<br>→ Innovation<br>Performance (via<br>Knowledge Sharing) | 0.280                        | 5.205   | <0.001  | 0.187           | 0.397           | Supported<br>(Indirect-only<br>Mediation) |
| H8         | Absorptive Capacity ×<br>Platform Openness →<br>Innovation<br>Performance         | -0.028                       | 0.410   | 0.682   | -0.153          | 0.115           | Not Supported                             |
| H9         | Absorptive Capacity ×<br>Knowledge Sharing →<br>Innovation<br>Performance         | 0.061                        | 0.757   | 0.449   | -0.094          | 0.220           | Not Supported                             |
| H10        | Absorptive Capacity ×<br>Strategic Collaboration<br>→ Innovation<br>Performance   | 0.073                        | 0.872   | 0.383   | -0.104          | 0.222           | Not Supported                             |

Source: Smart-PLS 4 Output (2026)

**Table 10** presents the results of the direct, indirect, and moderating effects estimated using bootstrapping in Smart-PLS 4. The statistical significance of each relationship was evaluated based on the path coefficient ( $\beta$ ), t-value, p-value, and the 95% bootstrap confidence interval (CI). Relationships were considered statistically significant when the confidence interval did not include zero. The findings indicate that H1, H3, H4, H5, H6, and H7 are supported, whereas H2 and the three moderating hypotheses (H8–H10) are not supported.

Regarding the mediation analysis, the indirect effect of Platform Openness on Innovation Performance through Knowledge Sharing is positive and significant ( $\beta = 0.077$ , 95% CI [0.018, 0.148]). Because both the direct and indirect effects are statistically significant and operate in the same direction, this relationship is classified as complementary mediation (Zhao, Lynch Jr., and Chen 2010). In contrast, the direct effect of Strategic Collaboration on Innovation Performance is not significant, whereas its indirect effect through Knowledge Sharing is positive and significant ( $\beta = 0.280$ , 95% CI [0.187, 0.397]). Therefore, this relationship is classified as indirect-only mediation, indicating that the association between Strategic Collaboration and Innovation Performance is transmitted through Knowledge Sharing.

**H1: Platform openness positively influences innovation performance.**

The results indicate that platform openness has a positive and statistically significant effect on innovation performance ( $\beta = 0.207$ ,  $p = 0.001$ ). This finding suggests that firms operating more open digital platforms tend to achieve stronger innovation outcomes. Nevertheless, the magnitude of the coefficient indicates a moderate contribution, implying that openness facilitates innovation but does not function as the sole driver of innovative performance.

**H2: Strategic collaboration positively influences innovation performance.**

The analysis shows that strategic collaboration does not have a statistically significant direct effect on innovation performance ( $\beta = 0.085$ ,  $p = 0.271$ ). Hence, **H2 is not supported**. This result

suggests that the mere existence of collaborative partnerships does not automatically translate into innovation outcomes unless knowledge exchange mechanisms are actively embedded within the collaboration process.

**H3: Platform openness positively influences knowledge sharing.**

The findings demonstrate that platform openness significantly enhances knowledge sharing ( $\beta = 0.157$ ,  $p = 0.010$ ). Thus, **H3 is supported**. Open platform architectures appear to facilitate information flows and enable greater interaction among ecosystem participants.

**H4: Strategic collaboration positively influences knowledge sharing.**

Strategic collaboration exhibits a strong and statistically significant influence on knowledge sharing ( $\beta = 0.572$ ,  $p < 0.001$ ). Accordingly, **H4 is supported**. This represents the strongest direct relationship in the structural model, highlighting the importance of relational coordination and structured partnerships in stimulating knowledge exchange within digital ecosystems.

**H5: Knowledge sharing positively influences innovation performance.**

Knowledge sharing has a significant and substantial effect on innovation performance ( $\beta = 0.489$ ,  $p < 0.001$ ). Therefore, **H5 is supported**. This finding indicates that innovation outcomes in digital ecosystems are strongly driven by the intensity and effectiveness of knowledge exchange among participating organisations.

**4.1.7 Mediation Effects**

**H6: Knowledge sharing mediates the relationship between platform openness and innovation performance.**

The indirect effect of platform openness on innovation performance through knowledge sharing is statistically significant ( $\beta = 0.077$ ,  $p = 0.020$ ). Because the direct effect of platform openness on innovation performance (H1) remains significant, knowledge sharing partially mediates this relationship. Hence, **H6 is supported**. This indicates that platform openness contributes to innovation both directly and indirectly by facilitating knowledge-sharing processes.

**H7: Knowledge sharing mediates the relationship between strategic collaboration and innovation performance.**

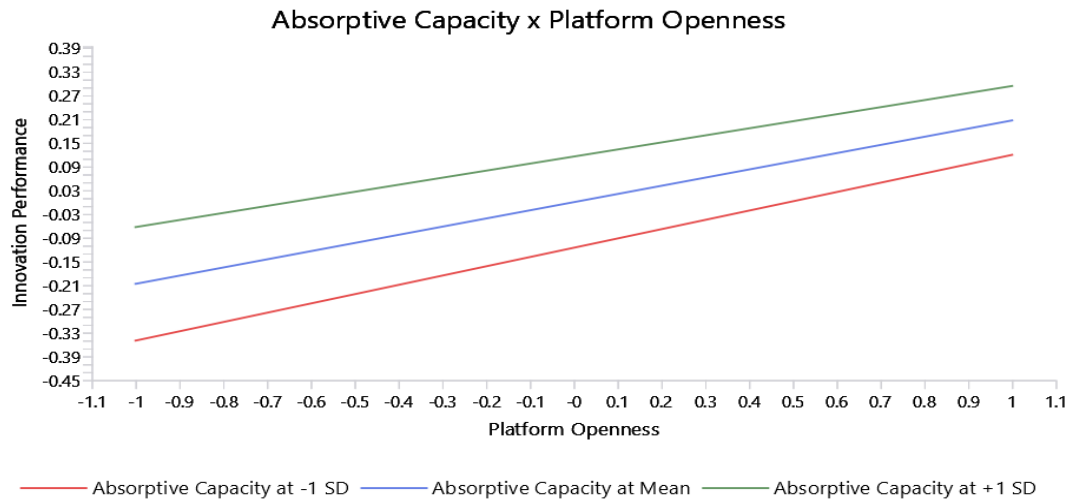
The indirect effect of strategic collaboration on innovation performance through knowledge sharing is strong and statistically significant ( $\beta = 0.280$ ,  $p < 0.001$ ), while the direct effect is insignificant. This confirms **full mediation**, meaning that strategic collaboration enhances innovation performance only when it effectively stimulates knowledge-sharing activities. Consequently, **H7 is supported**.

**4.1.8 Moderating Effects of Absorptive Capacity**

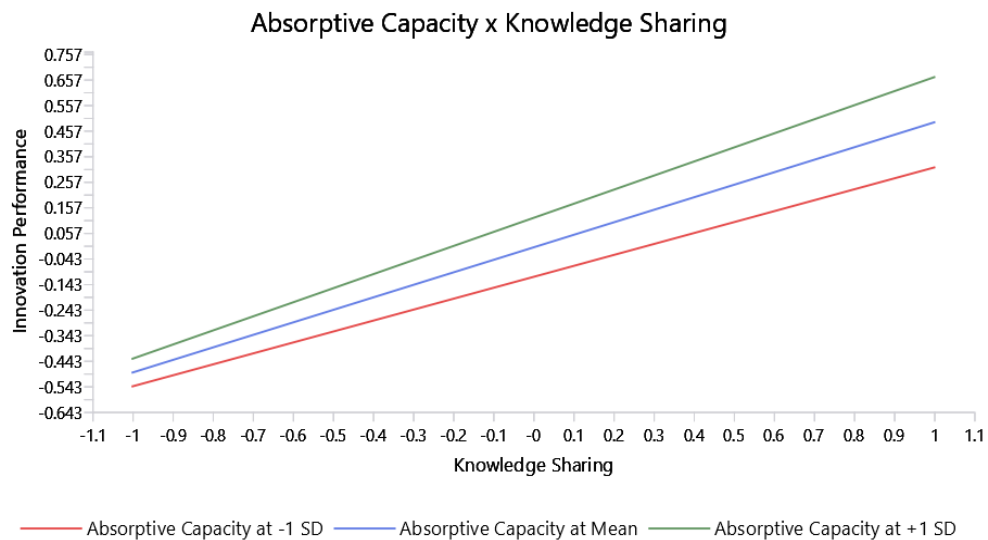
The moderating role of absorptive capacity was tested across three relationships in the model. The results indicate that none of the interaction effects are statistically significant. Specifically, absorptive capacity does not significantly moderate the relationships between platform openness and innovation performance ( $p = 0.682$ ), knowledge sharing and innovation performance ( $p = 0.449$ ), or strategic collaboration and innovation performance ( $p = 0.383$ ). Therefore, **H8, H9, and H10 are not supported**.

These findings suggest that absorptive capacity does not significantly strengthen the examined relationships within the present sample. One possible explanation is that many firms operating in digital ecosystems may already possess relatively developed absorptive capabilities, thereby reducing variability in this construct. As a result, absorptive capacity may function more as a baseline organisational capability rather than as a differentiating boundary condition in this context.

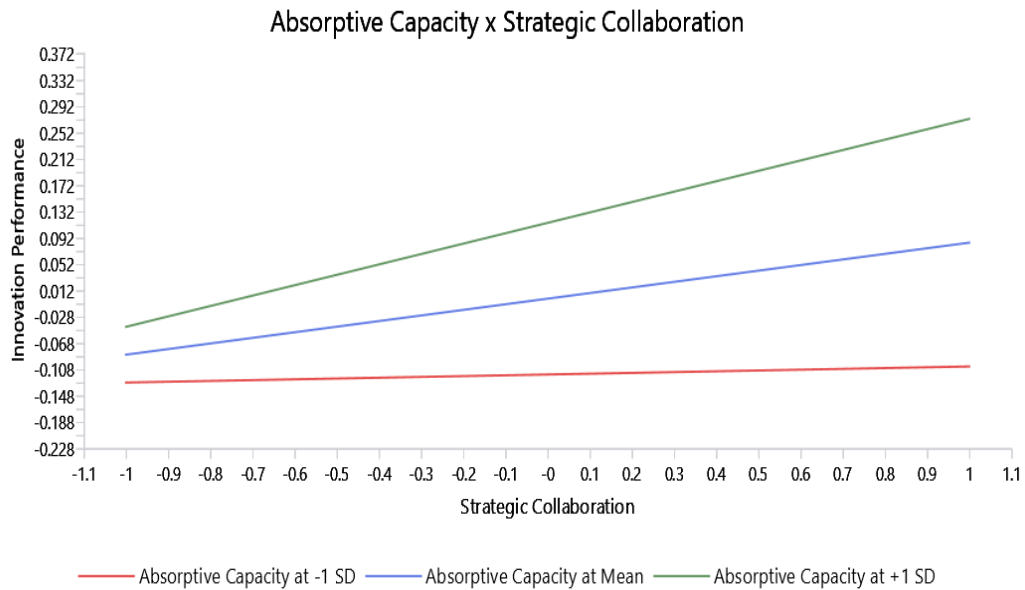
**Figure 3.** Simple Slope Analysis of Absorptive Capacity × Platform Openness



**Figure 4.** Simple Slope Analysis of Absorptive Capacity × Knowledge Sharing



**Figure 5.** Simple Slope Analysis of Absorptive Capacity × Strategic Collaboration



Figures 3–5 present the simple slope analyses for the moderating effects of absorptive capacity on the relationships between platform openness, knowledge sharing, strategic collaboration, and innovation performance. Across the three relationships, the regression lines at low, medium, and high levels of absorptive capacity remain relatively parallel, indicating that the strength of these relationships does not vary substantially across different levels of absorptive capacity. This visual pattern is consistent with the bootstrapping results, which show that the moderating effects are not statistically significant for platform openness ( $\beta = 0.025$ ,  $p = 0.682$ ), knowledge sharing ( $\beta = 0.061$ ,  $p = 0.449$ ), and strategic collaboration ( $\beta = 0.052$ ,  $p = 0.383$ ).

## 4.2 Discussion

This study examined how innovation performance is facilitated through within digital ecosystems by integrating platform openness, strategic collaboration, knowledge sharing, and absorptive capacity into a unified structural framework. The findings offer several theoretical insights that extend current discussions in ecosystem and open innovation research.

### 4.2.1 Platform Openness as Structural Access Rather Than Automatic Innovation

The results show that platform openness has a positive and significant effect on innovation performance, although the magnitude of the relationship is moderate. This suggests that openness alone does not function as a dominant driver of innovation outcomes.

Much of the platform literature assumes that increasing openness automatically enhances innovation by expanding access to external resources and complementary contributors. However, the present findings indicate that openness primarily creates **structural access**, rather than immediate value creation. In other words, openness enlarges the opportunity space but does not necessarily activate knowledge recombination.

The mediation results provide further support for this interpretation. Platform openness improves innovation performance partly through knowledge sharing, indicating that structural accessibility must be translated into active knowledge exchange before innovation benefits can emerge. These finding shifts attention from platform architecture to interaction

processes within ecosystems. Rather than treating openness as a direct performance lever, it may be more accurately understood as a structural condition whose effectiveness depends on relational and knowledge-sharing mechanisms.

#### **4.2.2 The Collaboration Paradox in Digital Ecosystems**

One of the most notable findings is the absence of a significant direct relationship between strategic collaboration and innovation performance. This result contrasts with many open innovation studies that report a positive direct effect of collaboration on innovation outcomes. However, the mediation analysis clarifies this apparent contradiction. Strategic collaboration strongly enhances knowledge sharing, while knowledge sharing significantly improves innovation performance. Once knowledge exchange is incorporated into the model, the direct relationship between collaboration and performance disappears.

This suggests that collaboration does not inherently generate innovation outcomes; instead, it provides a relational infrastructure that enables knowledge exchange. From this perspective, collaboration functions as an enabling structure rather than a direct value generator. The effectiveness of collaborative partnerships therefore depends largely on the intensity and quality of knowledge flows embedded within those relationships.

#### **4.2.3 Knowledge Sharing as the Central Innovation Mechanism**

Knowledge sharing emerges as the most influential predictor of innovation performance in the structural model. This finding highlights the central role of knowledge circulation in shaping innovation outcomes within digital ecosystems.

Ecosystem research frequently emphasises structural characteristics such as platform governance, network configuration, or levels of openness. The present results suggest that innovation performance is better explained by **process dynamics** rather than structural arrangements alone. The strongest pathway identified in the model—strategic collaboration leading to knowledge sharing and subsequently to innovation performance—demonstrates that innovation is primarily driven by the circulation and recombination of knowledge across organisational boundaries.

From a Knowledge-Based View perspective, firms achieve superior innovation outcomes when they can integrate dispersed knowledge into new value-creating combinations. In digitally connected ecosystems, this recombination process becomes the key mechanism through which structural access is transformed into competitive advantage.

#### **4.2.4 Reconsidering the Role of Absorptive Capacity**

Contrary to expectations derived from Dynamic Capabilities Theory, absorptive capacity does not significantly moderate the relationships between ecosystem mechanisms and innovation performance. This result suggests that absorptive capacity may not always function as a strong differentiating capability in digitally embedded environments.

One possible explanation is that many firms participating in digital ecosystems already possess a minimum level of absorptive capability required for effective participation. When such capabilities are widely distributed across firms, the variance in absorptive capacity becomes limited, thereby reducing its observable moderating influence.

Another explanation relates to the increasing codification of knowledge within digital platforms. Technologies such as APIs, shared repositories, and collaborative digital tools often standardise knowledge flows, making information more accessible and easier to interpret.

Under such conditions, ecosystem-level design may partially substitute for firm-specific knowledge-processing capabilities.

Rather than challenging Dynamic Capabilities Theory, these findings suggest that the role of absorptive capacity may depend on contextual conditions. In mature digital ecosystems, absorptive capacity may function more as a threshold capability required for participation rather than as a strong amplifier of innovation performance.

#### **4.2.5 Toward a Process-Oriented Perspective of Digital Ecosystem Innovation**

Taken together, the findings point to a shift from structural determinism toward a more process-oriented understanding of innovation in digital ecosystems. Participation in an ecosystem does not automatically generate innovation advantages, nor do openness and collaboration independently guarantee improved performance.

Innovation outcomes appear to emerge when structural access and relational coordination are translated into active knowledge-sharing processes. Within this framework, platform openness provides structural access, strategic collaboration establishes relational coordination, and knowledge sharing activates the processes through which innovation value is created.

The contribution of this study therefore lies not only in confirming the importance of openness and collaboration, but in clarifying how and under what conditions these mechanisms translate into innovation performance. Digital ecosystems generate innovation potential, but it is the circulation and integration of knowledge that ultimately transforms this potential into realised innovation outcomes.

### **5. Conclusion and Suggestion**

This study investigated how innovation performance is generated within digital ecosystems by integrating platform openness, strategic collaboration, knowledge sharing, and absorptive capacity into a unified analytical framework. The findings highlight that innovation outcomes in digitally embedded environments are not determined solely by structural or relational factors, but primarily by the effectiveness of knowledge-sharing processes.

The results demonstrate that platform openness contributes to innovation performance both directly and indirectly through knowledge sharing, indicating that structural access must be translated into active knowledge exchange before value can be realised. Strategic collaboration, meanwhile, does not exert a direct influence on innovation performance but operates through knowledge-sharing mechanisms, emphasising the importance of interaction quality rather than partnership quantity. Knowledge sharing emerges as the most influential predictor of innovation performance, confirming its central role in transforming ecosystem participation into tangible innovation outcomes.

Contrary to common assumptions within dynamic capability research, absorptive capacity does not significantly moderate the examined relationships, suggesting that in digitally mature ecosystems it may function more as a baseline capability than as a differentiating strategic resource.

Overall, the findings underscore the importance of process-oriented innovation within digital ecosystems. Innovation advantages arise not merely from participation in collaborative networks, but from the ability to activate and coordinate knowledge flows across organisational boundaries.

### **5.1 Theoretical Contributions**

This study contributes to the literature on digital ecosystems, open innovation, and dynamic capabilities in several ways.

**First**, the findings refine the theoretical role of strategic collaboration in innovation processes. Previous studies often treat collaboration as a direct determinant of innovation performance. However, the present results demonstrate that the influence of collaboration operates entirely through knowledge-sharing processes. This indicates that collaboration should be understood not as an immediate performance driver but as a relational structure that enables knowledge exchange. By empirically demonstrating full mediation, the study shifts attention from alliance formation to the effectiveness of knowledge utilisation within collaborative arrangements.

**Second**, this research advances a process-oriented perspective of ecosystem innovation. Much of the digital ecosystem literature focuses on structural characteristics such as platform openness, governance mechanisms, or network configuration. The findings suggest that while these structural conditions create opportunities for innovation, actual performance improvements depend primarily on the intensity of knowledge-sharing processes. In this respect, the study extends the Knowledge-Based View by demonstrating that competitive advantage within digital ecosystems emerges from the effective recombination of distributed knowledge across organisational boundaries.

**Third**, the study provides a contextual refinement of absorptive capacity within Dynamic Capabilities Theory. Contrary to widely held assumptions, absorptive capacity does not significantly strengthen the relationships between ecosystem mechanisms and innovation performance in this setting. This suggests that absorptive capacity may function as a baseline capability required for participation in digitally embedded environments rather than as a strong performance amplifier. The finding therefore highlights the importance of considering ecosystem maturity and digital infrastructure conditions when evaluating the strategic role of dynamic capabilities.

**Finally**, the study offers an integrated framework of digital ecosystem innovation by simultaneously examining platform openness (structural dimension), strategic collaboration (relational dimension), knowledge sharing (process dimension), and absorptive capacity (cognitive dimension). By analysing these dimensions within a unified empirical model, the research moves beyond fragmented explanations and provides a more systemic perspective on how innovation outcomes are generated within digital ecosystems.

### **5.2 Managerial Implications**

The findings also provide several practical insights for managers operating within digital ecosystems.

**First**, platform openness alone is insufficient as an innovation strategy. While openness increases access to external contributors and complementary resources, it does not automatically lead to innovation outcomes. Managers should therefore complement openness initiatives with mechanisms that facilitate knowledge exchange, such as collaborative innovation platforms, shared development routines, and transparent information-sharing protocols.

**Second**, firms should prioritise the depth of collaboration rather than the number of partnerships. The results show that collaboration does not directly enhance innovation

performance unless it stimulates active knowledge exchange. Managers should therefore focus on strengthening the quality of interactions with partners through joint problem-solving activities, co-development initiatives, and frequent knowledge-sharing engagements.

**Third**, organisations should institutionalise knowledge-sharing routines. Because knowledge sharing is the strongest predictor of innovation performance, firms should develop structured mechanisms that support continuous inter-organisational learning. These may include cross-organisational project teams, shared digital knowledge repositories, and collaborative experimentation initiatives.

**Fourth**, managers may need to reconsider the strategic role of absorptive capacity in mature digital ecosystems. While absorptive capability remains important, the findings suggest that many firms already possess the minimum level required for ecosystem participation. In such environments, improving external collaboration intensity may generate greater innovation benefits than marginal investments in internal knowledge-processing capabilities.

**Finally**, managers should approach digital ecosystems from a firm-level innovation mechanism perspective rather than a participation perspective. Innovation performance does not arise simply from joining an ecosystem network. Instead, it depends on the firm's ability to align structural access, collaborative relationships, and knowledge-sharing processes. Firms that actively orchestrate knowledge flows within ecosystems are therefore more likely to achieve sustained innovation advantages.

## **6. Limitations and Future Research**

Despite the contributions of this study, several limitations should be acknowledged, which also provide opportunities for future research.

**First**, this study focuses on firms operating within digitally embedded ecosystems. The non-significant moderating role of absorptive capacity suggests that ecosystem maturity may influence the effectiveness of firm-level capabilities. Future research could examine whether absorptive capacity plays a stronger role in less mature or less digitally integrated ecosystems. Comparative studies across emerging and advanced digital environments may provide further insight into how capability effects vary under different levels of digital infrastructure and knowledge codification.

**Second**, innovation performance is shaped not only by ecosystem mechanisms but also by broader environmental conditions. Variables such as market turbulence, technological uncertainty, and competitive intensity may influence how ecosystem-enabled innovation mechanisms operate. Future studies could incorporate these environmental contingencies as moderating factors in order to better understand when platform openness, collaboration, and knowledge sharing become more or less effective.

Third, the cross-sectional design of this study limits the ability to capture the dynamic evolution of ecosystem relationships. Innovation processes and knowledge-sharing routines often develop over time. Longitudinal research designs could therefore provide deeper insights into how collaborative interactions evolve and how changes in platform governance influence innovation trajectories. In addition, multi-level approaches that combine firm-level capabilities with ecosystem-level governance structures may offer a more comprehensive understanding of innovation process dynamics.

**Fourth**, although absorptive capacity did not demonstrate a moderating effect in the present model, other dynamic capabilities may play more prominent roles. Future research could

explore alternative capability configurations, such as digital agility, sensing capability, or integrative capability, to determine whether different capability bundles strengthen the transformation of ecosystem participation into innovation outcomes.

**Fifth**, the questionnaire did not explicitly require respondents to identify a single focal digital platform or ecosystem. Consequently, respondents may have evaluated different collaborative contexts when answering the measurement items. Future studies should instruct respondents to evaluate all constructs with reference to one specific platform or ecosystem to minimize referent ambiguity.

**Sixth**, this study did not explicitly control for organizational characteristics such as firm size, firm age, industry sector, or geographic location. Future studies may incorporate these variables as control variables or conduct multigroup analyses to examine the robustness of the proposed relationships across different organizational contexts.

**Last**, the empirical context of this study focuses on digitally integrated, platform-based firms. Future research could examine whether the proposed process-oriented firm-level innovation mechanism model also applies to more traditional industrial ecosystems or hybrid offline–online innovation networks. Such comparative analyses would help clarify the broader applicability and boundary conditions of the framework.

Overall, addressing these directions would further advance understanding of how innovation is orchestrated within digital ecosystems and how firms translate ecosystem participation into sustainable competitive advantage.

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

During the preparation of this manuscript, the authors used ChatGPT (OpenAI) to assist with language editing and manuscript organization. The authors reviewed and edited the AI-generated content as needed and take full responsibility for the content of the publication

#### **Reference**

- Abourokbah, S. H., Mashat, R. M., & Salam, M. A. (2023). Role of Absorptive Capacity, Digital Capability, Agility, and Resilience in Supply Chain Innovation Performance. In *Sustainability* (Vol. 15, Issue 4, p. 3636). <https://doi.org/10.3390/su15043636>
- Armstrong, J. Scott, & Overton, Terry S. (1977). Estimating Nonresponse Bias in Mail Surveys. *Journal of Marketing Research*, 14(3), 396–402. <https://doi.org/10.1177/002224377701400320>
- Boudreau, K. (2010). Open Platform Strategies and Innovation: Granting Access vs. Devolving Control. *Management Science*, 56(10), 1849–1872. <https://doi.org/10.1287/mnsc.1100.1215>
- Cenamor, J., Parida, V., & Wincent, J. (2019). How entrepreneurial SMEs compete through digital platforms: The roles of digital platform capability, network capability and ambidexterity. *Journal of Business Research*, 100(March), 196–206. <https://doi.org/10.1016/j.jbusres.2019.03.035>
- Chatterjee, S., Chaudhuri, R., Vrontis, D., & Giovando, G. (2023). Digital workplace and organization performance: Moderating role of digital leadership capability. *Journal of Innovation & Knowledge*, 8(1), 100334. <https://doi.org/https://doi.org/10.1016/j.jik.2023.100334>

- Cohen, J. (1992). A power primer. *Psychological Bulletin*, 112(1), 155–159. <https://doi.org/10.1037/0033-2909.112.1.155>
- Dyer, J. H., & Singh, H. (1998). The Relational View: Cooperative Strategy and Sources of Interorganizational Competitive Advantage. *Academy of Management*, 23(4), 660–679. <https://doi.org/10.2307/259056>
- Fleming, L. (2001). Recombinant Uncertainty in Technological Search. *Management Science*, 47(1), 117–132. <https://doi.org/10.1287/mnsc.47.1.117.10671>
- Galib, M., Haerani, S., Mamimg, J., & Munir, A. R. (2022). The Role of SMT and Business Network Accentuation on Value Distribution and Performance Consequences. *Journal of Distribution Science*, 20(5), 97–104. <https://doi.org/10.15722/jds.20.05.202205.97>
- Galib, M., Maulana, M., Syam, J., & Muharram, M. (2025). Authenticity and Brand Sensemaking Process : A Narrative Analysis of Marketing Managers in Building Trust Through Long-Term Collaboration with Nano-Influencers. *Journal of Marketing Management and Innovative Business Review*, 3(2), 146–153. <https://doi.org/10.63416/mrb.v3i2.421>
- Ghozali, I. (2021). *Partial Least Square: Konsep, Teknik dan Aplikasi Menggunakan Smart PLS 3.2.9* (3rd ed.). Universitas Diponegoro.
- Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal*, 17(S2), 109–122. <https://doi.org/10.1002/smj.4250171110>
- Gunawan, A., Rijal, S., Galib, M., & Maulana. (2024). Correlation Between Switching Costs and Customer Loyalty : Integration of AI in Theoretical and Practical Approaches. *Journal of Marketing Management and Innovative Business Review*, 2(2), 68–75. <https://doi.org/10.63416/mrb.v2i2.309>
- Hair, J. F., Howard, M. C., & Nitzl, C. (2021). Review of Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook. In *Structural Equation Modeling: A Multidisciplinary Journal* (Vol. 30, Issue 1). <https://doi.org/10.1080/10705511.2022.2108813>
- Hair, J. F., Page, M., & Brunsveld, N. (2022). *Essentials of Business Research Methods* (14th ed.). Routledge. <https://doi.org/10.4324/9780367330743>
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24. <https://doi.org/10.1108/EBR-11-2018-0203>
- Haleem, A., Javaid, M., Asim Qadri, M., Pratap Singh, R., & Suman, R. (2022). Artificial intelligence (AI) applications for marketing: A literature-based study. *International Journal of Intelligent Networks*, 3(August), 119–132. <https://doi.org/10.1016/j.ijin.2022.08.005>
- Halik, J. B., & Halik, M. Y. (2024). Open Innovation And Digital Marketing : A Catalyst For Culinary SMEs In Makassar. *Jurnal Manajemen*, 28(03), 588–612. <https://doi.org/10.24912/jm.v28i3.2059>
- Halik, J. B., Halik, M. Y., Basongan, S., & Mapau, J. (2026). *Strategic Distribution , Digital*

- Marketing , and Open Innovation : Toward Integrated Capability Development for SME Performance. *Asia Marketing Journal*, 27(4), 355–371. <https://doi.org/10.53728/2765-6500.1665>
- HALIK, J. B., PARAWANSA, D. A. S., SUDIRMAN, I., & Jusni, J. (2023). Implications of IT Awareness and Digital Marketing to Product Distribution on the Performance of Makassar SMEs. *유통과학연구 Journal of Distribution Science*, 21(7), 105–116. <https://doi.org/10.15722/jds.21.07.202307.105>
- Haryono, S. (2017). *Metode SEM untuk penelitian manajemen dengan AMOS LISREL PLS*. Luxima Metro Media, 450.
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
- Jung, Y., & Lyytinen, K. (2014). Towards an ecological account of media choice: a case study on pluralistic reasoning while choosing email. *Information Systems Journal*, 24(3), 271–293. <https://doi.org/https://doi.org/10.1111/isj.12024>
- Kastelli, I., Dimas, P., Stamopoulos, D., & Tsakanikas, A. (2024). Linking Digital Capacity to Innovation Performance: the Mediating Role of Absorptive Capacity. *Journal of the Knowledge Economy*, 15(1), 238–272. <https://doi.org/10.1007/s13132-022-01092-w>
- Kogut, B., & Zander, U. (1992). Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology. *Organization Science*, 3(3), 383–397. <https://doi.org/10.1287/orsc.3.3.383>
- Lin, H. (2007). Knowledge sharing and firm innovation capability: an empirical study. *International Journal of Manpower*, 28(3–4), 315–332. <https://doi.org/10.1108/01437720710755272>
- M'Chirgui, Z., & Pénard, T. (2011). How to provide Quality of Service guarantees in the Internet? Lessons learnt from the airline and card-based payment sectors. *European Management Journal*, 29(4), 306–318. <https://doi.org/https://doi.org/10.1016/j.emj.2010.12.003>
- Meireles, F. R. da S., Azevedo, A. C., & Boaventura, J. M. G. (2022). Open innovation and collaboration: A systematic literature review. *Journal of Engineering and Technology Management*, 65, 101702. <https://doi.org/https://doi.org/10.1016/j.jengtecman.2022.101702>
- Memon, M. A., Ramayah, T., Ting, H., & Cheah, J. (2025). PURPOSIVE SAMPLING : A REVIEW AND GUIDELINES FOR QUANTITATIVE RESEARCH. *Journal of Applied Structural Equation Modeling*, 9(1), 1–23. [https://doi.org/10.47263/JASEM.9\(1\)01](https://doi.org/10.47263/JASEM.9(1)01)
- Nahapiet, J., & Ghoshal, S. (1998). Social Capital, Intellectual Capital, and the Organizational Advantage. *The Academy of Management Review*, 23(2), 242–266. <https://doi.org/10.2307/259373>
- Podsakoff, Philip M, MacKenzie, Scott B, & Podsakoff, Nathan P. (2016). Recommendations for Creating Better Concept Definitions in the Organizational, Behavioral, and Social Sciences. *Organizational Research Methods*, 19(2), 159–203.

<https://doi.org/10.1177/1094428115624965>

- Sahetapy, H., Halik, M. Y., Sino, H. W., & Bokau, J. R. S. (2025). Big Data and Artificial Intelligence : Implications and Strategies for Business Development in Indonesia. *Journal of Marketing Management and Innovative Business Review (MARIOBRE)*, 3(1), 65–77. <https://doi.org/10.63416/mrb.v3i1.321>
- Santosa, P. I. (2018). *Metode Penelitian Kuantitatif: Pengembangan Hipotesis dan Pengujiannya Menggunakan SmartPLS* (Giovanny (ed.); 1st ed.). Penerbit ANDI.
- Singh, S. K., Gupta, S., Busso, D., & Kamboj, S. (2021). Top management knowledge value, knowledge sharing practices, open innovation and organizational performance. *Journal of Business Research*, 128(November 2018), 788–798. <https://doi.org/10.1016/j.jbusres.2019.04.040>
- Strutzenberger, A., & Ambos, T. C. (2014). Unravelling the Subsidiary Initiative Process: A Multilevel Approach. *International Journal of Management Reviews*, 16(3), 314–339. <https://doi.org/https://doi.org/10.1111/ijmr.12022>
- Sugiyono. (2020). *Metode Penelitian Kualitatif dan Kuantitatif* (Issue January).
- Teece, D. J. (2010). Business models, business strategy and innovation. *Long Range Planning*, 43(2–3), 172–194. <https://doi.org/10.1016/j.lrp.2009.07.003>
- Wang, N., Wan, J., Ma, Z., Zhou, Y., & Chen, J. (2023). How digital platform capabilities improve sustainable innovation performance of firms: The mediating role of open innovation. *Journal of Business Research*, 167, 114080. <https://doi.org/https://doi.org/10.1016/j.jbusres.2023.114080>
- Xie, X., & Yu, H. (2025). Collaborative innovation and knowledge spillovers in open innovation ecosystems: Exploring the roles of network stability and technological niche. *Technological Forecasting and Social Change*, 219, 124289. <https://doi.org/https://doi.org/10.1016/j.techfore.2025.124289>
- Xing, X., Zhu, C., Lin, Y., & Liu, T. (2024). Can digital platform empowers inbound and outbound open innovation? From the perspective of the innovation ecosystem. *Humanities and Social Sciences Communications*, 11(1), 1384. <https://doi.org/10.1057/s41599-024-03523-2>
- Zhao, X., Lynch Jr., J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. In *Journal of Consumer Research* (Vol. 37, Issue 2, pp. 197–206). Univ of Chicago Press. <https://doi.org/10.1086/651257>
- Hair, J. F., M. Page, and N. Brunsveld. 2022. *Essentials of Business Research Methods*. 14th ed. Routledge.
- Hair, Joe F., Matthew C. Howard, and Christian Nitzl. 2021. *Review of Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook*. Vol. 30.
- Sugiyono. 2020. *Metode Penelitian Kualitatif Dan Kuantitatif*. Alfabeta