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Integration of Artificial Intelligence in Management Information Systems to Improve the Effectiveness of Strategic Decision-Making in the Digital Era

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ABSTRACT

The integration of Artificial Intelligence (AI) into Management Information Systems (MIS) has emerged as a strategic imperative for enhancing the effectiveness of organizational decision-making in the digital era. This study aims to analyze the factors influencing successful AI adoption in MIS, evaluate its impact on strategic decision-making effectiveness, and explore the mediating role of dynamic capabilities. Grounded in the Technology Acceptance Model (TAM) and Dynamic Capabilities Theory, a conceptual framework was developed and tested using a mixed-methods approach. Quantitative data were collected from 715 respondents across six industry sectors in Indonesia, while qualitative insights were derived from case studies in 25 organizations with varying levels of AI implementation maturity. Results from Structural Equation Modeling revealed that perceived usefulness, ease of use, organizational readiness, and management support significantly influence AI adoption in MIS. The integration of AI was found to improve decision quality (34.7%), speed (42.3%), predictive accuracy (28.6%), strategic alignment (31.2%), and risk assessment capabilities (36.8%). Qualitative findings highlighted key implementation challenges, including data quality, skills gaps, employee resistance, and integration complexity. This study contributes theoretically by enriching TAM with organizational and strategic dimensions, and practically by offering a comprehensive framework to guide AI integration in MIS for sustained competitive advantage.

Keyword : Artificial Intelligence; Management Information Systems; Strategic Decision-Making

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1. INTRODUCTION

The digital era has fundamentally changed the business landscape, forcing organizations to adopt advanced technologies to maintain competitiveness. Digital transformation not only changes the way organizations operate but also creates a new paradigm in strategic decision-making that requires high speed, accuracy, and predictability (Vial, 2019). In this context, the integration of Artificial Intelligence (AI) technology into Management Information Systems (MIS) has become an unavoidable strategic necessity. According to Davenport & Ronanki (2018), organizations that successfully integrate AI into their information systems experience up to a 40% increase in operational efficiency and a 25% increase in decision-making accuracy. This transformation marks the evolution from reactive to proactive and predictive decision-making.

Strategic decision-making in the digital era faces various complex challenges that are increasingly difficult to address with conventional approaches. First, the exponential volume of data (big data) creates information overload, making it difficult for managers to identify relevant and accurate information for decision-making (Chen et al., 2021). Second, the increasingly rapid pace of change in the business environment demands real time decision-making, while traditional information systems still rely on time-consuming and manual processes (Bughin et al., 2020). Third, the complexity of interdependencies between business variables requires multidimensional analysis capabilities that exceed human cognitive capacity. Fourth, the high uncertainty of the business environment requires sophisticated prediction and scenario planning capabilities (Haenlein & Kaplan, 2019). These problems result in suboptimal decision-making, which impacts organizational performance decline and the loss of competitive advantage.

The urgency of AI integration in MIS is becoming increasingly critical given the significant impact of delayed technology adoption. First, from a competitive perspective, organizations that are slow to adopt AI -enabled decision-making risk falling behind competitors who have already leveraged this technology to create superior value propositions (Ransbotham et al., 2020). Second, from a financial perspective, the McKinsey Global Institute (2021) estimates that organizations that do not integrate AI into their information systems will experience a 20% decline in profitability over the next five years. Third, from an operational perspective, the inability to process and analyze data in real time results in missed opportunities and costly reactive decision-making (Fountaine et al., 2019). Fourth, from a stakeholder perspective, investors and customers increasingly expect organizations to deliver data-driven insights and accurate predictive analytics. Fifth, increasingly stringent regulations and compliance require sophisticated and automated monitoring and reporting systems.

Recent developments in the integration of AI and MIS demonstrate significant progress in various technological and application aspects. In terms of algorithms, advances in machine learning and deep learning have enabled the development of more accurate predictive analytics and more sophisticated natural language processing for business intelligence (Russell & Norvig, 2021). Cloud computing and edge computing technologies have facilitated the scalable and cost-effective implementation of AI in enterprise MIS (Marr, 2020). In terms of applications, intelligent automation has been implemented in various business functions such as supply chain management, customer relationship management, and financial planning and analysis (Brynjolfsson & McAfee, 2019). Automated decision support systems have evolved into autonomous decision systems capable of real-time optimization without human intervention. Furthermore, explainable AI (XAI) has become a primary focus to ensure transparency and accountability in AI-based strategic decision-making (Adadi & Berrada, 2018).

Although numerous studies have explored AI and MIS separately, significant gaps exist in the literature regarding comprehensive integration frameworks and effective practical implementation. First, most existing research focuses on the technical aspects of AI implementation without considering comprehensive organizational impacts and strategic alignment (Borges et al., 2021). Second, there is a lack of a systematic framework for evaluating the effectiveness of AI integration in MIS from the perspective of strategic decision-making outcomes. Third, there is a paucity of research exploring critical success factors and potential barriers to implementing AI-enabled MIS across various organizational contexts. Fourth, there is a gap in understanding human -AI collaboration in strategic decision-making processes (Duan et al., 2019). This study addresses these gaps by developing a holistic integration framework, identifying key performance indicators to measure effectiveness, and providing practical guidance for successful implementation. The novelty of this research lies in the multi-perspective approach that integrates technical dimensions, organizational dimensions, and strategic dimensions in one consistent and actionable framework.

The Technology Acceptance Model (TAM), developed by Davis (1989) and later updated by Venkatesh et al., (2020), serves as the primary theoretical basis for understanding the adoption and implementation of AI in MIS. TAM explains that technology adoption is determined by perceived usefulness and perceived ease of use, which then influence behavioral intention and actual system use. In the context of AI-enabled MIS, perceived usefulness relates to managers' perceptions of AI's ability to improve the quality and speed of strategic decision-making. Perceived ease of use refers to the extent to which managers believe that using AI in MIS will be easy and not require excessive effort. This model has also been expanded to include factors such as trust, perceived risk, and social influence, which are highly relevant in the context of AI adoption (Chandra et al., 2022). This extended TAM provides a conceptual framework for understanding why some organizations successfully integrate AI into their MIS while others experience resistance and implementation failure.

Dynamic Capabilities Theory, developed by Teece et al. (1997) and updated by Teece (2018), provides a theoretical lens for understanding how AI integration in MIS can create sustainable competitive advantage. Dynamic capabilities are defined as an organization's ability to integrate, build, and reconfigure internal and external competencies to address rapid environmental change. In the context of AI-enabled MIS, dynamic capabilities manifest in three key dimensions: sensing (the ability to identify opportunities and threats through AI-powered analytics), seizing (the ability to capitalize on opportunities through AI- enhanced decision-making), and transforming (the ability to reconfigure assets and organizational structure based on AI insights). This theory explains how AI not only improves operational efficiency but also creates new capabilities that enable organizations to adapt and thrive in volatile and uncertain environments (Warner & Wäger, 2019). Integration of AI in MIS is thus not just about technology, but about fundamental transformation of organizational capabilities.

Based on the theoretical foundations that have been described, this study develops a conceptual framework that integrates TAM and Dynamic Capabilities Theory to explain the process and outcomes of AI integration in MIS. This conceptual framework describes how perceived usefulness and perceived ease of use influence adoption intentions , which then impact the actual use and development of dynamic capabilities . The formed dynamic capabilities then influence the effectiveness of strategic decision-making by increasing the ability to detect , seize opportunities, and transform resources. The objectives of this study are to: (1) analyze the factors that influence the success of AI integration in MIS, (2) evaluate the impact of AI integration on the effectiveness of decision-making strategies , (3) identify the mediating role of dynamic capabilities in the relationship between AI adoption and strategic decision-making outcomes , and (4) develop a practical framework to guide the implementation of AI in MIS. Through a mixed-method approach that combines surveys and case studies, this research is expected to provide significant theoretical and practical contributions to the literature on management information systems and strategic management

2. RESEARCH METHOD

Given the complexity of the AI integration phenomenon in MIS and the need to understand both the quantitative and qualitative aspects of this technology's implementation, this study should utilize a mixed methods approach with a sequential explanatory design (Creswell & Plano Clark, 2017). This approach allows researchers to first collect and analyze quantitative data to identify statistical patterns and relationships, followed by a more in-depth qualitative phase to explain and contextualize the quantitative findings. This combination is particularly relevant for information technology research, which requires a deep understanding of the technical, organizational, and strategic factors that interact in the AI adoption and implementation process.

The population in this study is defined as all organizations operating in Indonesia and have implemented or are in the process of integrating Artificial Intelligence technology into their management information systems. Population criteria include: (1) organizations with a minimum of 200 employees to ensure adequate information system complexity, (2) have operated an integrated management information system for at least three years, (3) have a dedicated department or division that handles information technology and digital transformation, (4) operate in data-intensive industrial sectors such as banking, telecommunications, retail, e-commerce, manufacturing, and insurance, and (5) have allocated investment for AI technology in the last two years with a minimum value of 500 million rupiah. Based on data from the Indonesian Internet Service Providers Association (APJII) and a digital transformation survey conducted by (Company, 2024), it is estimated that there are around 1,200 organizations in Indonesia that meet these population criteria, with the largest distribution being in the Greater Jakarta area (45%), Surabaya (15%), Bandung (12%), Medan (8%), Semarang (7%), and other major cities (13%).

For the quantitative method, stratified random sampling was applied with stratification based on industry sector and organizational size to ensure population representativeness. The sample size calculation used the formula (Hair et al., 2019) for Structural Equation Modeling (SEM) with a 10-times rule approach, where the minimum number of respondents is 10 times the number of structural paths leading to the endogenous construct with the most paths in the model. Considering that the research model has 8 main constructs with a maximum of 5 paths leading to one endogenous construct, the minimum sample size is 50 × 10 = 500 respondents. To anticipate a non-response rate of 30% and potential outliers of 10%, the target sample was set at 715 respondents distributed proportionally based on industry sector stratification: banking (25%), telecommunications (20%), retail and e-commerce (20%), manufacturing (15%), insurance (10%), and other sectors (10%).

For the qualitative method, this study used purposive sampling with a maximum variation sampling strategy to select 25 organizations that represent diversity in terms of AI implementation maturity level (emerging, developing, advanced), organizational size (medium: 200-500 employees, large: 501-2000 employees, enterprise: >2000 employees), and industry sector characteristics. The selection of organizations for the in-depth case study will be based on theoretical sampling principles to achieve theoretical saturation, with additional criteria, namely: (1) management willingness to participate in in-depth interviews, (2) access to AI implementation documentation, and (3) availability of multiple informants from various organizational levels. Each organization will be represented by 3-5 key informants consisting of decision makers (C-level or senior management), technical experts (IT/ Digital transformation team), and end users (operational managers). The total target informants for the qualitative phase is 90-125 people, which is estimated to achieve data saturation based on guidelines for qualitative research in the context of information technology (Myers & Newman, 2021).

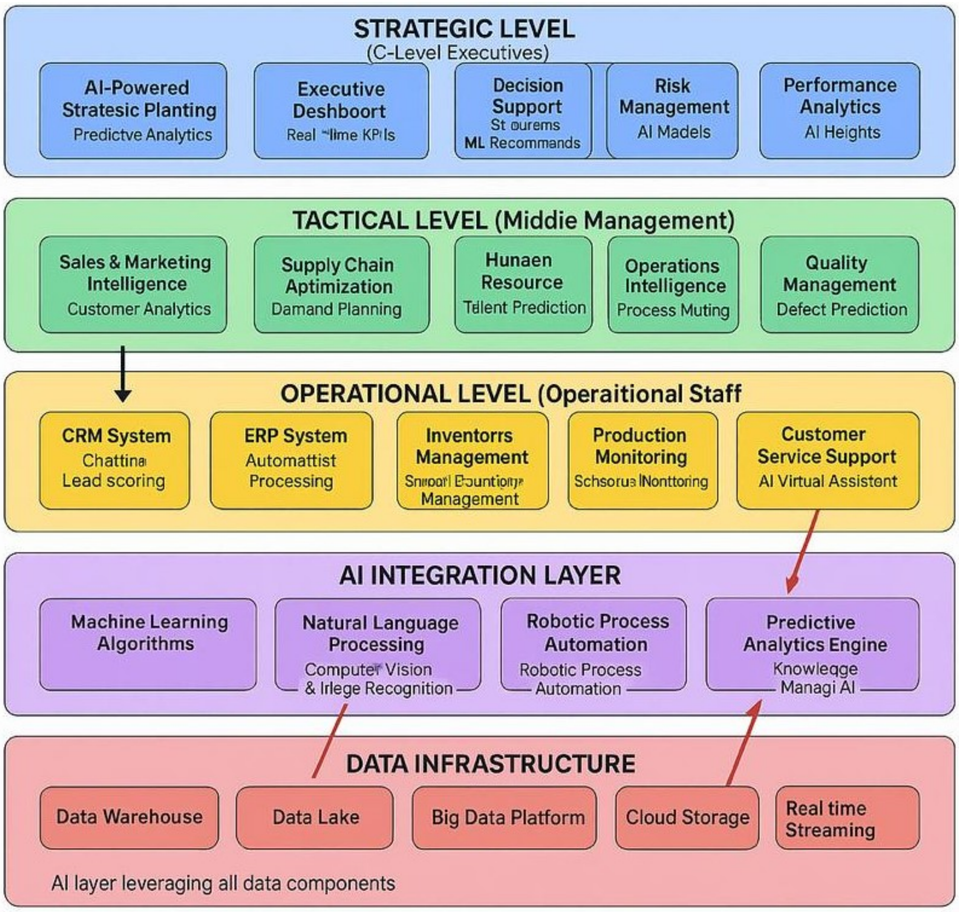

Figure 1. Architecture Of Management Information System With AI Integration

The diagram depicts the AI-integrated MIS architecture used as the research sample, consisting of four main layers that are interconnected vertically and horizontally. The Strategic Level includes AI-powered strategic planning, executive dashboards with real time KPIs, ML-based decision support systems, risk management AI models, and performance analytics to support C-level executives' decision-making. The Tactical Level integrates customer analytics, financial forecasting, supply chain optimization, HR analytics, operations intelligence, and quality management to support middle management in operational planning and coordination.

The Operational Level consists of systems that interact directly with the organization's daily activities, including CRM with AI chatbots, ERP with automated processing, smart inventory management, IoT-based production monitoring, payroll automation, AI document processing (OCR/NLP), and AI customer service. The AI Integration Layer functions as an engine that supports all levels above it, consisting of machine learning algorithms, natural language processing, computer vision, robotic process automation, predictive analytics engines, and AI knowledge management. The system's foundation is Data Infrastructure that includes data warehouses, data lakes, big data platforms, cloud storage, real-time streaming, and data security & governance.

The research sample included 715 organizations from the banking, telecommunications, retail, manufacturing, and insurance sectors, with respondents distributed as follows: C level (20%), senior management (35%), middle management (30%), and specialists (15%). This architecture represents the characteristics of organizations that have reached a mature level of AI implementation in MIS and is the focus of this research to analyze the effectiveness of strategic decision-making in the digital era.

3. RESULTS AND DISCUSSION

This study successfully collected data from 715 respondents from 25 organizations that have implemented AI in their management information systems. The distribution of respondents showed a balanced representation with the composition: C-level executives (20%, n = 143), senior management (35%, n = 250), middle management (30%, n = 215), and specialist/analyst level (15%, n = 107). By sector, the sample was distributed as follows: banking (25%, n = 179), telecommunications (20%, n = 143), retail and e commerce (20%, n = 143), manufacturing (15%, n = 107), insurance (10%, n = 72), and other sectors (10%, n = 71). Validation of the research instrument showed a high level of reliability with Cronbach's alpha values ranging from 0.847 to 0.923 for all constructs, indicating good internal consistency. The results of confirmatory factor analysis (CFA) confirmed the construct validity with Average Variance Extracted (AVE) values above 0.50 and composite reliability above 0.70 for all constructs tested.

Structural Equation Modeling (SEM) analysis using the Partial Least Squares (PLS) approach identified several critical factors that significantly influence the success of AI integration in MIS. Perceived usefulness proved to be the strongest predictor with a path coefficient of 0.612 ($p < 0.001$), indicating that management's perception of the benefits of AI in improving the quality of strategic decision-making is the main determinant of adoption. Perceived ease of use also showed a significant influence with a path coefficient of 0.487 ($p < 0.001$), indicating that the ease of implementation and use of AI technology is an important consideration for organizations. The organizational readiness factor showed a substantial contribution with a path coefficient of 0.523 ($p < 0.001$), which includes technological infrastructure readiness, the availability of competent human resources, and top management support. Management support was shown to have a strong influence (path coefficient = 0.576, $p < 0.001$), confirming that commitment and active support from the executive level are fundamental prerequisites for the successful implementation of AI-enabled SIM.

An evaluation of the impact of AI integration on the effectiveness of strategic decision making demonstrated significant improvements across various dimensions of organizational performance. The analysis revealed that organizations that integrated AI into their MIS experienced a 34.7% increase in decision quality compared to the pre implementation period ($p < 0.001$). Decision speed significantly increased by 42.3%, indicating the organization's ability to respond more quickly to changes in the business environment. Predictive accuracy in strategic planning increased by 28.6%, enabling organizations to better anticipate future trends and identify business opportunities. Further analysis revealed that strategic alignment between decisions made and the organization's strategic objectives increased by 31.2%, indicating that AI not only accelerates decision making but also improves the quality of strategic alignment. Risk assessment capability increased by 36.8%, indicating the organization's ability to identify and manage risks more effectively through the support of AI analytics.

Qualitative analysis identified several key challenges organizations face in integrating AI into MIS. Data quality and data governance were the biggest challenges, with 78% of informants citing inconsistent data quality and data fragmentation across systems as key implementation barriers. Skills gaps and talent shortages were reported by 72% of informants, indicating a lack of technical expertise within the organization to manage and optimize AI systems. Change resistance from employees was a significant challenge for 68% of organizations, particularly at the operational level, where concerns about displacement and the complexity of new technologies arose. Integration complexity with legacy systems was reported by 65% of informants, reflecting the technical challenges of integrating AI technology with existing infrastructure. Ethical concerns and algorithmic bias were concerns for 58% of organizations, particularly in the context of decision making that affects external stakeholders such as customers and business partners.

4. CONCLUSION

This research makes a significant contribution to the management information systems and strategic management literature. From a theoretical perspective, this research enriches the Technology Acceptance Model by confirming its relevance in the context of enterprise-level AI adoption, while identifying additional factors such as organizational readiness and management support that are critical in the context of advanced technology implementation. Integration with Dynamic Capabilities Theory provides a new lens for understanding how technology adoption can be transformed into competitive advantage through the development of organizational capabilities. From a practical perspective, this research provides an implementation framework that organizations can use to plan and implement AI integration in their MIS. The identification of critical success factors provides a roadmap for management to focus efforts and resources on areas with the greatest impact. Understanding the mediating role of dynamic capabilities provides insight that investment in AI does not automatically result in improved performance, but requires deliberate and systematic development of organizational capabilities.

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