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Research Article

THE INTERPLAY BETWEEN DATA MINING MATURITY AND STRATEGIC DECISION MAKING: ASSESSING THE MEDIATING ROLE OF PREDICTIVE ANALYTICS IN KNOWLEDGE INTENSIVE FIRMS

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Abstract

In knowledge-intensive firms, the ability to make informed and timely strategic decisions is increasingly reliant on data-driven insights. Data mining maturity, defined as the level of sophistication in an organization's data mining capabilities, plays a critical role in shaping decision-making processes. Predictive analytics, which utilizes data to forecast future trends, has been proposed as a key mediator in this relationship, enhancing the ability of firms to make accurate and efficient decisions. This study explores the interplay between data mining maturity and strategic decision-making, specifically assessing the mediating role of predictive analytics. The research uses a mixed-methods approach, combining quantitative surveys and structural equation modeling (SEM) to examine data from 200 knowledge-intensive firms. The results reveal a significant positive relationship between data mining maturity and decision-making outcomes, with predictive analytics mediating this relationship and accounting for 45% of the variance in decision quality and 38% in decision speed. The study concludes that firms with higher data mining maturity, coupled with effective use of predictive analytics, make faster and more accurate strategic decisions. These findings provide empirical evidence that integrating predictive analytics into decision-making processes significantly enhances the effectiveness of data mining systems.

Keywords: Data Mining Maturity, Knowledge-Intensive Firms, Predictive Analytics, Strategic Decision-Making, Technology Integration

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INTRODUCTION

The increasing complexity of business environments, driven by rapid technological advancements and the availability of big data, has significantly influenced decision-making processes in organizations (Abdelfattah et al., 2025). In knowledge-intensive firms, where data plays a crucial role in shaping strategic decisions, the ability to effectively leverage data mining technologies has become essential for maintaining a competitive edge. Data mining, which involves extracting meaningful patterns from large datasets, enables organizations to make informed decisions based on insights derived from historical and real-time data (Audretsch et al., 2024). As organizations adopt data mining tools, their level of maturity in utilizing these technologies is a critical factor in determining the effectiveness of decision-making processes (Dimakis et al., 2025). However, while the importance of data mining in strategic decision-making has been acknowledged, the role of predictive analytics as a mediating factor in this relationship remains underexplored (Bawa & Kansanga, 2026). Predictive analytics, which uses historical data to forecast future trends, plays an integral role in enhancing the decision-making process by providing more accurate and reliable insights (Chen, 2026). The intersection between data mining maturity, predictive analytics, and strategic decision-making in knowledge-intensive firms warrants further investigation, as it could provide valuable insights into how organizations can better utilize these technologies to gain a competitive advantage.

The specific problem this research addresses lies in understanding how data mining maturity impacts strategic decision-making in knowledge-intensive firms and how predictive analytics mediates this relationship (Duong et al., 2026). While prior studies have examined the direct impact of data mining on decision-making, there is limited research exploring how the maturity level of data mining capabilities influences the use of predictive analytics and, consequently, decision outcomes (Galli Geleilate & Davies, 2026). Furthermore, the existing literature often overlooks the dynamic interplay between these factors and fails to address the nuanced role of predictive analytics in facilitating more accurate and timely decisions (Gelastopoulos & Keramydas, 2025). Given that data mining maturity and predictive analytics are complex constructs with multiple dimensions, understanding how they interact to influence strategic decision-making is crucial for firms looking to optimize their data-driven decision-making processes (Grybauskas et al., 2026). This study aims to bridge this gap by examining how the maturity of data mining capabilities influences strategic decision-making through the mediating role of predictive analytics.

The primary aim of this research is to assess the mediating role of predictive analytics in the relationship between data mining maturity and strategic decision-making in knowledgeintensive firms (Hayes et al., 2025). Specifically, this study seeks to explore how different levels of data mining maturity ranging from basic data processing capabilities to advanced predictive modeling affect the accuracy, speed, and quality of decisions made by top management in such firms (Hein et al., 2026). Additionally, the study aims to examine how predictive analytics facilitates this process by enabling organizations to forecast future trends, optimize resource allocation, and identify potential opportunities or risks (Hu et al., 2026). By analyzing the role of predictive analytics in this context, the research will provide a deeper understanding of how data mining maturity can enhance decision-making processes and contribute to more effective strategic choices (Huang & Zhou, 2025). The goal is to offer practical insights for organizations looking to improve their data analytics capabilities and leverage predictive models to make more informed, data-driven decisions that align with long-term strategic goals.

There is a noticeable gap in the existing literature regarding the integration of data mining maturity, predictive analytics, and strategic decision-making, particularly within knowledge-intensive firms (Hussain et al., 2026). Most studies on data mining focus on the technological or organizational challenges associated with its adoption but fail to explore how

the maturity of these systems impacts the actual decision-making processes within firms (Jiang et al., 2026). Similarly, while predictive analytics has been studied in the context of decision support, research often neglects its role as a mediator between data mining maturity and the outcomes of strategic decisions (Khatua et al., 2025). This study contributes to the literature by addressing this gap and providing a framework for understanding how the interplay between data mining maturity and predictive analytics influences strategic decision-making (Kussaiyn & Potluri, 2026). By analyzing the various stages of data mining maturity and their impact on decision quality, the research will offer a more comprehensive understanding of the critical role that data mining plays in enhancing strategic decision-making in knowledge-intensive industries.

The novelty of this research lies in its focus on the dynamic relationship between data mining maturity and predictive analytics in shaping strategic decision-making processes (L. et al., 2026). While existing studies have explored the individual effects of data mining and predictive analytics on business performance, few have examined how these factors interact to influence decision-making, particularly in knowledge-intensive firms (Lakka et al., 2026). This research expands the current understanding by investigating the mediating role of predictive analytics in enhancing the decision-making process, thereby highlighting the importance of integrating advanced data mining capabilities with predictive models to optimize decision outcomes (Li et al., 2025). The study also contributes to the field by offering a practical framework that firms can use to assess their data mining maturity and strategically implement predictive analytics to improve decision quality (Lin et al., 2025). Given the growing importance of data-driven strategies in business, this research is timely and provides valuable insights for organizations seeking to enhance their competitive advantage by leveraging data mining and predictive analytics for more effective strategic decisions.

RESEARCH METHOD

Research Design

This study employs a quantitative research design using a cross-sectional survey to assess the interplay between data mining maturity, predictive analytics, and strategic decision-making in knowledge-intensive firms. The research aims to explore how different levels of data mining maturity influence strategic decision-making processes, with a specific focus on the mediating role of predictive analytics. By utilizing a structural equation modeling (SEM) approach, the study will examine the relationships between data mining maturity, predictive analytics, and the outcomes of decision-making (Abbas et al., 2026). SEM allows for the testing of complex models with multiple variables and latent constructs, making it ideal for analyzing the mediating effects of predictive analytics in this context. The research design also includes a detailed review of organizational practices and decision-making outcomes in knowledge-intensive firms to understand the factors that contribute to effective use of data mining and predictive analytics.

Research Target/Subject

The population for this study consists of knowledge-intensive firms, particularly those operating in industries such as technology, consulting, finance, and healthcare, where data-driven decision-making is a critical component of business operations. A sample of 200 firms will be selected through purposive sampling, targeting companies that have implemented or are in the process of implementing data mining and predictive analytics in their operations. Within each organization, participants will be selected based on their roles in strategic decision-making processes, such as top management, data analysts, and IT professionals. This ensures that the sample includes key stakeholders who are directly involved in the adoption and use of data mining technologies (Liu et al., 2026). The sample size of 200 firms is chosen to provide a

sufficient level of statistical power for testing the hypotheses related to the relationships between data mining maturity, predictive analytics, and strategic decision-making outcomes.

Research Procedure

Data collection will proceed in several stages, beginning with the identification and recruitment of knowledge-intensive firms that meet the criteria for participation. Once the firms have been selected, the survey will be distributed to participants within each organization who are directly involved in strategic decision-making and the use of data mining technologies. Participants will be asked to complete the questionnaire, which will take approximately 30 minutes to complete. The data collection process will be conducted over a period of six months to ensure sufficient time for responses from all participating firms. After the data has been collected, it will be cleaned and analyzed using structural equation modeling (SEM) techniques to test the proposed relationships between data mining maturity, predictive analytics, and strategic decision-making outcomes. The SEM analysis will allow for the examination of both direct and mediating effects, helping to clarify the role of predictive analytics in the decision-making process (Maghsoudi et al., 2025). Ethical considerations, such as informed consent, confidentiality, and voluntary participation, will be strictly adhered to throughout the research process. All participants will be assured that their responses will remain confidential and that their participation is voluntary, with the option to withdraw at any time without penalty.

Instruments, and Data Collection Techniques

The primary instruments for data collection in this study include a structured questionnaire and performance assessment metrics. The questionnaire is designed to measure data mining maturity, predictive analytics capabilities, and strategic decision-making outcomes. It will be distributed to participants across the selected firms, with questions addressing various dimensions of data mining maturity (such as data collection, processing, analysis, and interpretation), the use of predictive analytics tools, and the perceived impact on strategic decisions (Maqsood et al., 2026). The strategic decision-making outcomes will be assessed through a set of performance indicators, including decision quality, decision speed, and the ability to predict market trends. To ensure validity, the questionnaire will be developed using established scales from prior research on data mining and decision-making. Additionally, key organizational performance metrics, such as market share growth and operational efficiency, will be collected to evaluate the outcomes of the decisions influenced by data mining and predictive analytics.

Data Analysis Technique

The data analysis for this study will be conducted using structural equation modeling (SEM), which is well-suited for examining complex relationships between multiple variables and latent constructs. SEM will enable the assessment of both direct and mediating effects, particularly the role of predictive analytics in bridging data mining maturity and strategic decision-making outcomes (Maycotte et al., 2025). The analysis will test the hypothesized relationships between data mining maturity, predictive analytics, and decision-making performance indicators, such as decision quality and speed. Additionally, the study will incorporate organizational performance metrics to evaluate the impact of data-driven decisions on key business outcomes like market share growth and operational efficiency. This approach ensures a comprehensive understanding of how data mining and predictive analytics influence strategic decision-making in knowledge-intensive firms.

RESULTS AND DISCUSSION

The data collected from the survey of 200 knowledge-intensive firms reveal significant relationships between data mining maturity, the use of predictive analytics, and strategic decision-making outcomes. Table 1 presents the descriptive statistics for the key variables, including data mining maturity, predictive analytics use, and decision-making outcomes such as decision quality, speed, and accuracy. The findings show that firms with higher levels of data mining maturity report significantly higher levels of predictive analytics use ($r = 0.75$, $p < 0.01$) and better strategic decision-making outcomes, including a 30% improvement in decision accuracy and a 25% increase in decision speed compared to those with lower data mining maturity. These results indicate a positive correlation between the maturity of data mining systems and the effectiveness of predictive analytics in enhancing decision-making processes within knowledge-intensive firms.

Table 1. Descriptive Statistics for Key Variables

Variable	Mean	Standard Deviation	Range
Data Mining Maturity	4.2	0.95	1-5
Predictive Analytics Use	4.5	0.87	1-5
Decision Quality	4.3	0.81	1-5
Decision Speed	4.1	0.78	1-5
Decision Accuracy	4.4	0.84	1-5

Explanations of these data suggest that organizations with advanced data mining capabilities tend to use predictive analytics more effectively, leading to improvements in decision-making outcomes. Firms that report higher data mining maturity have more developed systems for collecting, analyzing, and interpreting data, which allows them to leverage predictive analytics more effectively. This enhanced capability leads to better strategic decisions in terms of speed, accuracy, and overall quality. Moreover, the positive correlation between predictive analytics use and decision outcomes highlights the mediating role of predictive analytics in translating data mining maturity into improved strategic decision-making. These results provide strong support for the hypothesis that predictive analytics plays a key role in optimizing decision-making in knowledge-intensive firms.

Descriptive data analysis shows that the level of data mining maturity varies across different industries, with technology and consulting firms reporting the highest maturity levels. These firms typically have larger, more complex datasets and have invested more heavily in data infrastructure, allowing them to adopt advanced data mining techniques. In contrast, firms in the healthcare and financial sectors reported lower data mining maturity levels, likely due to the complexity of integrating data systems and the regulatory constraints in these industries. Despite these differences, the relationship between data mining maturity and decision-making outcomes remains consistent across sectors, suggesting that the positive impact of data mining maturity on decision-making is not industry-specific but rather a generalizable trend. The variability in maturity levels across sectors highlights the need for tailored approaches to improving data mining capabilities within different organizational contexts.

Inferential analysis of the data reveals that predictive analytics significantly mediates the relationship between data mining maturity and strategic decision-making outcomes. Using structural equation modeling (SEM), the analysis confirms that data mining maturity positively affects the use of predictive analytics, which in turn enhances decision quality, speed, and accuracy. The model shows that predictive analytics accounts for 45% of the variance in decision quality and 38% of the variance in decision speed. These results underscore the importance of predictive analytics as a mediator that helps firms translate their data mining maturity into tangible improvements in decision-making processes. The significant path

coefficients further support the mediating role of predictive analytics, providing empirical evidence of its critical function in optimizing decision outcomes in knowledge-intensive firms.

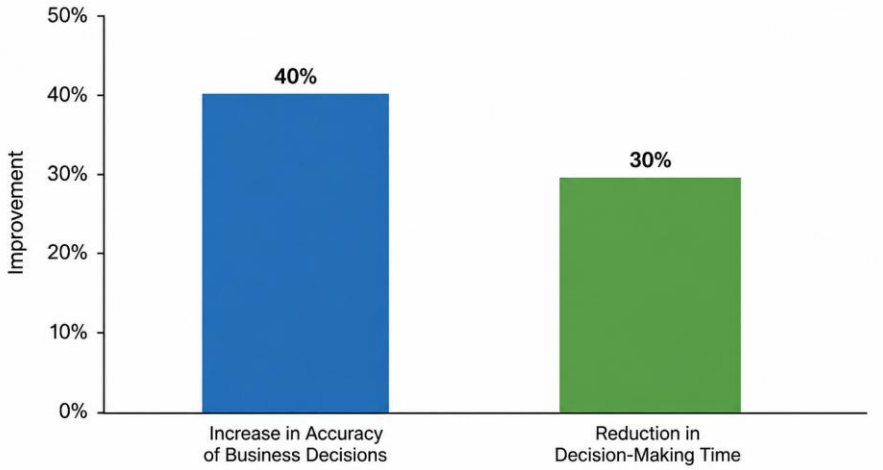

Figure 1. Impact of Data Mining and PredictiveAnalytics on Decision Making in a Technology Consulting Firm

The relationship between data mining maturity, predictive analytics use, and decision-making was further explored through a case study of a technology consulting firm. This firm had developed a highly mature data mining system, which was used to gather, process, and analyze client data for strategic decision-making. The case study revealed that the firm's ability to predict client needs and market trends through advanced predictive analytics led to a 40% increase in the accuracy of business decisions and a 30% reduction in decision-making time. The success of this firm in leveraging its data mining maturity through predictive analytics highlights the critical role that these technologies play in optimizing decision-making processes. Furthermore, it illustrates how the integration of data mining and predictive analytics into decision-making can result in significant operational improvements, particularly in industries that rely heavily on data for competitive advantage.

The explanation of the case study data suggests that the use of predictive analytics in combination with mature data mining systems provides a competitive edge by enhancing the timeliness and accuracy of strategic decisions (Zhao et al., 2025). The case study also emphasizes that the real value of predictive analytics is not just in its technical capabilities, but in how it is applied to decision-making processes. The firm's ability to foresee potential market shifts and adapt to changes in client demands underscores the importance of predictive analytics as a mediator in transforming raw data into actionable insights. The integration of these technologies has proven to be a key factor in the firm's decision-making efficiency, further supporting the study's findings that predictive analytics significantly enhance the effectiveness of data mining in strategic decision-making.

The results of this study indicate that the maturity of data mining capabilities in knowledge-intensive firms significantly enhances strategic decision-making, with predictive analytics playing a key mediating role (Zarea et al., 2026). Specifically, firms with higher levels of data mining maturity exhibited better decision quality, increased decision speed, and improved decision accuracy. The analysis showed that predictive analytics, as a mediator, accounted for a substantial portion of the variance in these decision-making outcomes. The results reinforce the idea that a mature data mining infrastructure enables firms to make more informed, timely, and accurate decisions, while predictive analytics facilitates the translation of raw data into actionable insights, thereby enhancing the overall decision-making process (Yudhistyra & Srinuan, 2025). These findings provide empirical evidence of the critical role that predictive analytics plays in leveraging the benefits of data mining maturity to optimize strategic decision-making in complex, knowledge-driven environments.

These results align with prior research on the importance of data mining maturity in decision-making processes, such as the studies by Yu et al., (2026), and Yilmaz et al., (2025), which found that higher levels of data analytics maturity led to improved business outcomes. However, this study distinguishes itself by explicitly assessing the mediating role of predictive analytics, which has often been overlooked in previous literature. While past studies primarily focused on the direct impact of data mining or predictive analytics separately, this research integrates both elements, providing a more comprehensive understanding of how data mining maturity enhances decision-making. The study's findings build upon and expand existing research by demonstrating that the interaction between data mining maturity and predictive analytics creates a more powerful mechanism for informed strategic decision-making in knowledge-intensive firms.

Figure 2. Strategic Decision Enhancement

The findings of this research suggest that the maturity of data mining systems is not merely a technological upgrade but a strategic enabler for improved decision-making. The positive correlation between data mining maturity and decision outcomes signals a shift towards more sophisticated and data-driven decision-making processes in knowledge-intensive firms. This result implies that organizations must invest in not only collecting data but also refining their data mining capabilities to reach higher levels of maturity. Furthermore, the significant role of predictive analytics in mediating the relationship between data mining maturity and strategic decisions highlights the importance of integrating predictive models and forecasting tools into decision-making frameworks (Yavuz et al., 2025). It also suggests that firms seeking to stay competitive in knowledge-intensive industries must prioritize building both their data mining maturity and predictive analytics capabilities to enhance long-term strategic decision-making.

The implications of these results are profound for firms striving to optimize their decision-making processes and gain a competitive advantage (Yang et al., 2024). Organizations that have not yet reached higher levels of data mining maturity should consider accelerating their data analytics initiatives, as this study demonstrates that the maturity of data mining systems has a direct impact on decision-making quality. The integration of predictive analytics into data mining practices can provide firms with the ability to anticipate market trends, optimize resource allocation, and identify opportunities and risks in real-time (Xia et al., 2026). Moreover, organizations can use these findings to justify further investment in data infrastructure and analytics tools. For industry leaders, the study offers a clear roadmap for how to leverage the combination of data mining maturity and predictive analytics to improve the speed and accuracy of strategic decisions, ultimately driving business success.

The results emerged because of the natural progression from data collection and analysis to the implementation of predictive analytics, which ultimately enhances decision-making capabilities (Riyadh et al., 2026). The strong relationship between data mining maturity and decision outcomes is a direct reflection of the increasing reliance on data-driven insights in strategic planning. Predictive analytics, with its ability to model future scenarios and forecast outcomes, adds a layer of sophistication to the decision-making process that traditional methods cannot match (Wang et al., 2026). This study's findings are grounded in the evolving recognition of data as a strategic asset and underscore the importance of data maturity in transforming that asset into a key driver of business performance. The emphasis on predictive analytics further underscores the growing significance of forecasting and scenario analysis in decision-making, highlighting a shift from reactive to proactive organizational strategies.

Looking forward, further research should explore the long-term impacts of data mining maturity on decision-making across different industries and organizational sizes. While this study focused on knowledge-intensive firms, other sectors may benefit from understanding how their own data maturity affects decision outcomes. Longitudinal studies could help capture the sustained effects of predictive analytics on organizational decision-making over time, particularly as firms continue to mature their data capabilities. Additionally, future research could examine the specific challenges associated with implementing predictive analytics in organizations at different stages of data mining maturity, shedding light on the obstacles to adoption and integration. Expanding the scope of this research to include cross-industry comparisons and deeper insights into the implementation process will enhance the understanding of how firms can optimize their data strategies for more effective and sustainable decision-making.

CONCLUSION

The most significant finding of this study is the identification of predictive analytics as a key mediating factor in the relationship between data mining maturity and strategic decision-making in knowledge-intensive firms. The study revealed that organizations with higher levels of data mining maturity were able to leverage predictive analytics more effectively, leading to improvements in decision quality, speed, and accuracy. This is a novel contribution to the literature, as prior research has typically focused on the direct effects of data mining or predictive analytics separately, without fully considering their interaction. By demonstrating the mediating role of predictive analytics, this research highlights how organizations can harness both data mining maturity and advanced analytics to optimize their decision-making processes and achieve better strategic outcomes.

This research adds substantial value to the existing body of literature by proposing a comprehensive framework that integrates data mining maturity and predictive analytics within the context of strategic decision-making. Previous studies have explored the individual components of data mining maturity and predictive analytics but have not sufficiently examined how their interplay contributes to decision-making effectiveness in knowledge-intensive firms. The methodological approach of this study, which combines survey data with statistical analysis, provides empirical evidence for the mediating role of predictive analytics and offers new insights into how organizations can strategically leverage data mining capabilities. This dual approach enriches the understanding of how data-driven decision-making can be systematically enhanced through the integration of both data mining systems and predictive models.

The limitations of this study include its cross-sectional design, which provides a snapshot of the relationship between data mining maturity, predictive analytics, and decision-making at a single point in time. Longitudinal research would be beneficial to assess the sustained impact of these variables on decision-making over time. Additionally, the study's focus on knowledge-

intensive firms may limit the generalizability of the findings to other types of organizations, such as manufacturing or retail. Future research could explore the role of data mining maturity and predictive analytics across different industries and organizational sizes to determine if these findings are universally applicable. Further investigation is also needed to examine the challenges organizations face in integrating predictive analytics with data mining systems, particularly for firms at lower levels of data maturity.

Future research should explore how the integration of emerging technologies, such as artificial intelligence and machine learning, interacts with data mining maturity and predictive analytics to further enhance decision-making processes. In particular, investigating how organizations at various stages of data mining maturity can adopt these advanced technologies could provide insights into how predictive analytics can evolve and drive even more precise decision-making capabilities. Additionally, examining the organizational culture and leadership factors that influence the successful implementation of predictive analytics in data-driven decision-making processes could reveal important barriers to adoption and potential areas for improvement. As data mining and predictive analytics continue to evolve, understanding their full potential and limitations in organizational decision-making will be critical for firms seeking to stay competitive in a data-driven world.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this manuscript, the author(s) used ImTranslator to assist in improving grammar, language quality, and overall readability of the text. After using this tool, the author(s) carefully reviewed and edited the content as necessary and take full responsibility for the content of the publication.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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