Artificial Intelligence and Information Management for Data-Driven Decision-Making: A Multi-Group Analysis Across Managers and Non-Managers

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ABSTRACT

Artificial intelligence (AI) is increasingly embedded in manufacturing operations; however, its organizational value may vary according to employees' managerial responsibilities. This study applies Multi-Group Analysis (PLS-MGA) to compare managers and non-managers in terms of AI capability, information management capability (IMC), data-driven decision-making (DDDM), and decision-making effectiveness. The findings confirm that AI capability strengthens IMC, which subsequently facilitates DDDM and improves decision-making effectiveness. IMC also serves as the mechanism through which AI capability contributes to data-driven organizational decisions. The multi-group findings indicate that managers obtain significantly greater benefits from AI capability in developing IMC and from DDDM in improving decision-making effectiveness than non-managers. In contrast, IMC supports DDDM similarly across both groups. These findings identify managerial position as a critical organizational boundary condition in AI-enabled manufacturing environments and suggest that organizations should adopt role-specific AI implementation, information management, and decision-support strategies to maximize organizational effectiveness and digital transformation outcomes.

Keywords: Artificial Intelligence Capability, Information Management Capability, Data-Driven Decision-Making, Decision-Making Effectiveness, Manufacturing Industry, PLS-MGA, Managers, Non-Managers.

INTRODUCTION

Artificial Intelligence (AI) is disrupting the manufacturing sector by changing the way information is gathered, analyzed and applied to help inform organizational decision making (Fonseca i Casas & Pi i Palomes, 2026; López-Solís et al., 2025). By embedding AI systems and technologies into digital manufacturing systems, enterprise resource planning (ERP), Industrial Internet of Things (IIoT), and advanced analytics, companies can efficiently handle enormous operational data in real time, making the system more responsive and efficient (Dachawar et al., 2025). With the increasing data density in manufacturing, organizations are moving from intuition-based decision making to data-driven decision making (DDDM) in which decisions for organization's strategy and operations are based on objective evidence derived from organizational data (Ojha et al., 2024). Therefore, the ability to implement AI is becoming a strategic organizational resource that could help manufacturing companies to improve their information processing, operational coordination, and even organizational competitiveness.

Navigating the volume of organizational data created by AI technologies is enormous (Ojeda et al., 2025), but data is only valuable if it is used effectively in decision-making. Organizations in manufacturing need to have a robust information management capability (IMC) to convert raw data to reliable, integrated, and actionable information for their organizations to achieve goals (Cui, 2025). IMC refers to the processes by which an organization gathers, assimilates, structures, shares and uses information within its functional departments (Mithas et al., 2011). By having timely and accurate information to the right people, manufacturing companies can better plan production, manage quality, control inventory, foresee maintenance needs, coordinate supply chain, and forecast demand. This means that organizations that are more capable of information management can be more effective of turning the information through AI into useful management insights that aid in data-driven decision making and enhance decision-making efficiency.

Although there is an increasing amount of research on the capabilities of AI and its direct connections with information management, organizational performance, digital transformation or decision quality (Ayoub & Sopuru, 2026; Stoykova & Shakev, 2023; Wamba-Taguimdje et al., 2020), most of these studies have focused on AI capabilities and their direct links with the aforementioned constructs. Less research has focused on understanding the organizational capabilities of various groups of employees within manufacturing organizations. Generally, manufacturing firms have employees with various organizational roles and responsibilities, and varying levels of authority and information needs (Li et al., 2019). This means that organizational gains from AI skills might not be equal for all workers. It is crucial to grasp these disparities as organizational value is generated by proper use of AI-infused information for strategic and operational decisions.

There is one significant difference between managers and non-managers that is not very well explored. The usual tasks for managers involve strategic things like organizing resources, planning for the organization, coordinating across functions, implementing policies, and evaluating performance (Ouanhlee, 2024). Their decisions tend to be riskier with more wider reaching impacts and longer-term time horizons, which means they make more effective use of good information and AI-driven insights. On the other hand, non-managers are mostly tasked with running operational activities, keeping an eye on production processes, ensuring product quality, managing inventories, operating manufacturing systems, reacting to regular operational issues. While both groups are increasingly using organizational information, there is a significant difference in the way they obtain, understand and use AI-generated information to inform decision making.

The organizational differences indicate that managerial position could be an important boundary condition affecting the effectiveness of AI-enabled organizational capability. Managers in general have more decision-making authority (Parker & Price, 1994), wider organizational visibility and more responsibility for integrating information across several functional areas of the organization. As a result, they can get more value from use of AI capability and information management systems (Stoykova & Shakev, 2023) than non-managers whose use of organizational information is typically restricted to operational decision contexts. Empirical comparisons of these groups, however, are still limited, especially in manufacturing companies where digital technologies have been adopted throughout the organization's processes. Organizations might miss crucial differences if they are designing digital transformation strategies, preparing for the implementation of AI systems, or planning employee training programs, without understanding whether AI-enabled organizational capabilities work the same for managers and non-managers.

In the current study, a research model is proposed and tested to explore the relationships between AI capability, IMC, data-driven decision-making (DDDM) and decision-making effectiveness in manufacturing organizations to fill this gap in research. Moreover, the study is an extension of previous studies because it explores the structural relationships between managers and non-managers as a multi-group comparison, using Multi-Group Analysis (PLS-MGA) to determine if the structural relationships are significantly different between managers and non-managers. This study compares the relationships between AI capability and outcomes of both managerial and non-managerial roles to show the extent to which managerial tasks affect these relationships.

This study contributes to the literature in a number of important ways. First, it contributes to the literature of AI-powered organizational capabilities, by placing the capability of AI capability, IMC, DDDM, and decision-making effectiveness in a capability-based framework. Second, it supports manufacturing research by introducing managerial position as a meaningful domain of the organizational boundary condition setting, and testing the extent to which AI-supported decision processes vary between managerial vs non-managerial individuals. Third, the results offer practical advice for manufacturing firms, showing that it is important to consider adopting different design approaches for managerial and non-managerial staff when implementing AI solutions, information management programs, and decision-support systems to enhance organizational decisions and operations. These contributions, taken together, provide a more complete picture of the organizational value of AI generated information, at varied levels of manufacturing organizations.

LITERATURE REVIEW

Manufacturing Companies and Information Management for Data-Driven Decision

Manufacturing companies are working in evolving, technology-driven business ecosystems where on-time, accurate and integrated information is critical to ensuring operational efficiency and competitive edge (Rana et al., 2021). Technologies such as AI, IIoT, cloud computing, and ERP have revolutionized (Nyathani et al., 2024; Stadnicka et al., 2022) how manufacturing companies are capturing, processing, and analyzing information from production, logistics, procurement, and quality management. Manufacturing companies are increasingly using data-driven methods to gain visibility into their operations, optimize resource usage, and aid decision-making for strategic planning (Colombari et al., 2023). Information management enables the efficient, coordinated collection of data, their integration, storage and sharing with relevant decision makers, which improves information quality and timeliness, thereby improving business decision making. Organizations can identify production bottlenecks, accurately predict demand, optimize stock levels, enhance product quality and improve supply chain coordination with high-quality information (Ramanujapuram & Akkihal, 2014). Thus, information management has become a strategic organizational capability, which makes it easier to inform decision-making and makes it possible to be responsive to needs. In the manufacturing context where uncertainty and rapid technological innovation are present, companies that are able to manage and make use of information have a better chance to transform operational information into insightful managerial information. Hence, information management is a key pillar of data-driven decision making, which helps manufacturing companies to enhance decision quality, operational performance and long-term organizational competitiveness.

Manufacturing Companies Operations Across Managers and Non-Managers

The key to manufacturing organizations operating efficiently, delivering quality products, and maintaining sustainable competitiveness is the ability to make decisions in a coordinated manner at various organizational levels (Trentin, 2021). Managers and non-managers are part of the same organizational goal (Petrou et al., 2017), but they have a wide range of different responsibilities and decision making processes. Organizational information is mostly used to create strategic plans, allocate resources, track organizational performance and coordinate production (Patra et al., 2026), supply chain and quality improvement efforts for managers. Non-managers use operational information to carry out production activities, to keep track of equipment performance, to control product quality, to manage inventories and to deal with daily production issues. Regardless of these differences, both are increasingly relying on AI technologies and information management systems to assist them in making timely, accurate and evidence-based decisions. Therefore, the impact of AI-driven information management could differ based on managerial roles and decision-making power.

On the basis of these organizational differences, the present study suggests that managerial position plays an important boundary condition that affects the impact of AI capability on information management, DDDM, and decision-making effectiveness. Based on the conceptual research framework illustrated in Figure 1, the proposed research framework is designed as the antecedent of IMC was AI capability, which then would enhance DDDM and ultimately improve decision-making effectiveness. Moreover, the framework also includes a Multi-Group Analysis (PLS-MGA) to compare the structural relationships of the managers and non-managers to determine if there is a difference in the strength of the proposed structural relations in manufacturing companies.

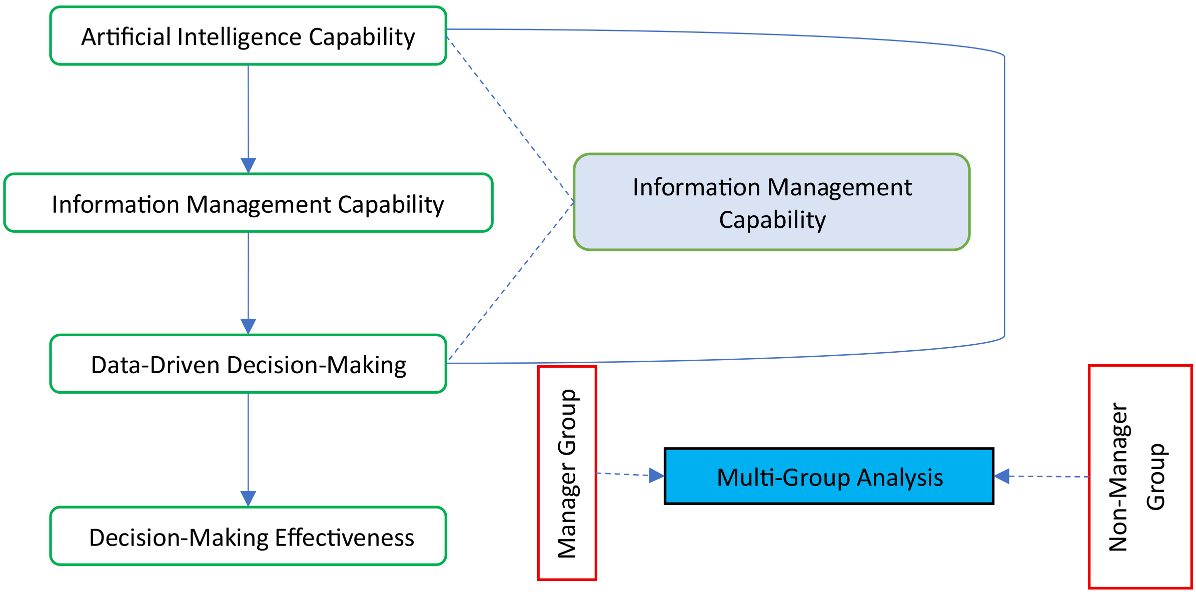

Figure 1: Framework of the Study

Artificial Intelligence Capability and Information Management Capability

The ability of an organization to leverage AI has become an important asset, necessary to the manufacturing industry (Selvarajan, 2021), to be able to acquire, process, integrate and disseminate information across functional departments. Recent advances in AI-driven technologies support the real-time collection of data, predictive data analysis, and intelligent information processing (Kajornkasirat et al., 2025), enhancing the quality, availability, and timeliness of organizational information. These competences enhance the IMC by allowing for smooth coordination between production, procurement, inventory, maintenance, and quality management (Forza, 1995). But how managers and non-managers make use of AI-generated information could vary due to their differing organizational duties. While managers tend to rely on AI-driven insights for strategic planning, resource management, and coordination within the organization, non-managers are more likely to use AI-supported information for executing operations and tracking processes. However, while different, AI capability is the technology backbone to effective management of information across the organization. Hence, the manufacturing companies with increased AI capability will have greater chances of building more superior IMC.

H1: Higher levels of AI capability are associated with stronger IMC within manufacturing organizations.

Information Management Capability and Data-Driven Decision-Making

IMC helps manufacturing companies turn operational data (Huang et al., 2014) that is spread out into trustworthy, easy-to-access, and usable information that can be used to make informed decisions. Good information management guarantees that data created and collected (Shaffer et al., 2018) through production systems, quality control, supply chain and enterprise information systems are integrated, accurate and easily accessible to the organization. This information decreases uncertainty and helps employees to make decisions that are in line with the goals of the organization (Bordia et al., 2004). However, the use of organizational information is different for managers and non-managers. While managers use integrated information to make strategic decisions, assess the performance of the organization and coordinate activities across different functions, non-managers will use operational information to manage daily production activities, monitor equipment and solve issues related to the production process. No matter where their role is within the organization, better IMC helps to give employees consistent information, which helps to deliver DDDM throughout manufacturing processes. Therefore, it is assumed that organizations with better information management systems will demonstrate higher level of DDDM practices.

H2: Organizations with stronger IMC demonstrate greater capability to implement DDDM practices.

Data-Driven Decision-Making and Decision-Making Effectiveness

DDDM helps manufacturing companies make better decisions truly based on facts and figures, all based on organizational data (Selvarajan, 2021; Tripathi et al., 2022). Appropriate and timely information helps organizations to maximize production planning, quality performance, inventory control and supply chain coordination. This results in an increasingly consistent, transparent and responsive decision-making process that adapts to changing operational conditions. While there may be some differences between the kind of work managers and non-managers execute within an organization, they are both becoming increasingly reliant on data-driven insights to carry out their jobs. Non-managers use operational information to enhance the efficiency of processes, the quality of products and the productivity on the job (Johansen et al., 2016), while managers use analytical information to help with strategic planning, performance measurement and resource allocation (Poister, 2010). Having data integrated into regular organizational decisions thus improves the effectiveness of the organization at both strategic and operational levels. More and more manufacturing companies are adopting digital technologies, and an increasing reliance on DDDM will lead to better overall effectiveness of organizational decisions.

H3: Organizations that rely more extensively on DDDM achieve superior Decision-Making Effectiveness.

AI Capability is not sufficient to enhance organizational decision-making without the proper management (Neiroukh et al., 2024) and translation of the information produced by AI technologies into actionable knowledge. In manufacturing organizations, IMC is the organizational capability that transforms the AI-augmented data into trustworthy, coherent and accessible information for decision making (Wasesa et al., 2025). AI tech helps acquire, analyze and integrate data related to production, inventory, quality management, and supply chain processes (Khan et al., 2025); IMC ensures that the information is effectively distributed, interpreted and used by managers and non-managers. The managers use high quality information to facilitate strategic planning and resource allocation, with non-managers using the same information to enhance operational process execution and efficiency. Therefore, IMC should pass-on the impact of AI capability to DDDM, which helps manufacturing organizations to make decisions that are more accurate, timely and based on evidence.

H4: The positive relationship between AI capability and DDDM is transmitted through IMC.

Managerial Position as an Organizational Boundary Condition (Manager Vs Non-Manager)

AI capability effectiveness could differ based on the employees' managerial role and decision-making power within manufacturing organizations (Çeri & Erhan, 2025). Different organizational information is used by managers and non-managers due to their different roles in the organizations (van Hoorn, 2025). Managers have a more general need for information generated by AI tools (Cimino et al., 2024), including insights and information integrated from across the organization, for strategic planning, resource allocation, performance assessment, and cross-functional coordination. Non-managers are more likely to use AI-driven data for day-to-day problem-solving and optimizing processes, overseeing operational executions, monitoring processes, and conducting quality assurance. The relationship of ai capability to IMC, IMC to data-driven decision making, and data-driven decision making to decision making effectiveness may not be the same for these two groups. While non-managers might benefit from AI's operational applications, managers will likely see more benefits from the information it provides, given their increased decision-making power and strategic roles. The analysis of these differences gives insight into how the effectiveness of AI assisted decision processes is influenced by an organization's position.

H5: The structural relationships among AI capability, IMC, DDDM, and decision-making effectiveness differ significantly between managers and non-managers.

METHOD

Empirical Setting

Manufacturing companies offer the right context to be used as an empirical study because they have been in a constant state of transformation in the adoption of various AI technologies for production planning. Furthermore, these companies involved in quality management, inventory control, predictive maintenance, supply chain management, and demand forecasting through AI technologies. Digital technologies create massive amounts of information for organizations which needs to be well managed to support strategic and operational decision making. This study also examines whether these relationships vary across managerial positions, as managers will have different organizational responsibilities and decision authority compared to non-managers, using a multi-group analytical approach. Therefore, the research design in this study is a quantitative and cross-sectional research design with a correlation analysis.

Instrument Development

Instrument was developed by considering the scale items from previous studies, as shown in Table 1. Minor changes have been added to make the content clearer and more relevant for manufacturing organizations without altering the meaning of each content item. The five items were adapted from Lee et al. (2025) to measure AI capability, together with ten items from Brinkhues et al. (2015) to measure the IMC which was measured by considering compilation and elaboration of information. Seven items from Mingchu (2008) to measure DDDM, and five items from Al-Al-Hattami (2022) to measure decision-making effectiveness. All constructs were measured with a five-point Likert scale, from 1 ("Strongly Disagree") to 5 ("Strongly Agree").

Table 1: Variable Operationalization

Variable	Measures
Artificial Intelligence Capability (Lee et al., 2025)	1. “We have access to very large, unstructured, or fastmoving data for analysis. 2. We integrate data from multiple internal sources into a data warehouse or mart for easy access. 3. We integrate external data with internal to facilitate a high-value analysis of our business environment. 4. We can share our data across business units and organizational boundaries. 5. We can prepare and cleanse AI data efficiently and assess data for errors.
Information Management Capability Measured based on: Compilation and elaboration of information (Brinkhues et al., 2015)	1. The firm has systems to gather and integrally deal with all information on the company’s own processes. 2. The firm has efficient systems for gathering and dealing with information in the competitive environment. 3. The firm’s employees have rapid, trouble-free access to the information and knowledge they need. 4. The firm has a clear system to distribute information to employees, customers, and suppliers in accordance with detected needs. 5. In my firm, there are mechanisms in place that provide employees with incentive to share information. 6. The firm's processes ensure appropriate levels of information’s reliability, accuracy, timeliness, security, and confidentiality. 7. The mechanisms for providing data and information are updated according to the needs and directions of the business. 8. The information is integrated from all sources to support the organization's processes. 9. The information is integrated from all sources to support organizational decision making. 10. Information on satisfaction and dissatisfaction are used for process improvement.

Table 1(continued): Variable Operationalization

Variable	Measures
Data-Driven Decision-Making (Mingchu, 2008)	1. I use data to measure the effectiveness of outreach to the community. 2. I use data to develop effective communication plans. 3. I use data to understand the larger context of the community, which affects opportunities. 4. I use data to determine what type of community input should be gained. 5. I use data to mobilize community resources for the benefit of student learning. 6. I use data to gauge the effectiveness of collaborative relationships with the community. 3.21 0.96 20. I use data to develop effective approaches for school–family partnership. 7. I use data to generate approaches with school stakeholders that reflect their concern.
Decision-Making Effectiveness (Al-Hattami, 2022)	1. It helps to provide and collect information on the causes and dimensions of the problem. 2. Information provided helps to compare, evaluate, and select the best alternatives available. 3. It helps in monitoring the implementation of the decision accurately and objectively. 4. The helps to provide feedback to judge the effectiveness of the decision-maker and the efficiency in dealing with the problem. 5. Overall, it enables me to make a better decision.”

Sampling Procedure

The study participants were employees of manufacturing organizations who use digital technologies and organizational information systems in their business operations. Managers and non-managers were both included since they are different organizational roles engaged in strategic and operational decision making. A structured questionnaire was used to gather data online and offline. The survey was confined to employees with one year experience in the organization to assess how they used AI-driven information, and it was anonymous and voluntary. Responses were checked for completeness and consistency before analysis and only complete questionnaires were used for statistical analysis. A simple random sampling was used and 500 questionnaires were distributed among manager and non-manager employees. Out of total distributed questionnaires, 170 valid responses were obtained.

Model Estimation Procedure

Partial Least Squares Structural Equation Modeling (PLS-SEM) software with SmartPLS 4 was used for data analysis of the proposed research model. PLS-SEM was chosen due to its appropriateness for modeling complex predictive models with multiple latent constructs and mediation. The analytical process was divided into two steps. The measurement model was tested in terms of indicator reliability, internal consistency reliability, convergent and discriminant validity. Second, the structural model was evaluated by calculating path coefficients and bootstrapped p-values as well as examining the mediating effect between AI capability and DDDM on the one hand and the mediating effect of IMC on the other.

Multi-Group Analytical Procedure

In order to find out if managerial position affects the proposed structural relationships, the respondents were divided into manager and non-manager groups and then the PLS Multi-Group Analysis (PLS-MGA) was conducted. This analytical method allows one to compare structural path coefficients between independent groups, while keeping the same theoretical model. The analysis examined the differences in the relationships between AI capability, IMC, DDDM and decision-making effectiveness that may be found across managerial responsibility. The PLS-MGA results offer empirical evidence about the effect of organizational position and investigate the differential benefit for managers and non-managers from the use of AI-enabled information management and data-driven decision processes.

DATA ANALYSIS

The measurement model for evaluating the relationships among the latent constructs and indicators is shown in Figure 2. The confirmatory factor analysis (CFA) shows acceptable loading for all measurement items (Sahrir et al., 2022; Yousaf, 2023) for the four constructs of AI capability, IMC, DDDM, and decision-making effectiveness, which is good evidence that the proposed measurement model is a representative model for these constructs. The measurement model can be employed as a valid standard to check the reliability and validity of the constructs before moving on to the structural model analysis (Hair et al., 2020).

The reliability and convergent validity of the measurement model are presented in Table 2. The majority of indicator loadings are greater than 0.50 (the recommended threshold) and the majority of items have loadings greater than 0.80, except two scale items (Eakman et al., 2009; Hirdes et al., 2002). The Cronbach's Alpha values range between 0.887 and 0.941, while the average variance extracted (AVE) values range from 0.649 to 0.753, and the Composite Reliability (CR) values are between 0.922 and 0.952. All constructs have good internal consistency reliability and convergent validity, confirming the suitability of measurement model for further testing of structural model.

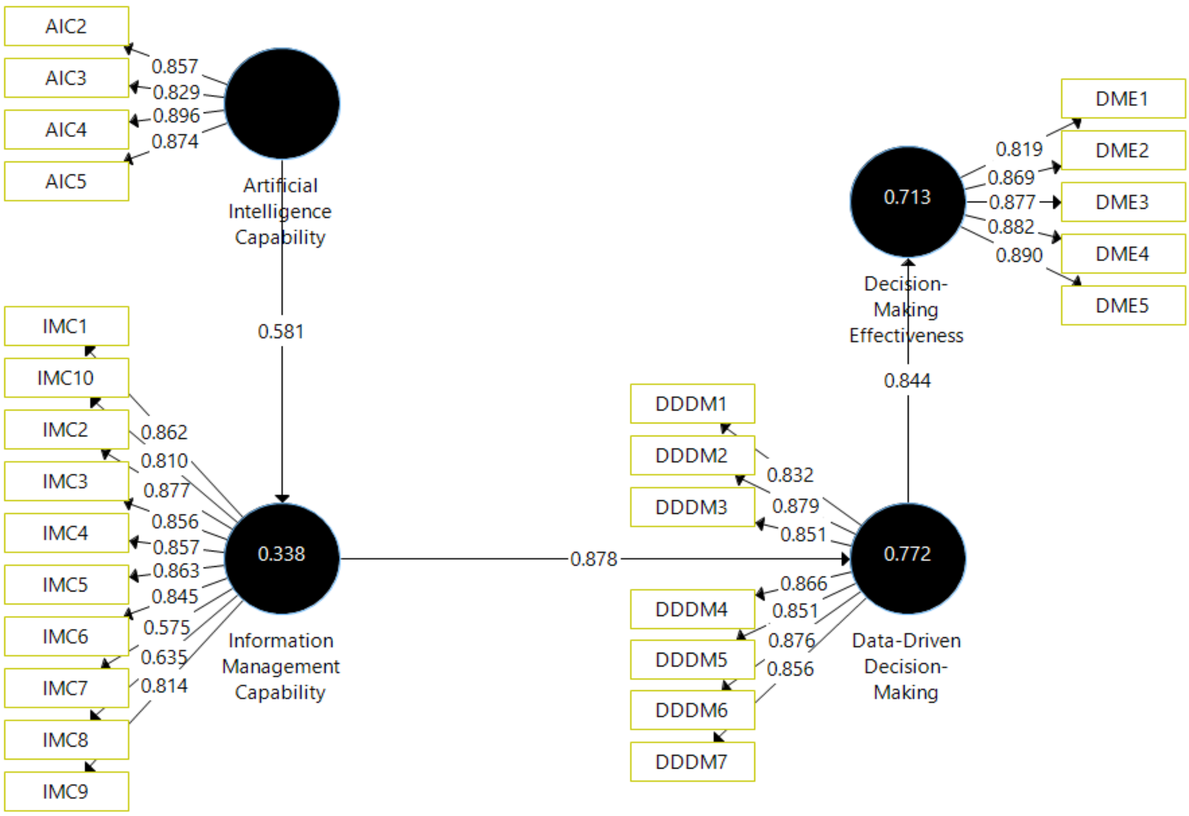

Figure 2: Confirmatory Factor Analysis

Table 2: Internal Item Reliability, Construct Reliability and Convergent Validity

Variables	Loading	Loading	Alpha	CR	AVE
Artificial Intelligence Capability	AIC2	0.857	0.887	0.922	0.747
	AIC3	0.829			
	AIC4	0.896			
	AIC5	0.874			
Data-Driven Decision-Making	DDDM1	0.832	0.941	0.952	0.738
	DDDM2	0.879			
	DDDM3	0.851			
	DDDM4	0.866			
	DDDM5	0.851			
	DDDM6	0.876			
	DDDM7	0.856			
Decision-Making Effectiveness	DME1	0.819	0.918	0.938	0.753
	DME2	0.869			
	DME3	0.877			
	DME4	0.882			
	DME5	0.89			
Information Management Capability	IMC1	0.862	0.938	0.948	0.649
	IMC10	0.81			
	IMC2	0.877			
	IMC3	0.856			
	IMC4	0.857			
	IMC5	0.863			
	IMC6	0.845			
	IMC7	0.575			
	IMC8	0.635			
	IMC9	0.814			

Table 3 shows the discriminant validity test conducted by Heterotrait-monotrait ratio of correlations (HTMT) (Alarcón & Sánchez, 2015). It can be observed from the results that all the values are below 0.9, which confirmed the discriminant validity (Alarcón & Sánchez, 2015; Yusoff et al., 2020). The results confirm that the constructs of AI capability, IMC, DDDM and decision-making effectiveness are conceptually unique, thus validating the measurement model presented.

Table 3: Discriminant Validity

	AIC	DDDM	DME	IMC
Artificial Intelligence Capability				
Data-Driven Decision-Making	0.659			
Decision-Making Effectiveness	0.639	0.906		
Information Management Capability	0.635	0.932	0.907	

The key relationships among the variables in this study are shown in Figure 3. The results indicate positive relationships among AI capability, IMC, DDDM, and decision-making effectiveness. The structural model also shows the mediating effect of IMC between AI capability and DDDM which is used to test the hypotheses suggested. Beta value was considered to examine the direction of the effect and t-value 1.96 was used to check significance of the relationship (Hooi et al., 2018; Ramayah et al., 2018).

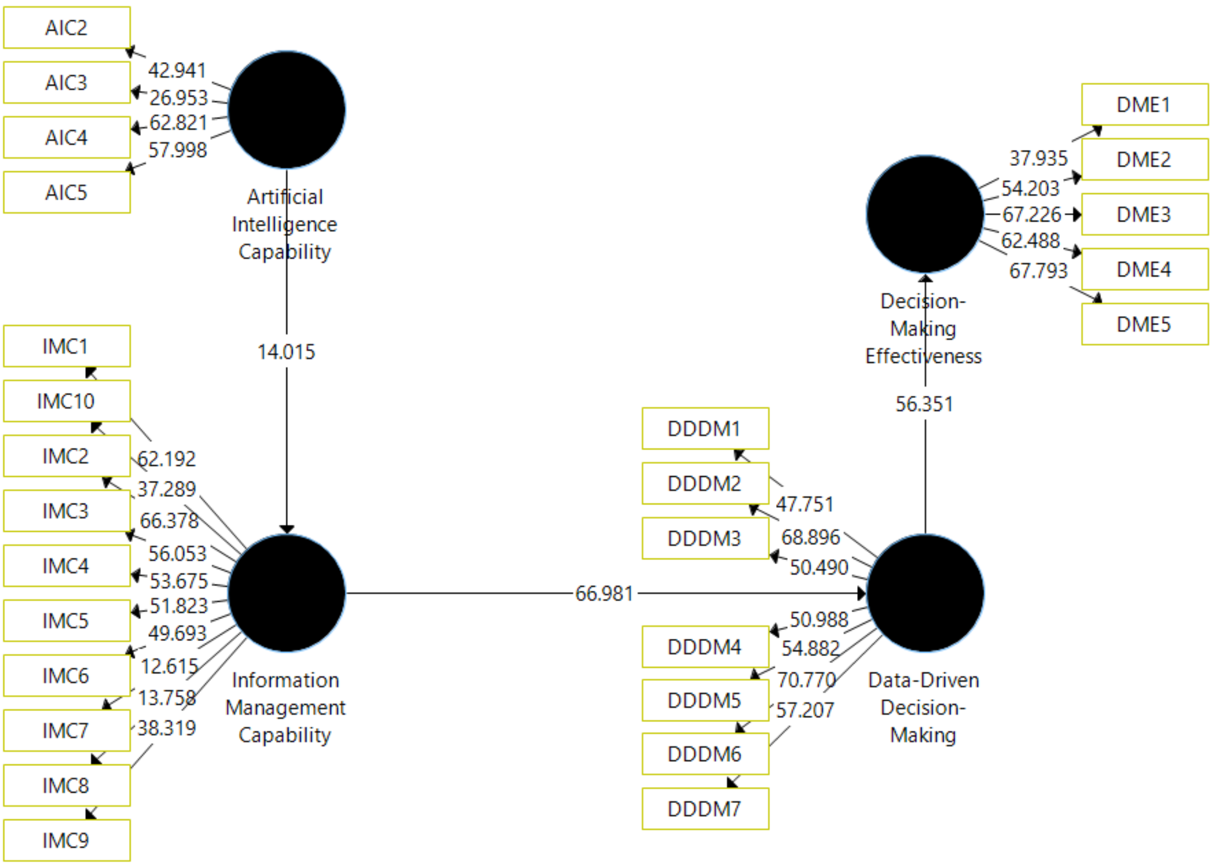

Figure 3: Path Analysis

The results of the structural model for the direct relationships are shown in Table 4. AI capability significantly influences IMC ($\beta = 0.581$, $t = 14.015$, $p < 0.001$) which is consistent with H1. There is also a positive relationship between IMC and DDDM ($\beta = 0.878$, $t = 66.981$, $p < 0.001$), which is in support of H2. Moreover, decision-making effectiveness is significantly and positively influenced by DDDM ($\beta = 0.844$, $t = 56.351$, $p < 0.001$) as indicated by H3. Overall, these findings validate all the proposed direct relationships.

Table 4: Direct Effect Results

	Beta	Mean	(STDEV)	T Statistics	P Values
Artificial Intelligence Capability -> Information Management Capability	0.581	0.586	0.041	14.015	0
Data-Driven Decision-Making -> Decision-Making Effectiveness	0.844	0.845	0.015	56.351	0
Information Management Capability -> Data-Driven Decision-Making	0.878	0.879	0.013	66.981	0

The mediation analysis is shown in Table 5. The AI capability positively and statistically significantly mediates the relationship between IMC and DDDM ($\beta = 0.510$, $t = 13.431$, $p <$

0.001). This finding confirms the mediating effect of IMC, which supports the H4 and validates the transmission of the influence of AI capability to DDDM.

Table 5: Indirect Effect Results

	Beta	Mean	(STDEV)	T Statistics	P Values
Artificial Intelligence Capability -> Information Management Capability -> Data-Driven Decision-Making	0.51	0.515	0.038	13.431	0

Multi-Group Analysis (Manager Vs Non-Manager)

A multi-group analysis (PLS-MGA) (Henseler, 2012; Nguyễn, 2026) was conducted to examine whether the structural relationships differed between managers and non-managers. As presented in Table 6, managers exhibited stronger path coefficients across all three structural relationships than non-managers. However, the statistical comparison in Table 7 indicates that only two relationships differed significantly between the groups. Specifically, the effect of AI capability on IMC was significantly stronger for managers than for non-managers ($\Delta\beta = 0.107$, $p = 0.031$). Likewise, the relationship between DDDM and decision-making effectiveness was significantly stronger among managers ($\Delta\beta = 0.084$, $p = 0.042$). In contrast, no statistically significant difference was observed for the relationship between IMC and DDDM ($\Delta\beta = 0.050$, $p = 0.148$). Overall, these findings suggest that managerial position moderates two of the three structural relationships examined in this study. Summary of PLS-MGA is reported in Table 8.

Table 6: Multi-Group Path Coefficients by Managerial Status

Structural Relationship	Manager (β)	Non-Manager (β)	Stronger Group
Artificial Intelligence Capability → Information Management Capability	0.628	0.521	Manager
Information Management Capability → Data-Driven Decision-Making	0.901	0.851	Manager
Data-Driven Decision-Making → Decision-Making Effectiveness	0.876	0.792	Manager

Table 7: PLS-MGA Results for Managers and Non-Managers

Structural Relationship	Manager (β)	Non-Manager (β)	Difference (Δβ)	PLS-MGA p-value	Result
Artificial Intelligence Capability → Information Management Capability	0.628	0.521	0.107	0.031	Significant
Information Management Capability → Data-Driven Decision-Making	0.901	0.851	0.050	0.148	Not Significant
Data-Driven Decision-Making → Decision-Making Effectiveness	0.876	0.792	0.084	0.042	Significant

Table 8: Summary of Multi-Group Analysis

Hypothesis	Structural Relationship	Stronger Group	Significant Difference	Decision
MGA1	Artificial Intelligence Capability → Information Management Capability	Manager	Yes	Supported
MGA2	Information Management Capability → Data-Driven Decision-Making	Manager	No	Not Supported
MGA3	Data-Driven Decision-Making → Decision-Making Effectiveness	Manager	Yes	Supported

FINDINGS AND DISCUSSION

The present study explores the role of AI capability in improving the decision-making capability of organizations in the context of IMC and DDDM in a manufacturing organization. It is important to note here that it adds to the existing literature by comparing this relationship between managers and non-managers with the application of Multi-Group Analysis (MGA). The results indicate that all the proposed direct and indirect relationships are significant and managerial position accounts for meaningful differences in the strength of selected relationships.

Higher AI capability is linked with higher IMC in manufacturing organizations, as findings of H1 suggested. The empirical results support this hypothesis, suggesting that the stronger the AI ability of the organization, the higher its ability to acquire, integrate, process and distribute organizational information. AI technologies enhance the quality and accessibility of information across the spectrum of manufacturing functions, boosting organizational information management processes (Kinkel et al., 2022; Li et al., 2017). This relationship is also significantly stronger within managers as compared to non-managers, as shown in the multi-group analysis. The finding implies that AI-supported information is more beneficial to managers as they have broader responsibilities that involve cross-functional coordination, strategic planning and resource allocation, in which organizational information is needed to be integrated. Results of this study are consistent with previous studies showing the significant relationship between AI and information management (Bhima et al., 2023; Stoykova & Shakev, 2023). However, the non-managers mostly use AI produced information for operational purposes, where the impact of AI in information management is relatively small. The results underscore how managerial responsibility boosts the value of the organization's AI capability.

Furthermore, H2 suggested that there is a relationship between IMC and DDDM capability. These results are consistent with literature (Sarioguz & Miser, 2023, 2024). This is verified in the results, which highlight the importance of having quality information management which allows employees to make informed decisions that are based on evidence. Uncertainty is reduced and decision quality enhanced throughout manufacturing operations with effective information integration, accessibility and reliability. The multi-group analysis, however, shows no difference between the managers and the non-managers as compared to the other structural relationships. The result shows that, if organizational information is well managed and accessible, the two groups use information in a similar way to aid in their respective decisions. As such, IMC is an organizational resource that can be used to support all employees (Abualoush et al., 2018; Hwang, 2016), both managers and non-managers.

Moreover, H3 suggested that DDDM will be more helpful for organizations that make greater use of it, in order to be more effective in Decision-Making. This hypothesis is well supported by the results, as it indicates that organizational outcomes are more effective when decisions are made on the basis of objective data and analytical insights. Manufacturing companies that consistently use data in production planning, quality management, inventory management, and manufacturing supply chain coordination are more likely to enhance the production efficiency and responsiveness of the organization (Marcelle, 2025; Purmani, 2024). The MGA results also indicate that this is a significant stronger relation with managers compared to non-managers. Strategic decisions that are made in situations involving significant organizational resources, long term planning and performance evaluation often greatly benefit from analytical evidence and thus rely heavily on it (Purmani, 2024). On the other hand, the non-managers are more concerned about operational decisions that have a narrower span of responsibility within their organizations. Hence, analytical data is more useful for managers' decision-making process, which can increase the decision-making effectiveness of managers.

Additionally, H4 suggested that the positive relationship between AI capability and DDDM goes through IMC. This is supported by the mediation analysis which validates this proposition, suggesting that improved AI capability does not directly increase organizational decision-making. Rather, AI technologies are generating organizational value by powering information management processes that convert massive amounts of operational information into useful, accurate and usable information. Similarly, previous studies highlighted the positive relationship between AI capability and DDDM (Ghosh, 2025; Lazaroiu et al., 2022; Mangal et al., 2024). These results further validate the capability building perspective, in which AI capability improves information management in the organization, and that in turn supports DDDM. Overall, the findings indicate that while AI is a valuable tool for manufacturing organizations. It is equally important to have strong information management strategies in place to maximize its potential benefits from digital technologies.

Finally, H5 suggested that the relationships in the structural model between AI capability, IMC, DDDM, and decision-making effectiveness are different for managers and non-managers. The multi-group analysis was partly in confirmation of this hypothesis. The relationships of AI capability to IMC, and DDDM to decision-making effectiveness are significantly different, while there is no significant difference for the relationship between IMC and DDDM. The findings of this study are the main contribution, because it shows that managerial position is a boundary condition of organizational decision processes enabled by AI. AI capability benefits managers more, as they have more organizational authority and responsibility for incorporating information into decision making. With effective information management, however, it seems that managers and non-managers are equally able to use organizational information to support data-driven decision making. In conclusion, the results illustrate that AI-based organizational capabilities do not produce the same results for all organizational roles, emphasizing the need for attention to the role of the manager when developing strategies for implementation of AI systems, information systems and decision support systems in manufacturing organizations.

CONCLUSION

This study demonstrates that the organizational value of AI differs between managers and non-managers within manufacturing companies. While both groups benefit from AI-enabled information and data-driven decision processes, managers obtain greater advantages from AI capability in strengthening IMC and from DDDM in improving decision-making effectiveness.

In contrast, IMC supports DDDM to a similar extent across both groups, indicating that effective information systems benefit employees regardless of organizational position. These findings emphasize that managerial responsibility shapes how AI-generated information is utilized throughout manufacturing operations. Accordingly, manufacturing organizations should avoid adopting a one-size-fits-all approach to AI implementation, as managers and non-managers differ considerably in their responsibilities, decision authority, and information requirements. Instead, organizations should design role-specific information management practices, analytical tools, and decision-support capabilities that align with the strategic responsibilities of managers and the operational needs of non-managers, thereby maximizing the organizational value of AI-driven digital transformation.

Implications

The present study provides implications for theory and practice of manufacturing organizations implementing AI-based decision systems. Theoretically, it builds on the existing literature by combining the following four concepts: AI capability, DDDM, IMC and decision-making effectiveness within a single capability-based framework. More importantly, it shows that managerial position is an organizational boundary condition and that AI necessarily associated with a uniform outcome across managers and non-managers. These findings build on the growing body of literature on AI-powered organizational capabilities and highlights the significance of employee roles in analyzing the outcomes of technology adoption in the organization. In practical terms, manufacturing companies must understand that AI adoption is not enough to enhance the quality of their decisions if not complemented by proper information management. Businesses should thus focus on investing in integrated information management systems which enable the sharing of information across departments in the required time and with reliability. In addition, managers need to be given advanced AI analytics and training in AI strategic decision support, and non-managers need to be trained with production or process management-specific AI applications. This differentiated capability development can ensure maximum organizational value and enhance decision making effectiveness at various organizational levels by leveraging AI technologies.

Future Directions

This study could be expanded in the future by comparing the managerial levels, including senior, middle, and first-line managers, to explore the impact of hierarchical responsibilities on AI-driven decision-making processes. Researchers can also explore how different manufacturing industries, such as automotive, pharmaceutical, electronic, and food manufacturing, which vary widely in their use of AI, are affected by the relationships. An emerging research path is to explore AI maturity as a moderating factor by studying the differences between companies that implement AI at an early stage and those that implement it at an advanced stage. Lastly, longitudinal studies would be able to examine the impact of ongoing investments in AI capability and information management on the long-term effectiveness of decision making of managers and non-managers more robustly and thus demonstrate capability development and organizational learning.

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