Beyond Data-Driven Decision-Making in Operations Management: The Serial Roles of Operational Agility and Environmental Complexity in Performance Outcomes

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ABSTRACT

Manufacturing organizations rely on operational data, however, converting information into decisions and performance improvements remains challenging. This study examines how analytics capability and sensing capability influence operational performance (OPP) through data-driven decision-making (DDDM) and operational adjustment agility, while assessing environmental complexity as a moderator. A cross-sectional survey yielded 174 valid responses from manufacturing professionals, and the model was evaluated using partial least square. Results show that sensing capability positively predicts DDDM, whereas analytics capability has no significant effect. DDDM positively predicts operational adjustment agility and OPP, while agility also improves performance. Indirect effects reveal that DDDM mediates the relationship between sensing capability and operational adjustment agility. It also mediates the relationship between analytical capability and operational adjustment agility. Furthermore, decision-making and operational adjustment agility sequentially mediate the sensing capability–performance relationship. The corresponding indirect pathways from analytics capability are not statistically significant. However, the moderating effect of environmental complexity is insignificant. The findings highlight sensing-led decisions and operational adaptation as routes to manufacturing performance, offering implications for capability development and research on contextual contingencies.

Keywords: Analytics capability; sensing capability; data-driven decision-making; operational adjustment agility; operational performance; environmental complexity.

INTRODUCTION

Manufacturing is a core part of economic development, and involves a series of interdependent activities that link procurement, production, inventory management, distribution and customer service (Ogumeyo et al., 2025). Digitalization of manufacturing systems provides access to a wealth of information regarding the system's operations, which can be used to enhance resource utilization, production planning, and managerial decision making. In recent research on smart manufacturing, advanced analytics is becoming crucial for the improvement of manufacturing operations (Presciuttini & Portioli-Staudacher, 2024), and in research on manufacturing agility, the importance of mapping organizational capabilities into timely responses to changing conditions is highlighted (Khan & Kribs, 2026; Rahman et al., 2026). However, technological improvement is not the only key to better operational results (Khurram, 2025). Manufacturers

need to learn how to interpret information, identify new changes, assess options for action, and efficiently reconfigure processes. Thus, the translation of information-related capabilities into operational performance (OPP) is still a significant concern in operations management.

The production companies often experience unpredictable demand, supply issues, production delays, shifting customer expectations and competitive pressures (Xu et al., 2013). Managers can have advanced analytical systems (Srivastava & Dixit, 2023), but still struggle with turning information into timely decisions and effective operational responses. For example, production data might show a potential capacity constraint, but OPP will not necessarily improve, unless managers choose the correct corrective action and production scheduling, staff allocation or resource use. The application of data analytics in manufacturing has been demonstrated in recent research to enhance machine utilization, production insights, and resource allocation (Seyedzadeh et al., 2025). Likewise, research on shopfloor management, which aims to manage the shopfloor based on data, highlights the need for the alignment of information systems with managerial routines and operational adaptation (Eichenseer & Winkler, 2025). An extensive meta-analysis also reveals that integration, flexibility and resilience are key mechanisms that link analytics capability to OPP (Raj et al., 2025). These results underscore the importance of comprehending not only the extent to which organizations are using data, but how data-driven decisions are translated into operational improvements.

While there have been previous studies that have found significant relationships between digital skills and performance (Omri, 2026; Qasim, 2024), there are still some research gaps. First, analytics capability and sensing capability are two different organizational resources and should be investigated together. The analytics capability allows organizations to combine and interpret information, while the sensing capability allows organizations to detect new opportunities, customer needs, and environmental changes. Research has focused on data analytics and digital capabilities in the context of sustainability, supply chain resilience, and OPP, such as the importance of organizational knowledge and government effectiveness (Cheng et al., 2023; Dubey et al., 2023; Hautala-Kankaanpää, 2023). But these views are not sufficient to capture the synergy between analytical and sensing capabilities in the context of DDDM and operational adjustment. Second, there is a need to look at the difference between making evidence-based decisions and effectively implementing these decisions. Previous studies have examined analytical capability in terms of employees' analytical skills, supply chain agility, and organizational digital capability, which shows the importance of complementary resources and adaptive processes (Çemberci & Civelek, 2022; Farivar et al., 2022; Wang et al., 2022). But an integrated explanation of decision making and operational adjustment agility as sequential mechanisms is useful.

Third, the impact of environmental complexity on the relationship between decision making and agility needs to be explored. Manufacturing firms exist in varying degrees of product variation, competitive intensity, and customer diversity, and this could change the value of managerial decisions. The study of business agility indicates that the agility capabilities of the organization are more important when the company is required to operate in a complex environment (Lin et al., 2020). In the context of dynamic capabilities, the organization should be able to reconfigure resources and routines to adapt to the changing environment (Pavlou & El Sawy, 2011). However, the impact of environmental complexity on the capability-to-performance pathway explored in this study is not sufficiently linked to the data-driven decision to operational agility of adjustment.

In this context, the present study proposes and tests a model that is called beyond data-driven decision-making (DDDM) in operations management: the serial roles of operational agility and environmental complexity in performance outcomes. Specifically, it examines the impact of analytics capability and sensing capability on DDDM, the impact of decision-making on operational adjustment agility and OPP, and how agility impacts on OPP. It also explores the mediating role of DDDM, the sequential mediating role of DDDM and operational adjustment agility, and the moderating role of environmental complexity between decision-making and agility. Therefore, the study brings a new perspective to the field of operations management research by combining the information-processing capabilities, managerial decisions, operational adaptation, and environmental complexity in a single framework. On the practical side, it brings attention to the need for manufacturers to have effective decision processes and the organizational flexibility to act on decisions in addition to analytical investments. The results can also assist managers to determine if their operating environment needs to be more adaptive to turn information into performance improvements.

CONCEPTUAL FRAMEWORK OF THE STUDY

In this research, a capability-to-performance framework is presented, based on the integration of the insights of organizational information processing theory and the dynamic capabilities perspective. Analytics capability is defined as an organization's capability to integrate and analyze operational information to make evidence-based decisions (Srinivasan & Swink, 2018). Sensing capability complements this resource by enabling organizations to detect new opportunities and changes in the environment (Pavlou & El Sawy, 2011). Therefore, both are suggested to affect the DDDM process, which is supported by studies that emphasize the role of analytical resources in organizational decision-making processes (Szukits & Móricz, 2023). The framework also suggests that DDDM increases operational agility for adjustment, by converting managerial judgments into timely operational responses. The influence of decision-making on OPP is also expected, and the influence of operational adjustment agility on performance is proposed to be through the adjustment of processes and capacities. These relationships are related to the research on analytics and sensing capabilities and operational outcomes (Wong & Ngai, 2023). Finally, environmental complexity is added as a moderator of the decision making-agility relationship, as there is evidence that complexity can influence the effectiveness of organizational capabilities (Lin et al., 2020). As such, the framework illustrates the ways in w hich information-related capabilities can contribute to OPP improvement via a series of organizational mechanisms. Consequently, the proposed research farmwork is reported in Figure 1.

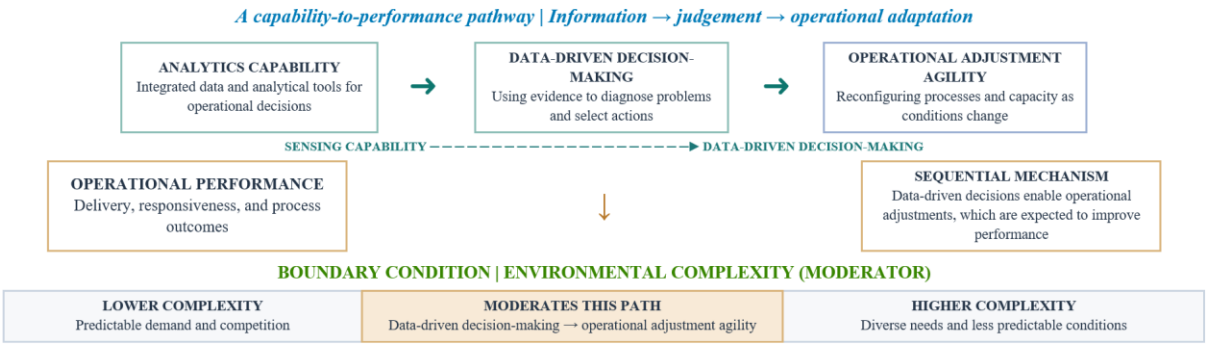


Figure 1: Proposed relationship between variables

HYPOTHESES DEVELOPMENT

Analytics Capability, Sensing Capability and DDDM

Analytical capability is the ability of an organization to access, integrate, analyse and interpret data using the right technology, methods and managerial skills (Raj et al., 2025). In manufacturing companies, this capability helps managers convert operational data, such as production rates, inventory levels, defect rates, and delivery timeliness into actionable insights that guide their decision-making. Li et al. (2022) found that the usage of big data analytics has a positive impact on decision-making quality, and the big data analytics capability is an important mediating factor. Likewise, Szukits and Móricz (2023) emphasized that the translation of advanced analytical information into usable insights in organizational decision-making processes is a key factor, and analytical resources are not enough unless managers can integrate them into their decision-making processes. Additionally, Cao and Duan (2024) discovered that business analytics has a positive effect on rational strategic decision-making, highlighting the significance of analytical information in considering alternatives and choosing the right path. The results indicate that analytics capability enhances the access, understanding, and utilization of relevant evidence to support decision making, allowing managers to make decisions based on evidence, not just intuition or personal experience. As such, companies that have better analytics skills are likely to show greater trust in operational data for various problems identification, evaluating alternatives, choosing solutions, and planning implementation. Based on this, the following hypothesis is proposed:

H1: Analytics capability positively influences DDDM.

Sensing capability is the ability of an organisation to detect, understand and predict shifts in customer needs, market conditions, technology and competition (Wong & Ngai, 2023). Day (1994) noted that market-sensing was a key feature of market-driven organizations and predict new customer needs. Teece (2007) also described sensing opportunities and threats as a basic organizational process in which firms detect changes that might necessitate strategic or operational reactions. Empirical studies by Hough and White (2004) also show that the scanning activities that organizations engage in to aid strategic decision-making are affected by the dynamism of their environment and by managerial conditions. Together, these views indicate that sensing capability offers managers external information that is timely and complements their internal information about operations. In the manufacturing environment, for instance, sensing customer preferences, competitor actions, supplier circumstances, and technological advances can be helpful in determining new operational issues and in reconsidering assumptions before deciding on a course of action. Thus, organizations with higher sensing capacities are likely to have a better opportunity to integrate environmental intelligence into systematic and evidence-based decision processes (Gong et al., 2025). Therefore, the sensing capability is expected to enhance the DDDM by increasing awareness of the relevant environmental developments for the managers and evaluate operational alternatives with respect to the changing business conditions. Therefore, the following hypothesis is suggested:

H2: Sensing capability positively influences DDDM.

DDDM, Operational Adjustment Agility and OPP

DDDM is the process of systematically using available data to solve problems, assess options, choose the right course of action, and track implementation (Goraya et al., 2025). In manufacturing companies, evidence-based decisions enable managers to pinpoint production bottlenecks, predict demand changes, plan resources and adjust operational schedules more efficiently. DDDM can help to make operational decisions on timely and consistent, as it eliminates relying on intuition alone. Supply chain analytics research shows that visibility and flexibility work hand-in-hand with analytics to assist in operational decision making (Srinivasan & Swink, 2018). Likewise, Schoenherr and Speier-Pero (2015) highlighted the benefits of data science and predictive analytics for better supply chain decision making. The abilities are especially important when business information needs to be converted into prompt changes. Moreover, the assimilation of analytics and organizational resources are responsible for the performance of the supply chain and organization (Gunasekaran et al., 2017). Akter et al. (2016) also showed how the capability of big data analytics can be useful and how it can be aligned with business strategy. The arguments indicate that DDDM can help in making the operations flexible and agile by allowing managers to adjust operations quickly to meet new needs. It can also enhance OPP by optimizing resource utilization, processing orders faster, minimizing delivery delays, and providing responsiveness (Wamba et al., 2017). Hence the following hypotheses are proposed.

H3: DDDM positively influences operational adjustment agility.
H4: DDDM positively influences OPP.

Operational Adjustment Agility and OPP

Operational adjustment agility is the capacity of an organization to adjust production or service capacity (Lu & Ramamurthy, 2011), to reorganize production processes, and to react rapidly to unexpected changes in supply and demand. This is crucial in manufacturing, as fixed production structures can lead to postponed order fulfillment, reduced operational efficiency, and diminished responsiveness to customer needs. Organizational agility is the ability of firms to adapt their resources and routines to changing business situations from dynamic capabilities perspective. Swafford et al. (2005) laid the foundation of the significance of process flexibility in the creation of supply chain agility, especially in manufacturing, procurement and distribution processes. Similarly, Lee and Xing Qi (2021) explored the link between lean and agile practices and the OPP of a supply chain in manufacturing. The study conducted by Abdelilah et al. (2021) also confirms the need for agility and other complementary operational practices to boost performance. Therefore, performance is one of the integral parts of any organization (Hashmi & Abdullah, 2026) which can be promoted through agility. More recently, Rahman et al. (2026) highlighted the contribution of agility and integration to performance amid supply chain disruptions. Together, these arguments indicate that agile manufacturing firms are more likely to be able to adjust capacity, speed up delivery, meet special customer needs, and keep the operation running. Thus, agility in operational adjustment will be expected to improve OPP.

H5: Operational adjustment agility positively influences OPP.

Mediating role of DDDM

The mediating role of DDDM can be understood by the difference between having organizational capabilities and making them operational responses. Analytics capability is the technological and analytical tools necessary to create insights, but insights need to guide managerial decisions for operational changes. Mikalef et al. (2020) highlighted that big data analytics capability helps organizations to achieve their performance by building dynamic and operational capabilities. Likewise, Dubey et al. (2023) found that big data analytics capability is positively associated with the agility of supply chain, showing the need to transform big data analytics resources into agility. Sensing also provides information on evolving customer preferences, market opportunities, and new threats. But environmental signals only help to make the operation agile when managers interpret them, evaluate the alternatives and choose the right response. Organizations always need to have the sensing and responding capacity alignment. Taasiringan (1997) discussed how organizational resources and capabilities enable adaptive responses. Therefore, DDDM is expected to convey the impact of analytics capability and sensing capability to operational adjustment agility by turning analytical insights and environmental intelligence into evidence-based and timely operational decisions. Hence, the following hypotheses are proposed.

H6: DDDM mediates the relationship between analytics capability and operational adjustment agility.
H7: DDDM mediates the relationship between sensing capability and operational adjustment agility.

Sequential Mediate

The proposed sequential mediation is based on the assumption that the organizational capabilities influence the OPP in two interrelated ways: evidence-based decision-making and operational adjustment. While analytics capability can produce and process insights related to operations, sensing capability can help managers to detect shifts in customer expectations, market conditions, and new threats. These inputs can enhance DDDM and thus contribute to the selection of appropriate operational responses. However, choosing the right answer is not enough to enhance performance; managers need to make changes to the production, capacity, sourcing and delivery processes. The research findings on analytics capability suggest that operational capabilities can be used to explain the competitive performance benefits of analytics resources (Mikalef et al., 2020). Likewise, Gunasekaran et al. (2017) emphasized the necessity for analytics assimilation for supply chain and organization performance. The importance of adaptive capabilities is also evident in research linking operational agility with performance improvements (Abdelilah et al., 2021). Additionally, Raj et al. (2025) found that integration, flexibility, and resilience are mechanisms that link analytics capability with OPP. Therefore, it is expected that DDDM and operational adjustment agility will be a sequential pathway between which the contribution of analytics and sensing capabilities to OPP will take place.

H8: DDDM and operational adjustment agility sequentially mediate the relationship between analytics capability and OPP.
H9: DDDM and operational adjustment agility sequentially mediate the relationship between sensing capability and OPP.

Moderating role of Environmental Complexity

Environmental complexity is the variety of customers, competition, products, and operating conditions that organizations need to take into account when deciding. Manufacturing companies are required to process more information under complex conditions, as managers need to weigh the conflicting requirements and react to the interdependent operational issues. According to information-processing theory, the effectiveness of an organization is determined by the congruence between the information-processing needs of the organization and its ability to meet them (Tushman & Nadler, 1978). Galbraith (1974) also noted that organizational information-processing arrangements are important in the management of uncertainty. As seen in practice in manufacturing plants, supply chain complexity can have a significant effect on OPP, thus making organizational responses to complex operating structures important. Flynn and Flynn (1999) also studied other information-processing strategies for adapting to the complexity of the manufacturing environment. Furthermore, literature identified that operational practices can have different performance consequences in different environments. Based on this discussion, this research suggests that DDDM is especially useful when the environment is complex, as managers need to interpret the data and make quick operational decisions to meet a variety of demands and competitive pressures. Therefore, it is predicted that the positive relationship between DDDM and operational adjustment agility will be enhanced by environmental complexity.

H10: Environmental complexity positively moderates the relationship between DDDM and operational adjustment agility, such that the positive relationship is stronger when environmental complexity is high.

METHODOLOGY

The study used an explanatory research design with a quantitative and cross-sectional approach to explore the relationship between analytics capability, sensing capability, DDDM, operational adjustment agility, environmental complexity, and OPP in manufacturing organizations. Quantitative data was collected from employees of manufacturing organizations by using a structured questionnaire. The cross-sectional design was suitable for the investigation of the proposed relationships at a specific time, and the explanatory approach allowed for the testing of direct, mediating, sequential mediating, and moderating effects in the proposed framework.

The target population of the study was manufacturing organisations. The unit of analysis was the manufacturing organization, and the employees who participated in the production, operations management, supply chain management, planning, analytics, or related decision-making within the manufacturing organization were targeted. These respondents were deemed appropriate because their roles and duties might offer insights into the organizational analytical practices, environmental awareness, operational changes, and performance results. The non-probability convenience sampling method was used to access the eligible respondents who were accessible and willing to participate. The technique was suitable for the purpose of securing responses from manufacturing professionals from a variety of organizational settings where a complete sampling frame of all manufacturing organizations and their employees was not available.

Each of the six constructs was assessed with a multi-item scale that had been used in previous research, with items adapted to the manufacturing context when applicable. The analytics capability was evaluated with five items adapted from Srinivasan and Swink (2018) that capture advanced analytical techniques, information integration, data visualization, root-cause analysis, and dashboard accessibility. Sensing capability was measured by four items adapted from Pavlou and El Sawy (2011) which included environmental scanning, monitoring changes related to customers, matching product development with customer needs, and implementing product improvement ideas. DDDM was assessed with eight items adapted from the items used by Szukits and Móricz (2023) which included data dependence in situation assessment, problem identification, alternative assessment, action selection, implementation planning, communication, and monitoring. Operational adjustment agility was assessed by three items from Lin et al. (2020): dealing with supply disruptions, dealing with changes in demand, and responding to special customer requests. Environmental complexity included three items from Lin et al. (2020) which represent diversity in customer buying habits, competition, and product lines. Finally, OPP was assessed through seven items adapted from Wong and Ngai (2023) which include delivery-cycle time, responsiveness, product and market introduction, order confirmation, complaint handling, and customer relationships. The Likert-type response format was used for all items Table 1.

Table 1: Questionnaire Items

Variable	Items	Sources
Analytics Capability	Please tell us the degree to which data management and analysis techniques are used to improve strategies and activities: 1. "We use advanced analytical techniques (e.g., simulation, optimization, regression) to improve decision making. 2. We easily combine and integrate information from many data sources for use in our decision making. 3. We routinely use data visualization techniques (e.g., dashboards) to assist users or decision-maker in understanding complex information. 4. Our dashboards give us the ability to decompose information to help root cause analysis and continuous improvement. 5. We deploy dashboard applications/information to our managers' communication devices (e.g., smart phones, computers)."	(Srinivasan & Swink, 2018)
Sensing Capability	1. "We frequently scan the environment to identify new business opportunities. 2. We periodically review the likely effect of changes in our business environment on customers. 3. We often review our product development efforts to ensure they are in line with what the customers want. 4. We devote a lot of time implementing ideas for new products and improving our existing products."	(Pavlou & El Sawy, 2011)

Table 1(continued): Questionnaire Items

Variable	Items	Sources
DDDM	1. "In our organization, top management relies on available data in assessing the current situation. 2. In our organization, top management relies on available data when identifying problems. 3. In our organization, top management relies on available data exploring alternative courses of action. 4. In our organization, top management relies on available data in the assessment of alternative courses of action. 5. In our organization, top management relies on available data when choosing between alternative courses of action. 6. In our organization, top management relies on available data when planning the implementation of decisions. 7. In our organization, top management relies on available data in communicating decisions. 8. In our organization, top management relies on available data to monitor the implementation of decisions."	(Szukits & Móricz, 2023)
Operational Adjustment Agility	1. "Whenever a disruption in supply from our suppliers occurs, we can quickly make necessary alternative arrangements and internal adjustments. 2. We can quickly scale up or down our production/service levels to support fluctuations in demand from the market. 3. We fulfill demands for rapid-response and special requests of our customers whenever such demands arise."	(Lin et al., 2020)
Environmental Complexity	1. "In our industry, there is considerable diversity in customer buying habits. 2. In our industry, there is considerable diversity in the nature of competition. 3. In our industry, there is considerable diversity in product lines."	(Lin et al., 2020)
Operational Performance	1. "We prefer decreasing product/service delivery cycle time. 2. We prefer rapidly responding to market demand changes. 3. We prefer rapidly bringing new products/services to the market. 4. We prefer rapidly entering new markets. 5. We prefer rapidly confirming customer orders. 6. We prefer rapidly handling customer complaints. 7. Establishing a strong and continuous bond with customers."	(Wong & Ngai, 2023)

Data were gathered using a structured questionnaire with measurement items that have been previously developed. Responses were screened for usability prior to analysis and only valid responses were kept. The questionnaire was designed in a way that the six constructs in the conceptual framework were measured consistently and then the measurement and structural models were assessed. A total of 174 valid responses were used for statistical analysis. Sample adequacy was judged based on the complexity of the proposed structural model and the most demanding regression equation, namely DDDM, environmental complexity, and their interaction, as predictors of operational adjustment agility. The final sample of 174 valid responses is reasonable basis for estimating the proposed relationships. However, the adequacy of individual indirect and interaction effects also relies on the size of the effects and the quality of the measures.

DATA ANALYSIS

Factor loadings, reliability, and convergent validity for each scale is reported in Table 2. The questionnaire items are related to the corresponding latent constructs as shown in Figure 2, which is the PLS Outer Model Assessment. The factor loadings vary from 0.625 to 0.867, with some items better representing the factor than others. While a few loadings are below the desired value of 0.70, the overall reliability and convergent validity scores support the continued use of the measurement scales for evaluation, because the factor above 0.5 is also accepted which is reported in previous studies (Anwer et al., 2021; Hair et al., 2010).

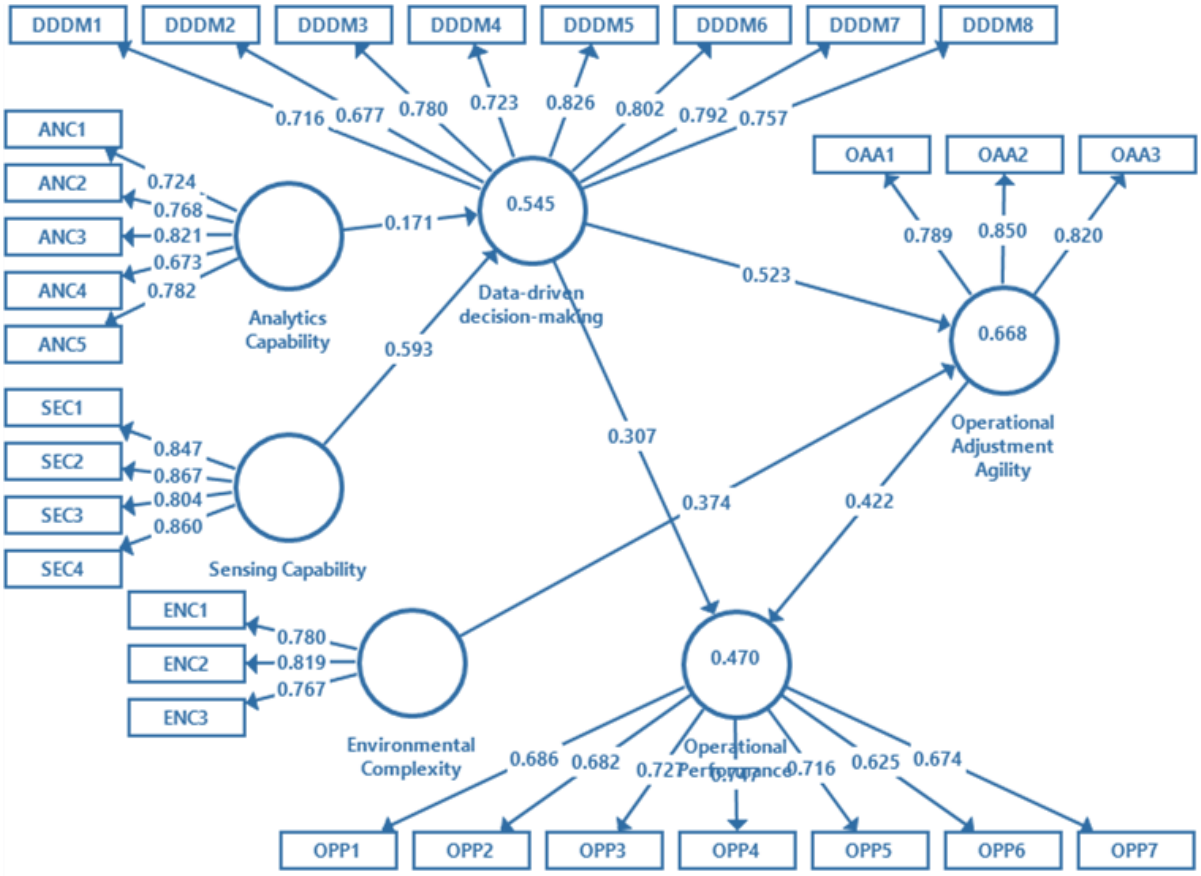


Figure 2: PLS Outer Model Assessment

Table 2: Table: Measurement Model Assessment – Factor Loadings, Reliability, and Convergent Validity

Constructs	Items	Factor Loadings	Cronbach's Alpha	rho_A	Composite Reliability	AVE
Analytics Capability	ANC1	0.724	0.812	0.825	0.869	0.571
	ANC2	0.768				
	ANC3	0.821				
	ANC4	0.673				
	ANC5	0.782				
DDDM	DDDM1	0.716	0.895	0.897	0.916	0.578
	DDDM2	0.677				
	DDDM3	0.780				
	DDDM4	0.723				
	DDDM5	0.826				
	DDDM6	0.802				
	DDDM7	0.792				
	DDDM8	0.757				
Environmental Complexity	ENC1	0.780	0.706	0.709	0.832	0.622
	ENC2	0.819				
	ENC3	0.767				
Operational Adjustment Agility	OAA1	0.789	0.757	0.759	0.861	0.673
	OAA2	0.850				
	OAA3	0.820				
OPP	OPP1	0.686	0.823	0.832	0.867	0.503
	OPP2	0.682				
	OPP3	0.727				
	OPP4	0.747				
	OPP5	0.716				
	OPP6	0.625				
	OPP7	0.674				
Sensing Capability	SEC1	0.847	0.866	0.867	0.909	0.714
	SEC2	0.867				
	SEC3	0.804				
	SEC4	0.860				

The reliability of the analytics capability is satisfactory with Cronbach's alpha of 0.812, rho_A of 0.825, composite reliability of 0.869, and AVE of 0.571. The DDDM also shows good reliability, with values of 0.895, 0.897 and 0.916, respectively, and an AVE of 0.578. Environmental complexity has a composite reliability of 0.832 and an AVE of 0.622, and operational adjustment agility has a composite reliability of 0.861 and an AVE of 0.673. The composite reliability of OPP is 0.867 and the AVE is 0.503, which is slightly above the minimum value of 0.50 for convergent validity. Sensing capability has good measurement properties: composite reliability is 0.909 and AVE is 0.714. Furthermore, Table 3 displays the HTMT ratios that were calculated to determine if the six constructs are empirically distinct

from each other. The reported ratios are all below the commonly used threshold of 0.85, which is indicative of discriminant validity.

Table 3: Discriminant Validity (HTMT)

	ANC	DDDM	ENC	OPA	OPP	SEC
Analytics Capability						
DDDM	0.751					
Environmental Complexity	0.74	0.821				
Operational Adjustment Agility	0.743	0.693	0.584			
OPP	0.667	0.702	0.656	0.811		
Sensing Capability	0.654	0.831	0.783	0.752	0.618	

The VIF results for the predictors in the model are shown in Figure 3. The reported values are around 1.73, 2.422, and 2.887, and all of these values are below the threshold of 3.3 used in the study. Under this criterion, these findings show that there is no problematic multicollinearity among the reported predictors in the model. The findings indicate that the estimated structural relationships are not significantly affected by too much predictor overlap.

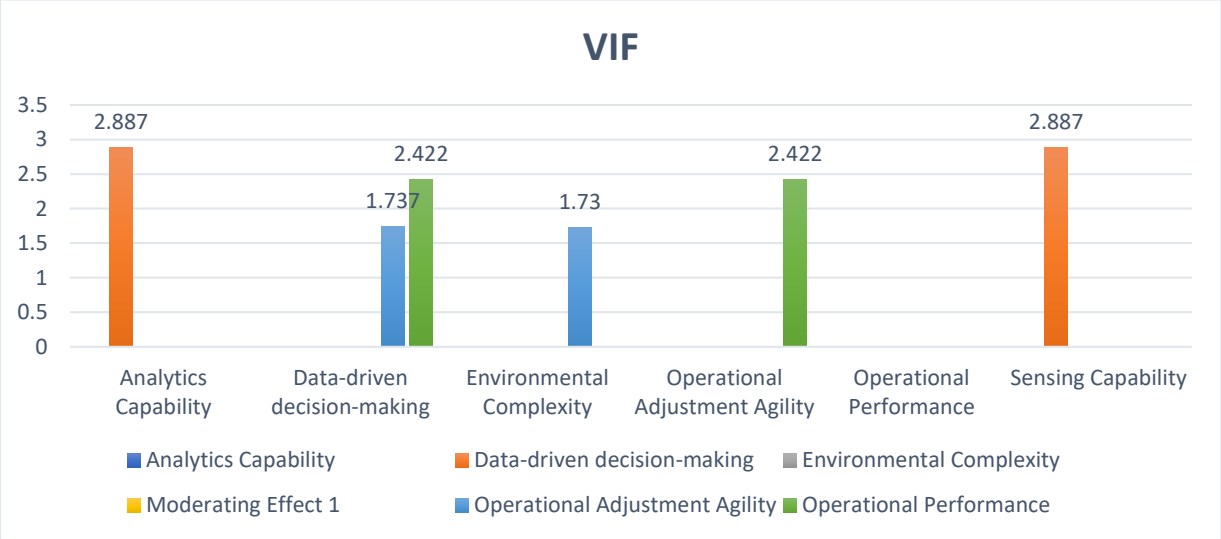


Figure 3: Variation Inflation Factor

The estimated path coefficients, standard deviations, t-statistics and p-values for direct and moderating relationships are reported in Table 4. The overall structural relationships are shown in PLS Inner Model Assessment (Figure 4). The results support several proposed relationships, but not all of the hypotheses are statistically significant. According to the results, the correlation between analytics capability and DDDM is positive but not statistically significant (beta=0.171; t=1.770; p=0.077). Therefore, H1 is rejected at the 5% level of significance. However, there is a positive and statistically significant correlation between sensing capability and DDDM (beta=0.593; t=6.807; p<0.001), which supports H2. The capacity to sense changes in the market and new opportunities is more closely linked to DDDM than the actual analytics measured in this sample. Supporting H3, DDDM positively influences operational adjustment agility, with a (beta=0.530; t=7.565; p<0.001). It also positively affects OPP (beta=0.307; t=2.964; p=0.003), supporting H4. In addition, operational adjustment agility is positively and

significantly related to OPP (beta=0.422; t=4.439; p<0.001), which is in favor of H5. The results show that evidence-based decision making is linked to improved OPP and higher capacity to adapt operations, and agility positively affects OPP. The moderating effect of environmental complexity is insignificant (beta=0.065; t=1.350; p=0.178). Hence, H10 is not supported. The findings do not show that environmental complexity enhances the linkage between DDDM and operational adjustment agility.

Table 4: Direct and Moderation Effect

	β	Mean	SD	T Statistics	P Values
Analytics Capability -> DDDM	0.171	0.186	0.097	1.77	0.077
DDDM -> Operational Adjustment Agility	0.53	0.531	0.07	7.565	0
DDDM -> OPP	0.307	0.315	0.104	2.964	0.003
Moderating Effect 1 -> Operational Adjustment Agility	0.065	0.065	0.048	1.35	0.178
Operational Adjustment Agility -> OPP	0.422	0.42	0.095	4.439	0
Sensing Capability -> DDDM	0.593	0.585	0.087	6.807	0

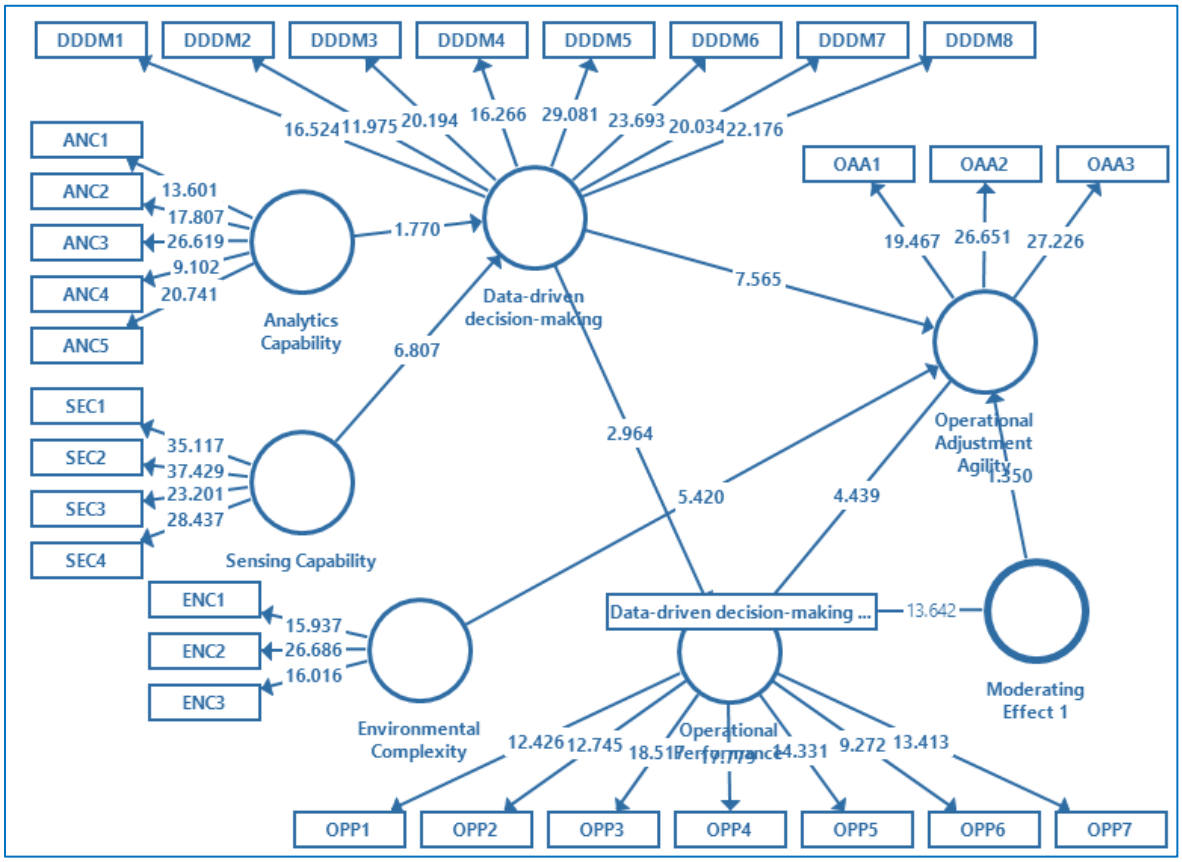


Figure 4: PLS Inner Model Assessment

The indirect relationships between DDDM and operational adjustment agility are presented in Table 5. These results support the structural relationships shown in Figure 4 by examining the statistical significance of the proposed structural relationships between organizational

capabilities, agility and performance. The indirect effect of analytics capability on operational adjustment agility via DDDM is positive but not statistically significant (beta=0.091; t=1.683; p=0.093). Consequently, H6 is not accepted at the 5% level of significance. The indirect effect of sensing capability on operational adjustment agility via DDDM is positive and significant (beta=0.314; t=5.062; p<0.001), which supports H7. The findings suggest that DDDM is an important intervening variable between sensing capability and operational adjustment agility, while the indirect path between analytics capability and operational adjustment agility is not statistically supported.

Table 5: Indirect Effect

	β	Mean	SD	T Statistics	P Values
Analytics Capability -> DDDM -> Operational Adjustment Agility -> OPP	0.038	0.041	0.024	1.601	0.11
Sensing Capability -> DDDM -> Operational Adjustment Agility -> OPP	0.133	0.128	0.033	3.959	0
Analytics Capability -> DDDM -> Operational Adjustment Agility	0.091	0.099	0.054	1.683	0.093
Sensing Capability -> DDDM -> Operational Adjustment Agility	0.314	0.31	0.062	5.062	0

The sequential mediation results are also reported in Table 5. The indirect effect of analytics capability on OPP via DDDM and operational adjustment agility is positive, but not significant) (beta=0.038; t=1.601; p=0.110). Thus, H8 is not supported. The indirect effect of sensing capability on OPP through DDDM and operational adjustment agility is positive and significant (beta=0.133; t=3.959; p<0.001), which is consistent with H9. This finding suggests that sensing capability is linked with better OPP via a sequential process of evidence-based decision-making and operational adjustment agility.

DISCUSSION

This study examined how analytics capability and sensing capability influence OPP through DDDM and operational adjustment agility, while assessing environmental complexity as a moderator. The moderating effect of environmental complexity was examined on the relationship between analytics capability and sensing capability and how these two factors influence OPP via DDDM and operational adjustment agility. The results offer differentiated insights into the capability-to-performance pathway, as not all organizational capabilities act in the same manner to improve OPP.

First, there was no support for H1 at the 5% significance level as analytics capability had a positive but insignificant effect on DDDM (beta=0.171, p=0.077). This is contrary to a study that showed that analytical resources can enhance organizational decision processes and performance when used in conjunction with proper organizational arrangements (Srinivasan & Swink, 2018). Similarly, Szukits and Móricz (2023) demonstrated that analytical culture and perceived data quality are important factors in organizational practices related to analytics, and that more centralization does not necessarily lead to DDDM. The current finding indicates that it is not enough to have data integration tools and analytical tools to ensure their consistent use in managerial decisions. The outcome also suggests that the ability to do business analytics

does not necessarily lead to evidence-based decisions in all organizational contexts (Cao & Duan, 2024).

Second, DDDM was significantly related to the sensing capability (beta=0.593, p<0.001) which supported H2. This result highlights the importance of detecting customer preferences, competitive developments, and environmental changes before selecting operational responses. Wong and Ngai (2023) found that sensing capability, analytics capability and OPP were positively related. The current study takes a further step in this direction by recognizing the significance of DDDM as an important bridge between sensing capability and operational adjustment agility. The finding also aligns with the dynamic capabilities theory that posits that organizations need to recognize emerging opportunities and threats to then mobilize resources to respond (Pavlou & El Sawy, 2011). Therefore, it is of great importance to be aware of the changing operating conditions for evidence-based operational decisions.

Third, DDDM had a positive effect on operational adjustment agility (beta=0.530, p<0.001) and OPP (beta=0.307, p=0.003), which supported H3 and H4. The relationships suggest that systematic information and alternative evaluation is linked to more responsive operations and better performance results. Mikalef et al. (2020) showed that dynamic and operational capabilities are important to understand in explaining the link between big data analytics capability and competitive performance. Likewise, Gunasekaran et al. (2017) correlated the big data and predictive analytics assimilation with supply chain and organizational performance. The current results confirm this evidence and highlight managerial decision making as an operational process that can create benefits from information.

Fourth, operational adjustment agility significantly contributed to OPP (beta=0.422, p<0.001), which was in favor of H5. This outcome is consistent with Swafford et al. (2005) who found that process flexibility is a key element in the agility of a supply chain. Similar findings have been reported by manufacturing executives in more recent research, where there are some contextual conditions that can affect the relationship between supply chain agility and OPP (Srivastava & Dixit, 2023). The results indicate that decisions are more valuable in terms of operations when the organization can alter production, capacity, and responses to customer needs.

Fifth, the above mechanisms are further clarified in the mediation results. H7 was supported at the 5% level as DDDM significantly mediated the relationship between sensing capability and operational adjustment agility (beta=0.314, p<0.001), while the relationship between analytics capability and operational adjustment agility was not significant at the 5% level (beta=0.091, p=0.093), supporting H6 was not supported at the 5% level. Likewise, the sequential indirect effect of sensing capability on OPP via decision-making and agility was significant (beta=0.133, p<0.001), which provided support to H9. The equivalent pathway for analytics capability was negligible (beta=0.038, p=0.110), which indicated that H8 was not supported. The results support the hypothesis that analytics resources bring value to the organization through complementary capabilities, not just by directly enhancing performance (Wamba et al., 2017). Similarly, Raj et al. (2025) found that integration, flexibility, and resilience are key mechanisms linking analytics capability and OPP. The current evidence is especially significant for the supported sequential pathway of sensing-led decision-making.

Finally, the interaction between DDDM and environmental complexity was not significant (beta=0.065, p=0.178), thus did not support H10. This result is contrary to the result of Lin et al. (2020) that environmental complexity reinforced the relationship between e-commerce capability and operational adjustment agility. Literature also identified that the performance impact of specific operational practices can vary depending on the environmental complexity. But Akın Ateş et al. (2021) highlighted the need for understanding the complexity of the supply chain in terms of firm performance. The findings indicate that complexity can drive adaptation on its own, rather than enhancing the effects of DDDM.

CONCLUSION

The study examined the relationship between OPP, DDDM and operational adjustment agility, with the environmental complexity as a boundary condition, and how these are related to analytics capability and sensing capability. The results indicate that the sensing capability has a significant impact on DDDM, which in turn leads to better agility in operational adjustment and better OPP. Operational adjustment agility also has a positive impact on OPP, thus establishing the significance of making managerial decisions and responding to them in an operational activity. Moreover, the relationship between sensing capability and OPP is mediated by DDDM and operational adjustment agility, respectively. However, the moderating effect of environmental complexity on decision-making–agility relationship is not significant. These findings update the knowledge about the relationship between information-related capabilities and operational outcomes. In particular, they propose that the ability to detect environmental changes and to convert that information into actionable decisions can be more impactful than having analytical tools. The study offers an integrated explanation of decision-making, operational adaptation and performance and emphasises the importance of differentiating direct effects from indirect and contingent effects. However, the results are limited in their interpretation to statistical associations and not necessarily causal effects, due to the cross-sectional design and sampling procedure.

IMPLICATIONS AND LIMITATIONS

Theoretically, this study separates out analytical resources from sensing capability and defines DDDM and operational adjustment agility as interconnected mechanisms. The important sequence from sensing capability to OPP provides a new insight into the value of environmental intelligence in operations. The nonsignificant analytics-related pathways also indicate that complementary managerial routines may be necessary to make the benefits of the analytics infrastructure visible. In practice, manufacturing managers need to improve environmental scanning, incorporate market and operational data into decision making processes, and define the steps to take between decisions and changes in production, capacity and delivery. Employee analytical skills, data-quality controls, and managerial accountability are essential to investments in analytical tools. Managers should also evaluate operational complexity in the development of adaptation practices and not presume that complexity leads to more effective evidence-based decision making.

Moreover, this study limited to few of the perspectives which could be considered by other studies. First, the OPP scale contains preference-oriented statements relating to speed of delivery, responsiveness to the market and customer relationships. These items can reflect priorities in performance and not actually reflect the outcomes of the performance. Future

studies could be conducted by integrating perceptual measures with actual delivery times, order-fulfilment rates and production-adjustment records. Second, the capability to use analytics was assessed by looking at analytical techniques, but not whether managers use the results of analytics in consequential decisions. Future studies might focus on decision logs or on a process of analytics-to-action that is traceable. Third, environmental complexity was assessed by variety of customers, competitors and product lines. The insignificant interaction might be due to this operationalization not being sufficiently capturing technological disruption, volatility or supply uncertainty.

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