

ENHANCING OPERATIONAL AGILITY THROUGH DIGITAL PROCESS INTEGRATION AND SUPPLY CHAIN VISIBILITY: THE MEDIATING ROLE OF DECISION-MAKING SPEED IN SERVICE FIRMS

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Abstract: This study examines the role of digital process integration and supply chain visibility in enhancing operational agility, with decision-making speed as a mediating variable in service firms. Using a quantitative approach, data were collected from 195 respondents across major cities in Indonesia and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings reveal that digital process integration has a positive and significant effect on both decision-making speed and operational agility, although its direct impact on agility is relatively modest. In contrast, supply chain visibility does not significantly influence operational agility directly, but exerts a strong indirect effect through decision-making speed, indicating a full mediation. Furthermore, decision-making speed is identified as a key determinant of operational agility, highlighting its critical role in translating digital capabilities into responsive actions. These results suggest that digital investments alone are insufficient to achieve agility unless supported by rapid and effective decision-making processes. The study contributes to the literature by proposing a decision-centric perspective of digital transformation, emphasizing the importance of organizational responsiveness over mere technological adoption. Practically, the findings encourage managers to align digital systems with decision processes to maximize agility outcomes.



INTRODUCTION

In an increasingly volatile and digitally driven business environment, service firms are under mounting pressure to enhance operational agility to remain competitive and responsive to market dynamics. Operational agility refers to a firm's capability to rapidly sense, respond to, and adapt operational processes in response to changing customer demands and environmental uncertainties (Asghar et al., 2026; Walter, 2021). In the context of service industries, where customer experience and responsiveness are critical value drivers, agility is not merely a strategic advantage but a survival imperative. The rapid diffusion of digital technologies has transformed how organizations design and execute their operational processes, particularly through digital process integration and enhanced supply chain visibility.

Digital process integration enables seamless coordination across functional units and external partners by leveraging advanced information systems, cloud computing, and real-time data exchange (Halik, Halik, et al., 2026; Sahetapy et al., 2025). Concurrently, supply chain visibility provides firms with real-time insights into the flow of information, goods, and services across the supply chain network, thereby reducing uncertainty and enabling proactive

decision-making (Dubey et al., 2020). Empirical evidence suggests that firms adopting integrated digital processes and high levels of visibility tend to exhibit superior responsiveness and operational (Jing & Fan, 2024; Williams et al., 2013). However, despite these advancements, many service firms still struggle to translate digital investments into tangible agility outcomes, indicating the presence of underlying mechanisms that remain insufficiently explored.

Recent studies highlight that the effectiveness of digital transformation initiatives is contingent upon organizational capabilities, particularly decision-making speed (Dubey et al., 2020; Jing & Fan, 2024). Decision-making speed refers to the ability of an organization to process information and execute decisions rapidly without compromising quality. In digitally integrated environments, the availability of real-time data does not automatically lead to improved agility unless firms can convert such data into timely and effective decisions (Mikalef & Krogstie, 2020; Teece, 2018). This suggests that decision-making speed may function as a critical mediating variable that bridges digital capabilities and operational outcomes.

Despite growing scholarly attention, existing literature exhibits several notable gaps. First, most studies focus on manufacturing contexts, with limited empirical investigation in service firms, where operational processes are inherently more intangible and customer-centric (Dubey et al., 2020; Yang et al., 2020). Second, prior research tends to examine digital process integration and supply chain visibility in isolation, rather than as complementary capabilities that jointly influence agility. Third, the mediating role of decision-making speed remains underexplored, particularly in emerging market contexts where digital maturity levels vary significantly.

To further contextualize the urgency of this research, recent industry data highlight the challenges faced by service firms in leveraging digital transformation for operational agility:

Table 1. Key Indicators Highlighting the Urgency of Digital Agility in Service Firms

Indicator	Global Findings (Recent Studies/Reports)	Implication for Service Firms
Digital Transformation Success Rate	Only 30–35% of digital transformation initiatives achieve intended outcomes (Verhoef et al., 2021).	Indicates inefficiency in translating digital investments into performance
Supply Chain Disruptions	Over 70% of firms experienced significant disruptions post-pandemic (Samosir et al., 2025)	Highlights the need for improved visibility and responsiveness
Decision-Making Delays	Firms with slow decision cycles experience up to 20% lower operational efficiency (Mahmudah & Indriyani, 2025)	Emphasizes the strategic role of decision-making speed
Data Utilization Gap	Less than 40% of firms effectively utilize real-time data for decision-making (Sahetapy et al., 2025)	Suggests underutilization of digital integration capabilities

Source: Adapted from previous research (2026)

These data underscore a critical paradox: while firms invest heavily in digital technologies, many fail to achieve expected agility improvements due to organizational and decision-making constraints.

Given the accelerating pace of digital disruption and the increasing complexity of service operations, understanding how digital process integration and supply chain visibility translate into operational agility has become an urgent research priority. More specifically, identifying the mediating role of decision-making speed is essential to uncover the underlying mechanisms that enable firms to convert digital capabilities into strategic outcomes. Without such insights, service firms risk underutilizing their digital investments, thereby compromising competitiveness and long-term sustainability.

Building on this background, the present study aims to address these gaps by examining the interplay between digital process integration, supply chain visibility, decision-making speed, and operational agility in service firms.

Research Questions

Based on the above discussion, the research seeks to address the following questions:

1. To what extent does digital process integration influence operational agility in service firms?
2. How does supply chain visibility affect operational agility in service firms?
3. What is the impact of digital process integration on decision-making speed?
4. How does supply chain visibility influence decision-making speed?
5. Does decision-making speed significantly enhance operational agility?
6. Does decision-making speed mediate the relationship between digital process integration and operational agility?
7. Does decision-making speed mediate the relationship between supply chain visibility and operational agility?

LITERATURE REVIEW

Grand Theoretical Foundation: Dynamic Capability Theory and Resource Based View (RBV)

This study is primarily grounded in the Dynamic Capabilities Theory (DCT) and supported by the Resource-Based View (RBV). These theories provide a robust conceptual foundation to explain how firms leverage digital capabilities to enhance operational agility.

The Resource-Based View posits that firms achieve competitive advantage through valuable, rare, inimitable, and non-substitutable resources (Gerhart & Feng, 2021). In the context of digital transformation, technological infrastructure, data integration, and visibility capabilities represent strategic resources that enable superior operational performance (Williams et al., 2013). However, RBV alone is insufficient to explain how firms adapt to rapidly changing environments.

Therefore, Dynamic Capabilities Theory extends RBV by emphasizing a firm's ability to integrate, build, and reconfigure internal and external competencies in response to environmental turbulence. Within supply chain and service operations, dynamic capabilities manifest through sensing opportunities, seizing them via rapid decisions, and reconfiguring processes accordingly (Teece, 2018). This aligns with the notion that operational agility is not merely a static capability but an emergent outcome of coordinated sensing, decision-making, and response mechanisms.

Recent literature further reinforces that digital transformation acts as a dynamic capability by enabling real-time data processing, visibility, and responsiveness across organizational processes (Verhoef et al., 2021). Thus, digital process integration and supply chain visibility can be conceptualized as enabling capabilities, while decision-making speed and operational agility represent higher-order outcomes.

Operational Agility

Operational agility is commonly defined as the ability of a firm to respond rapidly and flexibly to changes in the environment, particularly fluctuations in customer demand and operational conditions. In service settings, agility becomes even more critical due to the intangible and time-sensitive nature of service delivery (Asghar et al., 2026). Recent studies suggest that agile organizations are better positioned to manage uncertainty, enhance customer satisfaction, and sustain competitive advantage (Dubey et al., 2020; Sahetapy et al., 2025).

Thus, operational agility represents a higher-order capability that emerges from the effective orchestration of organizational resources and processes.

Digital Process Integration

Digital process integration is conceptualized as the extent to which digital technologies enable seamless coordination across organizational functions and external partners. It involves the synchronization of workflows, systems, and data streams to ensure real-time information exchange and process alignment. Prior research indicates that digital integration reduces information silos, enhances coordination efficiency, and enables faster response to operational changes (HALIK et al., 2023; Rai et al., 2006). In service firms, where coordination across multiple touchpoints is essential, digital process integration serves as a foundational capability that supports agility.

Supply Chain Visibility

Closely related to digital integration is supply chain visibility, which refers to the degree to which firms can access accurate, timely, and comprehensive information across the supply chain. Visibility enhances situational awareness by enabling firms to monitor operations, anticipate disruptions, and respond proactively (Rai et al., 2006). Empirical evidence demonstrates that higher levels of visibility are associated with improved coordination, reduced uncertainty, and enhanced responsiveness (Dubey et al., 2020; Qi et al., 2017). In dynamic environments, visibility is not merely informational but strategic, as it enables firms to align decisions with real-time conditions.

Decision-Making Speed

Decision-making speed refers to an organization's capability to process information and execute decisions in a timely manner while preserving decision quality. It represents a critical organizational competence, particularly in dynamic and data-intensive environments where delays can significantly undermine responsiveness and performance (Sahetapy et al., 2025). In the context of digital transformation, the availability of real-time data alone is insufficient; firms must also possess the capacity to interpret and act upon such data swiftly and effectively.

Conceptually, decision-making speed encompasses the rapid processing of real-time information, responsiveness within managerial decision cycles, and efficiency in converting data into actionable outcomes. These dimensions reflect not only the technical capability to access information but also the organizational readiness to act upon it (Rialti et al., 2019). As such, decision-making speed can be viewed as a cognitive and procedural capability that bridges information availability and operational execution (Mikalef & Krogstie, 2020).

Within digitally integrated environments, this construct assumes a more strategic role. Digital process integration and supply chain visibility enhance the volume, velocity, and variety of available information, yet without corresponding improvements in decision-making speed, such information may remain underutilized (Warner & Wäger, 2019). Consequently, decision-making speed functions as a critical mechanism that transforms data availability into actionable insights, enabling firms to respond proactively to changes and disruptions.

Recent empirical studies highlight that organizations with faster decision-making processes are better positioned to leverage digital capabilities for improved operational outcomes (Dubey et al., 2020; Teece, 2018). In particular, effective and timely decision-making has been shown to play a central role in translating digital integration and supply chain visibility into enhanced operational agility, especially under conditions of uncertainty and environmental turbulence (Dubey et al., 2020; Rialti et al., 2019). This underscores the

importance of decision-making speed not merely as a supporting function, but as a key enabler in the realization of agile operations.

Digital Process Integration and Operational Agility

Digital process integration enhances coordination, reduces information silos, and enables real-time communication across organizational units. From a dynamic capabilities perspective, integrated digital systems strengthen a firm's ability to sense and respond to environmental changes.

Empirical studies indicate that digital integration significantly improves responsiveness and operational performance by facilitating seamless information flow and process synchronization (Mikalef & Krogstie, 2020; Qi et al., 2017). Therefore:

H1: Digital process integration positively affects operational agility.

Supply Chain Visibility and Operational Agility

Supply chain visibility provides real-time insights that enable firms to anticipate disruptions and respond proactively. Visibility enhances situational awareness, which is essential for agile decision-making and operational flexibility. Prior research demonstrates that visibility improves coordination, reduces uncertainty, and enhances responsiveness, thereby contributing to agility (Dubey et al., 2020; Sahetapy et al., 2025).

H2: Supply chain visibility positively affects operational agility.

Digital Process Integration and Decision-Making Speed

Digital integration enables faster access to accurate and timely information, thereby accelerating decision-making processes. Integrated systems reduce delays caused by fragmented information and manual processes.

Studies show that digital technologies enhance decision efficiency by facilitating real-time data processing and analytics (Halik, Lambe, et al., 2026; Sahetapy et al., 2025).

H3: Digital process integration positively affects decision-making speed.

Supply Chain Visibility and Decision-Making Speed

Visibility enhances the availability of real-time data, which supports faster and more informed decisions. When firms have access to transparent and accurate supply chain information, they can respond more quickly to disruptions and opportunities.

Empirical evidence suggests that visibility improves decision support systems and accelerates managerial responses (Mikalef & Krogstie, 2020; Peretz-Andersson et al., 2024).

H4: Supply chain visibility positively affects decision-making speed.

Decision-Making Speed and Operational Agility

Decision-making speed is a critical determinant of operational agility. According to Dynamic Capabilities Theory (Teece, 2018), the ability to respond quickly depends not only on available resources but also on how fast decisions are made and executed.

Firms with faster decision cycles are better positioned to adapt to environmental changes and maintain competitive advantage.

H5: Decision-making speed positively affects operational agility.

The Mediating Role of Decision-Making Speed

Digital process integration and supply chain visibility provide the necessary information and infrastructure; however, their impact on agility depends on how effectively organizations utilize this information.

Decision-making speed acts as a transformation mechanism that converts digital inputs into agile outcomes. This mediating role aligns with the dynamic capabilities' perspective (Teece, 2018), where intermediate capabilities enable the conversion of resources into performance outcomes (Warner & Wäger, 2019).

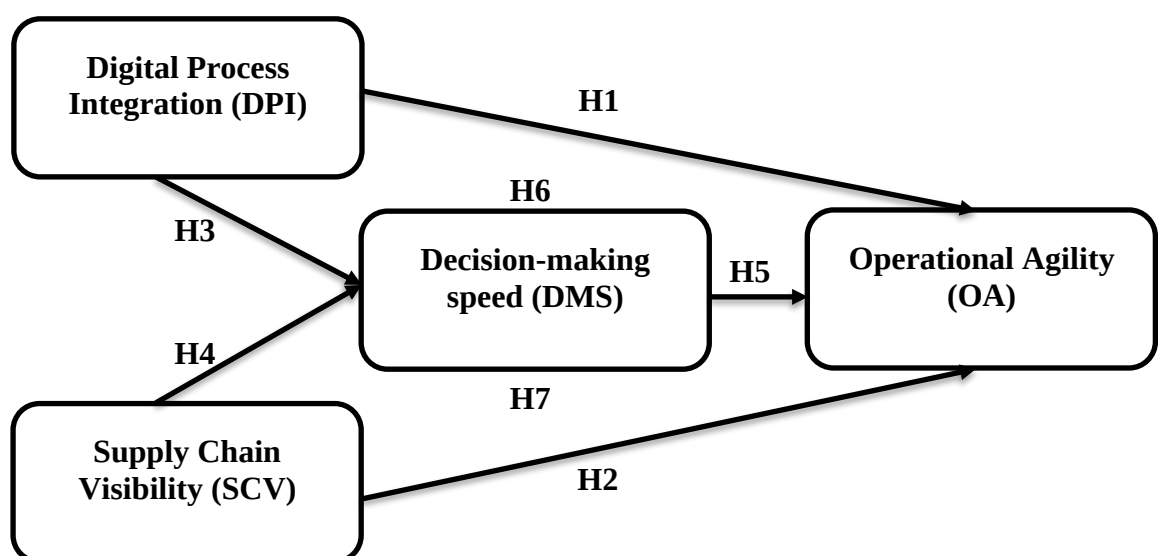
H6: Decision-making speed mediates the relationship between digital process integration and operational agility.

H7: Decision-making speed mediates the relationship between supply chain visibility and operational agility.

Before presenting the conceptual framework, it is important to synthesize the theoretical arguments and empirical evidence discussed in the preceding section. Drawing upon the Resource-Based View and Dynamic Capabilities Theory, this study posits that digital process integration and supply chain visibility serve as critical enablers that enhance a firm's ability to respond to environmental changes. However, the effectiveness of these digital capabilities in driving operational agility is contingent upon the firm's ability to process information and make timely decisions.

In this regard, decision-making speed is positioned as a key mediating mechanism that transforms digital inputs into agile operational outcomes. It reflects the organization's capacity to convert real-time data into rapid and effective actions, thereby bridging the gap between technological capability and operational performance. Accordingly, this study proposes an integrated conceptual model that examines both the direct and indirect relationships among digital process integration, supply chain visibility, decision-making speed, and operational agility in service firms.

The proposed relationships are illustrated in **Figure 1**



Source: Author's thought
Figure 1. Conceptual Framework

METHODS

Research Design

This study adopts a quantitative research design with an explanatory approach to examine the causal relationships among digital process integration, supply chain visibility, decision-making speed, and operational agility in service firms. A cross-sectional survey method is employed, as it enables the collection of standardized data from a relatively large number of respondents within a specific time frame (Sugiyono, 2020). This design is appropriate for testing theoretically grounded hypotheses and estimating structural relationships using multivariate analysis techniques (Hair et al., 2022).

The study is deductive in nature, as it builds upon established theories, namely the Resource-Based View and Dynamic Capabilities Theory, and empirically tests the proposed hypotheses using primary data collected from service sector organizations.

Population, Sample, and Sampling Technique

The population of this study comprises managers and operational-level employees working in service firms, particularly those involved in decision-making processes, operations management, and digital system utilization. The focus on service firms is justified by the increasing reliance on digital technologies and the critical role of responsiveness in service delivery.

Given the absence of a comprehensive sampling frame, this study employs a non-probability sampling approach, specifically purposive sampling. Respondents are selected based on the following criteria: (1) actively working in a service organization, (2) having at least one year of work experience, and (3) being involved in operational or managerial decision-making processes. This approach ensures that respondents possess sufficient knowledge and experience to provide reliable information.

The minimum sample size is determined based on the requirements of Structural Equation Modeling using Partial Least Squares (PLS-SEM). Following the “10-times rule” and recent recommendations, a minimum of 150–200 respondents is considered adequate for achieving robust statistical power (Hair et al., 2021). Therefore, this study targets a sample size of approximately 200 respondents.

Research Location and Time

The research is conducted in major urban areas in Indonesia, with a focus on service firms operating in cities such as Makassar, Jakarta, Surabaya, and Bandung. These cities are selected due to their high level of economic activity and digital adoption in the service sector.

Data collection is carried out over a three-month period, from January to March 2026. The data are collected using an online questionnaire distributed through professional networks, email, and social media platforms to ensure broader reach and efficiency.

Data Collection Technique

Primary data are collected using a structured questionnaire. All measurement items are adapted from prior validated studies to ensure content validity and reliability. Responses are measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), which is widely used in behavioral and management research.

Before the main data collection, a pilot test is conducted with a small group of respondents to ensure clarity, readability, and relevance of the questionnaire items.

Measurement of Variables

The constructs in this study are operationalized using reflective indicators adapted from established literature. The measurement items for each variable are presented in **Table 2**.

Table 2. Measurement Items

Variable	Code	Measurement Items	Source
Digital Process Integration (DPI)	DPI1	Our organization integrates digital systems across departments	(Halik, Halik, et al., 2026; Halik & Halik, 2024)
	DPI2	Information flows seamlessly between internal functions	
	DPI3	Digital tools enable real-time coordination of processes	
	DPI4	Our systems are well integrated with external partners	
Supply Chain Visibility (SCV)	SCV1	We have real-time visibility of supply chain operations	(Dubey et al., 2020; Qi et al., 2017; Rai et al., 2006)
	SCV2	Information across the supply chain is transparent and accessible	
	SCV3	We can track operational activities in real time	
	SCV4	Our organization quickly identifies disruptions in the supply chain	
Decision-Making Speed (DMS)	DMS1	Decisions are made quickly in response to changes	(Mikalef & Krogstie, 2020; Rialti et al., 2019; Teece, 2018)
	DMS2	Managers respond rapidly to new information	
	DMS3	Decision-making processes are efficient	
	DMS4	We quickly translate data into actionable decisions	
	DMS5	Organizational decisions are made without unnecessary delays	
	DMS6	Real-time data supports faster decision-making	
Operational Agility (OA)	OA1	Our organization responds quickly to customer demands	(Asghar et al., 2026; Dubey et al., 2020)
	OA2	We can adapt operations rapidly to changes	
	OA3	Our processes are flexible and responsive	
	OA4	We quickly adjust to unexpected disruptions	
	OA5	Our organization can reconfigure operations efficiently	
	OA6	We maintain high responsiveness under uncertainty	

Source: Adapted from previous research (2026)

RESULTS AND DISCUSSION

Overview of the Research Object

This study investigates service firms operating in major urban centers in Indonesia, particularly Makassar, Jakarta, Surabaya, and Bandung. These cities represent key economic hubs characterized by a relatively high level of digital adoption and service sector development. The research focuses on organizations that have begun integrating digital technologies into their operational processes, including the use of enterprise systems, cloud-based platforms, and real-time data analytics.

The service sector examined in this study includes industries such as banking and financial services, hospitality, logistics, healthcare, and professional services. These sectors are selected due to their strong dependence on information flow, customer interaction, and responsiveness, all of which are closely related to operational agility. In such environments, digital process integration and supply chain visibility are expected to play a pivotal role in enhancing organizational responsiveness and adaptability.

From an organizational perspective, most firms included in the study have implemented some form of digital infrastructure to support operational activities. However, the level of integration and visibility varies significantly across firms, which provides a suitable context for examining how these capabilities influence decision-making speed and operational agility.

Respondent Characteristics

A total of 195 valid responses were collected and analyzed in this study. The respondents consist of managerial and operational-level employees who are directly involved in decision-making processes and the use of digital systems within their organizations. The demographic and professional characteristics of the respondents are presented in **Table 3**.

Table 3. Respondent Characteristics (N=195)

Category	Classification	Frequency (n)	Percentage (%)
Gender	Male	112	57.4
	Female	83	42.6
Age	< 25 years	38	19.5
	25–34 years	87	44.6
	35–44 years	49	25.1
	> 44 years	21	10.8
	Diploma	29	14.9
Education Level	Bachelor's Degree	121	62.1
	Master's Degree	45	23.0
Work Experience	< 2 years	34	17.4
	2–5 years	76	39.0
	6–10 years	53	27.2
	> 10 years	32	16.4
	Operational Staff	78	40.0
Position	Supervisor	56	28.7
	Manager	61	31.3
	Financial Services	52	26.7
	Hospitality	41	21.0
Industry Sector	Logistics	36	18.5
	Healthcare	29	14.9
	Others	37	19.0
Research Location	Makassar	58	29.7

Category	Classification	Frequency (n)	Percentage (%)
	Jakarta	52	26.7
	Surabaya	45	23.1
	Bandung	40	20.5

Source: Primary data processed (2026)

The data indicate that the majority of respondents are in the productive age range of 25–34 years, suggesting familiarity with digital technologies and adaptability to organizational change. Most respondents hold a bachelor's degree and possess between two to five years of work experience, which implies adequate exposure to operational processes and decision-making environments. Furthermore, the distribution across managerial levels ensures that the data capture both strategic and operational perspectives. The inclusion of geographic distribution provides a more comprehensive representation of the research context. The data indicate that respondents are relatively well distributed across four major cities in Indonesia, with Makassar contributing the largest proportion (29.7%), followed by Jakarta (26.7%), Surabaya (23.1%), and Bandung (20.5%). This distribution strengthens the generalizability of the findings within the context of urban service firms, as it captures variations in digital adoption and operational practices across different economic regions.

Descriptive Statistical Analysis

Descriptive statistical analysis is conducted to provide an initial overview of the data distribution and to assess the general tendency of respondents' perceptions toward each construct. This analysis is essential in quantitative research as it helps identify patterns, central tendencies, and variability within the dataset before proceeding to more complex inferential techniques. In the context of this study, descriptive statistics are particularly useful for evaluating how respondents perceive digital process integration, supply chain visibility, decision-making speed, and operational agility based on the measurement items outlined in **Table 2**.

Furthermore, descriptive analysis allows researchers to detect potential anomalies, such as extreme values or inconsistent responses, and to ensure that the data meet basic assumptions for further statistical testing (Hair et al., 2021; Santosa, 2018). The mean value reflects the central tendency of responses, while the standard deviation indicates the degree of variation among respondents.

Table 4. Results of Descriptive Statistical Analysis

Variable	Indicator	Mean	Standard Deviation	Interpretation
Digital Process Integration (DPI)	DPI1	3.985	1.020	High
	DPI2	3.908	1.101	High
	DPI3	3.790	1.024	Moderate–High
	DPI4	3.538	0.924	Moderate
Supply Chain Visibility (SCV)	SCV1	3.862	1.140	High
	SCV2	3.877	1.161	High
	SCV3	3.621	1.057	Moderate–High
	SCV4	3.390	0.951	Moderate
Decision-Making Speed (DMS)	DMS1	3.790	0.896	Moderate–High
	DMS2	3.805	0.978	High
	DMS3	4.005	1.074	High
	DMS4	3.918	1.049	High
	DMS5	3.590	0.980	Moderate

Variable	Indicator	Mean	Standard Deviation	Interpretation
Operational Agility (OA)	DMS6	3.851	0.968	High
	OA1	3.395	0.919	Moderate
	OA2	3.687	1.141	Moderate–High
	OA3	3.287	0.982	Moderate
	OA4	3.323	0.924	Moderate
	OA5	3.292	0.935	Moderate
	OA6	3.503	1.015	Moderate

Source: Smart-PLS 4 output (2026)

At the indicator level, several important patterns emerge that refine the earlier construct-level interpretation.

For **Digital Process Integration**, DPI1 and DPI2 exhibit the highest mean values, indicating that internal system integration and information flow across departments are relatively well established. This aligns with the measurement items in Table 2, suggesting that firms are more mature in internal digital coordination. However, DPI4 shows a noticeably lower mean, indicating weaker integration with external partners. This reveals a structural limitation; firms are internally digitized but not fully integrated across the supply chain ecosystem. This asymmetry is critical and often overlooked in prior studies.

In the case of **Supply Chain Visibility**, SCV1 and SCV2 score high, reflecting strong transparency and accessibility of information. However, SCV4, which relates to the ability to detect disruptions, has the lowest mean. This suggests that visibility is still largely reactive rather than predictive. In other words, firms can “see” operations but are less capable of anticipating risks, which weakens the strategic value of visibility as defined in Table 2.

For **Decision-Making Speed**, DMS3 records the highest mean, indicating that respondents perceive decision processes as efficient. Similarly, DMS4 and DMS6 confirm that firms are relatively capable of translating data into action. However, DMS5 has a lower mean, suggesting that delays still occur in organizational decision processes. This inconsistency is theoretically important, it indicates that while digital tools support speed, organizational bureaucracy or hierarchy may still slow down execution.

The most critical insight emerges from **Operational Agility**. Almost all indicators (OA1–OA6) fall within the moderate range, with OA3, OA4, and OA5 being particularly low. Based on Table 2, these items relate to flexibility, adaptability, and operational reconfiguration. This implies that although firms can respond to customer demands to some extent (OA2), they struggle with deeper structural agility, especially in reconfiguring processes under uncertainty.

Measurement Model Evaluation

Measurement model evaluation is conducted to assess the reliability and validity of the constructs before testing the structural relationships. In Partial Least Squares Structural Equation Modeling (PLS-SEM), this step is essential to ensure that the observed indicators adequately represent their respective latent constructs (Hair et al., 2019). Without a sound measurement model, any conclusions drawn from the structural model may be biased or invalid.

The evaluation typically involves examining indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Indicator reliability is assessed through outer loadings, where values above 0.70 are considered acceptable (Hair et al., 2019). Internal consistency is evaluated using Cronbach’s alpha and composite reliability (CR), with recommended thresholds exceeding 0.70. Convergent validity is assessed using the Average Variance Extracted (AVE), which should be greater than 0.50, indicating that the construct explains more than half of the variance of its indicators. Discriminant validity is commonly evaluated using the Heterotrait-Monotrait ratio (HTMT), where values below 0.85 or 0.90

indicate adequate distinctiveness between constructs (Hair et al., 2019; Henseler et al., 2015; Santosa, 2018).

Table 5. Measurement Model Evaluation

Construct	Code	Outer Loading	Cronbach's Alpha	CR	AVE	HTMT (Max)
Digital Process Integration	DPI1	0.910	0.904	0.914	0.778	0.438
	DPI2	0.893				
	DPI3	0.914				
	DPI4	0.806				
Supply Chain Visibility	SCV1	0.908	0.907	0.915	0.782	0.685
	SCV2	0.916				
	SCV3	0.892				
	SCV4	0.818				
Decision Making Speed	DMS1	0.808	0.896	0.904	0.661	0.703
	DMS2	0.785				
	DMS3	0.891				
	DMS4	0.860				
	DMS5	0.714				
	DMS6	0.807				
Operational Agility	OA1	0.842	0.905	0.912	0.679	0.703
	OA2	0.887				
	OA3	0.815				
	OA4	0.842				
	OA5	0.795				
	OA6	0.756				

Source: Smart-PLS 4 output (2026)

The results demonstrate that all constructs meet the required criteria for reliability and validity. First, in terms of **indicator reliability**, all outer loading values exceed the minimum threshold of 0.70, indicating that each indicator contributes significantly to its respective construct. Although DMS5 (0.714) and OA6 (0.756) are relatively lower compared to others, they still fall within acceptable limits and do not warrant removal. Retaining these indicators is justified to preserve content validity, particularly since they represent important dimensions outlined in **Table 2**.

Second, internal consistency reliability is well established. All Cronbach's alpha values range from 0.896 to 0.907, and composite reliability (CR) values range from 0.904 to 0.915. These values exceed the recommended threshold of 0.70, indicating that the indicators consistently measure their respective constructs.

Third, convergent validity is confirmed as all AVE values exceed 0.50. Specifically, Digital Process Integration (0.778) and Supply Chain Visibility (0.782) exhibit particularly strong convergent validity, suggesting that their indicators share a high proportion of variance. Decision-Making Speed (0.661) and Operational Agility (0.679), while slightly lower, still demonstrate adequate explanatory power.

Fourth, discriminant validity is supported by HTMT values, all of which are below the conservative threshold of 0.85. The highest HTMT value (0.703) remains well within acceptable limits, indicating that the constructs are empirically distinct from one another.

The adequacy of discriminant validity is further examined using the Fornell–Larcker criterion. This approach assesses whether each construct shares more variance with its own indicators than with other constructs in the model. In practical terms, the square root of the Average Variance Extracted (AVE) for each construct should be greater than its correlations with other constructs (Fornell & Larcker, 1981; Hair et al., 2021). This test complements the HTMT analysis by providing an additional layer of validation for construct distinctiveness.

Table 6. Discriminant Validity with the Fornell and Larcker Approach

Variable	Digital Process Integration	Supply Chain Visibility	Decision Making Speed	Operational Agility
Digital Process Integration	0.882			
Supply Chain Visibility	0.223	0.884		
Decision Making Speed	0.337	0.626	0.813	
Operational Agility	0.398	0.439	0.638	0.824

Source: Smart-PLS 4 output (2026)

The results presented in **Table 6** confirm that discriminant validity is satisfactorily established. The diagonal elements, representing the square root of AVE for each construct, are all higher than the corresponding inter-construct correlations in their respective rows and columns (Fornell & Larcker, 1981). For instance, Digital Process Integration has a square root of AVE value of 0.882, which exceeds its correlations with Supply Chain Visibility (0.223), Decision-Making Speed (0.337), and Operational Agility (0.398). This pattern is consistently observed across all constructs.

Notably, the highest correlation is found between Decision-Making Speed and Operational Agility (0.638). While this value is relatively strong, it remains below the square root of AVE for both constructs (0.813 and 0.824, respectively), indicating that they are empirically distinct. This finding is important given the conceptual proximity between these variables discussed earlier. It suggests that although closely related, decision-making speed and operational agility capture different dimensions of organizational capability.

Similarly, the relationship between Supply Chain Visibility and Decision-Making Speed (0.626) reflects a meaningful association, yet still satisfies the discriminant validity requirement. This supports the theoretical argument that visibility enhances decision-making processes without overlapping conceptually.

Overall, the Fornell–Larcker results reinforce the findings from the HTMT analysis, confirming that all constructs in the model exhibit adequate discriminant validity. This strengthens the robustness of the measurement model and ensures that subsequent structural model evaluation can be conducted with confidence.

Structural Model Evaluation

Following the establishment of a reliable and valid measurement model, the next step involves evaluating the structural model. This stage aims to assess the predictive power and explanatory capability of the proposed model, as well as to test the hypothesized relationships among constructs. In PLS-SEM, structural model evaluation typically includes examining the coefficient of determination (R^2), path coefficients, effect sizes (f^2), predictive relevance (Q^2), and model fit indices (Hair et al., 2021).

The coefficient of determination (R^2) is particularly important as it indicates the proportion of variance in the endogenous constructs explained by their predictor variables. Higher R^2 values suggest stronger explanatory power of the model. According to Hair et al. (2019), R^2 values of 0.75, 0.50, and 0.25 can be described as substantial, moderate, and weak, respectively, although acceptable thresholds may vary depending on the research context.

Table 7. R-Square

	R-Square	R-Square Adjusted
Decision Making Speed	0.433	0.427
Operational Agility	0.447	0.439

Source: Smart-PLS 4 output (2026)

The results in **Table 7** indicate that the model demonstrates a moderate level of explanatory power. Specifically, the R^2 value for Decision-Making Speed is 0.433, meaning that approximately 43.3% of the variance in decision-making speed is explained by digital process integration and supply chain visibility. This suggests that both predictors play a meaningful role in shaping how quickly organizations make decisions, although more than half of the variance is still influenced by other factors not included in the model.

Similarly, the R^2 value for Operational Agility is 0.447, indicating that 44.7% of its variance is explained by digital process integration, supply chain visibility, and decision-making speed. This level of explanatory power can be categorized as moderate, suggesting that the model is reasonably effective in capturing the key determinants of operational agility in service firms.

The adjusted R^2 values (0.427 for decision-making speed and 0.439 for operational agility) are slightly lower but remain very close to the original R^2 values, indicating that the model does not suffer from overfitting and maintains good generalizability.

After evaluating the explanatory power of the model through R^2 , the next step is to assess the **effect size (f^2)**. The f^2 statistic measures the individual contribution of each exogenous construct to the R^2 value of an endogenous construct (Hair et al., 2021). In other words, it evaluates how much an endogenous variable's explanatory power changes when a specific predictor is included or excluded from the model.

According to Hair et al. (2019), f^2 values can be interpreted as follows: 0.02 indicates a small effect, 0.15 a medium effect, and 0.35 a large effect. This analysis is crucial because a model may exhibit acceptable R^2 values while individual predictors contribute unevenly. Therefore, f^2 provides a more nuanced understanding of the relative importance of each relationship in the structural model.

Table 8. F-Square Value

Variable	Digital Process Integration	Supply Chain Visibility	Decision Making Speed	Operational Agility
Digital Process Integration			0.072	0.068
Supply Chain Visibility			0.563	0.004
Decision Making Speed				0.289
Operational Agility				

Source: Smart-PLS 4 output (2026)

The f^2 results reveal important differences in the strength of relationships within the model.

First, the effect of Digital Process Integration on Decision-Making Speed ($f^2 = 0.072$) is categorized as small. This suggests that while digital integration contributes to faster decision-making, its impact is relatively limited when compared to other predictors. Similarly, its effect on Operational Agility ($f^2 = 0.068$) is also small, indicating that digital integration alone is not a dominant driver of agility.

In contrast, Supply Chain Visibility exhibits a very large effect on Decision-Making Speed ($f^2 = 0.563$). This is a critical finding. It indicates that visibility is the most influential factor in accelerating decision-making processes within service firms. Access to real-time, transparent information appears to be far more impactful than system integration alone in enabling rapid managerial responses.

However, an interesting anomaly emerges in the relationship between Supply Chain Visibility and Operational Agility ($f^2 = 0.004$). This value is below the threshold for a small effect, indicating a negligible direct impact. This finding challenges the common assumption in the literature that visibility directly enhances agility. Instead, it suggests that visibility primarily influences agility indirectly, through decision-making speed.

Furthermore, Decision-Making Speed has a medium effect on Operational Agility ($f^2 = 0.289$). This confirms its role as a key driver of agility and supports its positioning as a mediating variable in the model. Compared to digital integration and visibility, decision-making speed has a more substantial and direct impact on operational responsiveness.

In addition to assessing explanatory power through R^2 and effect size through f^2 , it is important to evaluate the model's predictive relevance (Q^2). The Q^2 statistic is obtained using the blindfolding procedure in PLS-SEM and reflects the model's ability to accurately predict the observed values of endogenous constructs.

A Q^2 value greater than zero indicates that the model has predictive relevance for a given construct, while values of 0.02, 0.15, and 0.35 can be interpreted as small, medium, and large predictive relevance, respectively (Hair et al., 2021). Unlike R^2 , which measures in-sample explanatory power, Q^2 provides insight into the model's out-of-sample predictive capability, making it particularly important for validating the robustness of the model.

Table 9. Predictive Relevance (Q^2)

Construct	Q^2 Value	Interpretation
Decision Making Speed	0.276	Medium Predictive Relevance
Operational Agility	0.301	Medium Predictive Relevance

Source: Smart-PLS 4 output (2026)

The results in **Table 9** indicate that both endogenous constructs exhibit positive Q^2 values, confirming that the model has adequate predictive relevance (Hair et al., 2021). Specifically, the Q^2 value for Decision-Making Speed (0.276) suggests a moderate level of predictive capability. This implies that digital process integration and supply chain visibility are not only statistically significant predictors but also practically relevant in predicting decision-making speed in service firms.

Similarly, the Q^2 value for Operational Agility (0.301) also falls within the medium range, indicating that the combination of digital process integration, supply chain visibility, and decision-making speed provides a reasonably accurate prediction of agility outcomes. This reinforces the robustness of the proposed model in capturing key determinants of operational agility.

From a comparative perspective, the slightly higher Q^2 value for operational agility suggests that the model performs marginally better in predicting agility than decision-making speed. This is theoretically consistent, as operational agility is influenced by both direct and indirect effects within the model, particularly through the mediating role of decision-making speed.

In addition to assessing the measurement and structural models, evaluating overall model fit provides further evidence of how well the proposed model reproduces the observed data. Although PLS-SEM is primarily prediction-oriented, recent methodological advancements recommend reporting model fit indices such as the Standardized Root Mean Square Residual (SRMR), Normed Fit Index (NFI), and discrepancy measures (d_{ULS} and d_G) to enhance model assessment rigor (Hair et al., 2021; Henseler et al., 2015).

SRMR is the most commonly used global fit index in PLS-SEM, where values below 0.08 indicate a good model fit. The NFI compares the proposed model to a null model, with values closer to 1 indicating better fit, while values above 0.80 are generally considered acceptable in exploratory research. The d_{ULS} and d_G values represent the discrepancy between observed and model-implied correlations; smaller values indicate better fit, although no strict cutoff thresholds are universally established.

Table 10. Model Fit Result

	Saturated Model	Estimated Model
SRMR	0.055	0.055
d_ULS	0.625	0.625
d_G	0.356	0.356
Chi-square	390.423	390.423
NFI	0.865	0.865

Source: Smart-PLS 4 output (2026)

The results in **Table 10** indicate that the proposed model demonstrates an acceptable to good level of overall fit. The SRMR value of 0.055 is well below the recommended threshold of 0.08, suggesting that the difference between the observed and predicted correlations is minimal. This provides strong evidence that the model fits the data well.

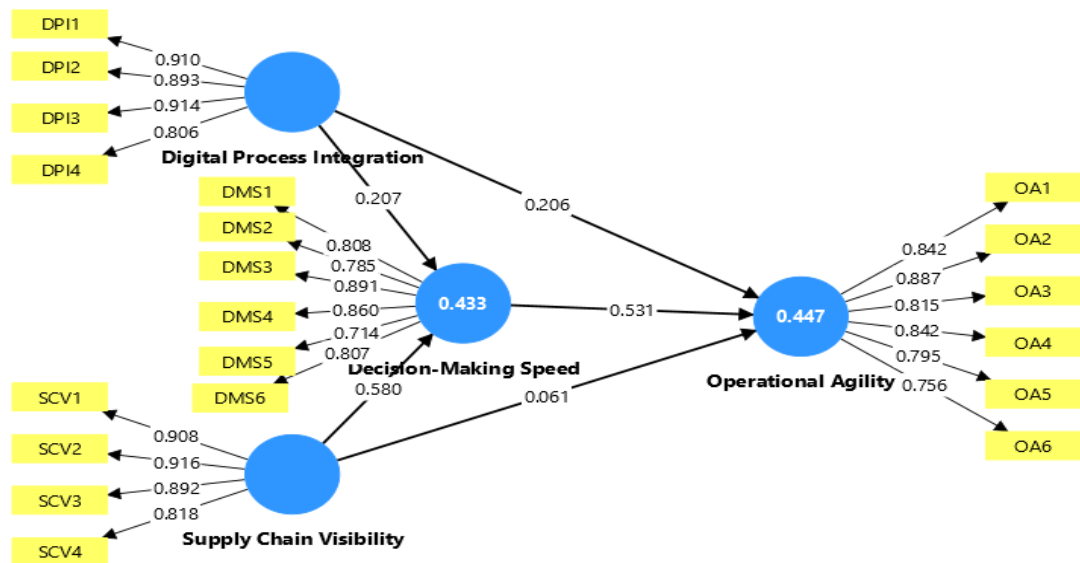
The NFI value of 0.865 further supports this conclusion. Although it does not reach the ideal benchmark of 0.90, it exceeds the acceptable threshold of 0.80, indicating that the model performs substantially better than a null model. Given the complexity of the model and the behavioral nature of the constructs, this level of fit is considered adequate.

The discrepancy measures, d_ULS (0.625) and d_G (0.356), are relatively low, indicating a small difference between empirical and model-implied covariance matrices. While these indices do not have strict cutoff values, their relatively modest magnitude suggests that the model does not suffer from serious misspecification.

The Chi-square value is reported primarily for completeness, as it is sensitive to sample size and often less informative in PLS-SEM contexts. Therefore, greater emphasis is placed on SRMR and NFI in evaluating model fit.

Before presenting the results of hypothesis testing, it is important to visualize the structural relationships among the constructs in the proposed model. The structural equation model illustrates the magnitude and direction of the relationships between digital process integration, supply chain visibility, decision-making speed, and operational agility, as well as the mediating role of decision-making speed.

This visualization provides a comprehensive overview of the model's structure and serves as a foundation for interpreting the path coefficients and testing the proposed hypotheses. The structural relationships obtained from the Smart-PLS analysis are presented in Figure 2.



Source: Smart-PLS 4 output (2026)

Figure 2. Structure Equation Model

Hypothesis Testing

Hypothesis testing in this study is conducted using the bootstrapping procedure in PLS-SEM to evaluate the significance and strength of the relationships among constructs. The assessment is based on path coefficients (original sample), t-statistics, and p-values. A hypothesis is considered supported if the t-statistic exceeds 1.96 and the p-value is below 0.05, indicating statistical significance at the 5% level (Ghozali, 2021; Hair et al., 2021; Santosa, 2018). (See **Table 11**)

Table 11. Path Coefficient and Hypotheses Testing

Hypothesis	Relation	Original Sample	Mean	SD	T-Statistics	P-Values	Description
H1	DPI → OA	0.206	0.208	0.066	3.138	0.002	Supported
H2	SCV → OA	0.061	0.060	0.079	0.763	0.445	Not Supported
H3	DPI → DMS	0.207	0.209	0.064	3.235	0.001	Supported
H4	SCV → DMS	0.580	0.580	0.057	10.151	0.000	Supported
H5	DMS → OA	0.531	0.532	0.076	6.945	0.000	Supported
H6	DPI → DMS → OA	0.110	0.111	0.039	2.832	0.005	Supported
H7	SCV → DMS → OA	0.308	0.309	0.056	5.523	0,000	Supported

Note: DPI = Digital Process Integration, SCV = Supply Chain Visibility, DMS = Decision Making Speed, OA = Operational Agility

Source: Smart-PLS 4 output (2026)

The results provide strong empirical support for most of the proposed hypotheses, with one notable exception that offers important theoretical insight.

First, **H1 is supported**, indicating that digital process integration has a positive and significant effect on operational agility ($\beta = 0.206$, $p < 0.05$). This suggests that integrated digital systems enhance coordination and responsiveness, enabling firms to adapt more effectively to operational changes. However, the effect size is relatively modest, indicating that digital integration alone is not a dominant driver of agility.

In contrast, **H2 is not supported**, as supply chain visibility does not have a significant direct effect on operational agility ($\beta = 0.061$, $p > 0.05$). This finding is particularly important because it challenges a widely held assumption in the literature. It suggests that visibility, by itself, does not automatically translate into agile operations. Instead, its value may depend on how effectively the information is utilized within the organization.

The results for **H3 and H4** show that both digital process integration ($\beta = 0.207$, $p < 0.01$) and supply chain visibility ($\beta = 0.580$, $p < 0.001$) significantly influence decision-making speed. Notably, the effect of supply chain visibility is substantially stronger, indicating that access to real-time, transparent information plays a more critical role in accelerating decision processes than system integration alone.

Furthermore, **H5 is supported**, confirming that decision-making speed has a strong positive effect on operational agility ($\beta = 0.531$, $p < 0.001$). This finding underscores the central role of decision-making as a driver of organizational responsiveness and supports its positioning as a key mediating variable.

The mediation results provide deeper insights into the underlying mechanisms. **H6 is supported**, indicating that decision-making speed partially mediates the relationship between digital process integration and operational agility ($\beta = 0.110$, $p < 0.01$). This suggests that digital integration enhances agility both directly and indirectly through faster decision-making.

More importantly, **H7 is supported**, showing that decision-making speed fully mediates the relationship between supply chain visibility and operational agility ($\beta = 0.308$, $p < 0.001$). Combined with the non-significant direct effect in H2, this indicates a full mediation

effect. In other words, supply chain visibility influences operational agility only through its impact on decision-making speed.

Discussion

The Effect of Digital Process Integration on Operational Agility.

The results indicate that digital process integration has a positive and significant effect on operational agility, although the magnitude of the effect is relatively modest. This finding suggests that integrating digital systems across functions enhances coordination and reduces process fragmentation, which in turn improves the firm's ability to respond to operational changes.

From a theoretical standpoint, this supports the Resource-Based View, where digital infrastructure functions as a strategic resource (Abdurrahman et al., 2024; Teece, 2018). It also aligns with Dynamic Capabilities Theory, as integration facilitates the reconfiguration of processes in response to environmental shifts. Prior studies have similarly found that integrated systems improve responsiveness and operational efficiency (Mikalef & Krogstie, 2020; Qi et al., 2017).

However, the relatively small effect size indicates that integration alone is insufficient to produce high levels of agility. This nuance is important. Many studies implicitly assume that digital integration directly leads to agility, but the present findings suggest that its impact is conditional. In practice, integration provides the technical foundation, but not the execution capability required for agility.

The Effect of Supply Chain Visibility on Operational Agility

Contrary to expectations, supply chain visibility does not have a significant direct effect on operational agility. This result challenges a dominant assumption in the literature that visibility inherently enhances responsiveness and flexibility.

One plausible explanation is that visibility primarily improves information availability, not action capability. Firms may have access to real-time data, but without effective internal processes, this information does not automatically translate into operational change. This interpretation is consistent with recent arguments that data richness does not guarantee performance improvement unless supported by organizational capabilities (Dubey et al., 2020; Sahetapy et al., 2025).

This finding represents a key point of novelty. Rather than confirming a direct linkage, the study reveals that visibility is a necessary but not sufficient condition for agility. This shifts the theoretical focus from technology adoption to capability utilization.

The Effect of Digital Process Integration on Decision-Making Speed

The analysis shows that digital process integration significantly enhances decision-making speed. Integrated systems enable faster access to information, reduce duplication, and streamline communication across departments. As a result, decision cycles become shorter and more efficient.

This finding is consistent with prior research emphasizing the role of digital infrastructure in accelerating organizational processes (Rialti et al., 2019). From a dynamic capabilities' perspective, integration strengthens the firm's ability to "seize" opportunities by enabling rapid interpretation and response.

However, the effect size remains moderate, suggesting that technological integration alone does not fully determine decision speed. Organizational structure, hierarchy, and managerial practices likely play an additional role, an aspect that warrants further investigation (Samosir et al., 2025).

The Effect of Supply Chain Visibility on Decision-Making Speed

Supply chain visibility exhibits a strong and highly significant effect on decision-making speed, making it the most influential predictor in this relationship. This result indicates that access to real-time, transparent information is critical for accelerating managerial responses.

Unlike digital integration, which focuses on system connectivity, visibility directly enhances situational awareness. Managers are able to identify disruptions, monitor performance, and respond to changes more quickly when information is readily available. This aligns with prior studies highlighting the importance of data-driven decision-making in dynamic environments (Mikalef & Krogstie, 2020; Peretz-Andersson et al., 2024).

The strength of this relationship suggests that visibility plays a more immediate and operational role in decision-making processes compared to integration. This distinction is theoretically important and often underemphasized in prior research.

The Effect of Decision-Making Speed on Operational Agility

Decision-making speed is found to have a strong and significant effect on operational agility. This confirms that agility is not solely a function of technological capability but is heavily dependent on how quickly organizations can act on available information.

From a Dynamic Capabilities perspective, decision-making speed represents a micro-foundation that enables firms to transform insights into action. Faster decisions allow organizations to respond more effectively to environmental uncertainty, thereby enhancing flexibility and responsiveness (Teece, 2018).

This finding reinforces prior research suggesting that agility emerges from the alignment between information processing and execution capability. It also supports the argument that decision-making is a central mechanism linking digital capabilities to performance outcomes (Rialti et al., 2019).

The Mediating Role of Decision-Making Speed

The mediation analysis provides the most significant insight of this study. Decision-making speed partially mediates the relationship between digital process integration and operational agility, and fully mediates the relationship between supply chain visibility and operational agility.

The partial mediation in the first relationship suggests that digital integration influences agility both directly and indirectly. In contrast, the full mediation in the second relationship indicates that supply chain visibility affects agility only through decision-making speed. This means that visibility alone does not create agility; it must first be translated into rapid decisions.

This finding offers a clear theoretical contribution. It challenges the prevailing assumption of a direct relationship between visibility and agility and introduces a decision-centric mechanism. In this model, visibility enhances information availability, decision-making speed converts information into action, and agility emerges as the final outcome.

Theoretical Implications

This study contributes to the literature in several important ways. First, it extends Dynamic Capabilities Theory by explicitly identifying decision-making speed as a micro-foundational capability that links digital resources to operational outcomes. Second, it refines the understanding of supply chain visibility by demonstrating that its impact is indirect rather than direct. Third, it integrates digital process integration and visibility into a unified framework, highlighting their complementary but distinct roles.

More importantly, the study shifts the analytical focus from technology adoption to capability utilization. This perspective addresses a gap in prior research, which often assumes that digital technologies automatically lead to improved performance.

Practical Implications

From a managerial standpoint, the findings indicate that investments in digital technologies must be complemented by improvements in organizational decision-making processes. While many service firms have adopted integrated digital systems, the results show that such investments do not automatically translate into operational agility. Managers should therefore prioritize reducing bureaucratic layers, streamlining decision workflows, and empowering employees with greater autonomy to act on real-time information. Faster decision cycles enable firms to respond more effectively to dynamic market conditions.

Furthermore, the results highlight that supply chain visibility, although important, does not directly enhance operational agility. Its value lies in how effectively it is utilized. Managers should ensure that real-time data is not only accessible but also actionable. This requires developing analytical capabilities, fostering data-driven decision cultures, and integrating decision-support systems that facilitate rapid interpretation of information. Without these capabilities, visibility remains informational rather than strategic.

In addition, alignment between digital systems and organizational processes is critical. Firms often invest heavily in digital integration but fail to redesign workflows and decision structures accordingly. This misalignment can limit the effectiveness of digital initiatives. Managers should therefore adopt a holistic approach that synchronizes technology, processes, and human capabilities to maximize the impact of digital transformation.

Finally, the strong role of decision-making speed suggests that firms should treat it as a strategic capability rather than a byproduct of digitalization. Organizations that deliberately design for speed, through simplified procedures, decentralized authority, and real-time performance monitoring, are more likely to convert digital resources into tangible operational agility.

CONCLUSION

Three key findings emerge from this study. (1) Digital process integration contributes to operational agility, but its effect is limited and not sufficient on its own. This indicates that technology integration primarily provides an enabling infrastructure rather than directly driving agile outcomes. (2) Supply chain visibility does not have a direct impact on operational agility, challenging a widely accepted assumption in the literature. Instead, its influence operates entirely through decision-making processes, suggesting that visibility without action remains merely informational. (3) Decision-making speed plays a central and transformative role, acting as the primary mechanism through which digital capabilities are converted into operational agility. These findings position decision-making speed as a critical organizational capability rather than a secondary outcome of digitalization.

These insights shift the perspective from a technology-centric view to a decision-centric framework, where the effectiveness of digital transformation depends on how quickly and effectively organizations act on available information. In this sense, operational agility is not simply a result of having advanced systems, but of aligning those systems with responsive and efficient decision processes.

Despite its contributions, this study has several limitations. First, the use of non-probability sampling limits the generalizability of the findings beyond the observed sample. Second, the cross-sectional design restricts the ability to capture dynamic changes over time, particularly in rapidly evolving digital environments. Third, the model explains a moderate proportion of variance in operational agility, indicating that other relevant factors, such as

organizational culture, leadership style, or technological readiness, were not included in the analysis.

Future research should address these limitations by adopting longitudinal designs to better capture causal dynamics and temporal effects. Expanding the model to include behavioral and organizational variables would also provide a more comprehensive understanding of agility formation. In addition, comparative studies across industries or countries could offer deeper insights into contextual differences in digital transformation outcomes. Finally, future studies may explore alternative mediating or moderating variables, such as organizational learning or innovation capability, to further refine the mechanisms linking digital capabilities and operational performance.

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