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THE INTEGRATION OF MATHEMATICS AND TECHNOLOGY IN *DATA-DRIVEN DECISION MAKING*: A LITERATURE REVIEW

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Abstract

Advances in digital technology have driven the transformation of decision-making from an intuition-based approach to a data-driven approach. The use of Artificial Intelligence (AI), Big Data Analytics, and predictive analytics is increasingly widespread across various sectors; however, most research still examines these technologies separately and has not yet fully integrated the role of mathematics as the conceptual foundation supporting the data-driven decision-making process. Therefore, this study aims to analyze the contributions of mathematics and technology in supporting sound decision-making through a synthesis of various recent studies. The study employs a literature review method by examining scientific journal articles, conference proceedings, and reports from international organizations published between 2021 and 2026. The literature was obtained through a systematic search, selected based on topic relevance, and then analyzed using content analysis techniques to identify themes, research trends, and conceptual relationships. The findings indicate that the application of mathematical methods—such as statistics, probability, optimization, and machine learning—combined with AI and Big Data Analytics technologies can improve prediction accuracy, operational efficiency, risk management, and the quality of decision-making in the healthcare, education, business, finance, and government sectors. However, their implementation still faces challenges related to data quality, algorithmic bias, privacy protection, and low data literacy. The research findings emphasize that strengthening mathematical literacy, data literacy, and responsible technology governance are essential prerequisites for realizing adaptive, transparent, and sustainable decision-making systems in the era of digital transformation.

INTRODUCTION

Digital technology have transformed the way humans generate, manage, and utilize information in various aspects of life. The Fourth Industrial Revolution, which has since evolved toward Society 5.0, is driving the integration of digital technology with economic activities, education, healthcare, government, and even the social lives of communities (Bousdekis et al., 2021). One of the primary consequences of this transformation is the increasing volume of data generated daily through digital devices, social media, *Internet of Things* (IoT) sensors, electronic transactions, and various organizational information systems. Data that previously served only as archives has now evolved into a strategic resource that determines the effectiveness of decision-making processes at both the individual and organizational levels (Di Battista et al., 2023).

This phenomenon has driven the emergence of the *data-driven decision-making* (DDDM) paradigm—an approach to decision-making based on empirical data analysis rather than intuition or experience alone (Elgendy et al., 2022). Within this paradigm, decisions are made through the processes of data collection, processing, analysis, and interpretation using mathematical approaches and computational technologies. Modern organizations increasingly rely on DDDM to improve the accuracy of predictions, optimize resource utilization, reduce uncertainty, and enhance operational efficiency (Hakami et al., 2025). Various studies show that organizations that systematically apply data analytics are better able to respond to environmental changes and develop evidence-based strategies compared to organizations that still rely on conventional approaches (Kim et al., 2025).

Technological advancements such as *Artificial Intelligence* (AI), *Machine Learning* (ML), *Big Data Analytics*, *Cloud Computing*, and *the Internet of Things* are accelerating this transformation. The integration of these technologies enables the processing of massive amounts of data at high speeds, resulting in more accurate and relevant information (Khan & Kribs, 2026). According to a World Economic Forum report (2025), competencies in data analysis, AI, and technological literacy will be among the most in-demand skills in the global job market in the coming years. This indicates that the ability to understand and process data is no longer exclusive to the field of information technology but has evolved into a cross-disciplinary competency that supports decision-making processes across various sector.

Behind these technological advancements, mathematics plays a fundamental role as the foundation for the development of various analytical methods. Statistics, probability, optimization, linear algebra, graph theory, and mathematical modeling are key components in the development of AI and *machine learning* algorithms (Janiesch et al., 2021). Through a mathematical approach, complex data can be transformed into models capable of recognizing patterns, making predictions, classifying objects, and even generating decision recommendations (Davenport & Harris, 2017). Thus, mathematics functions not only as a computational tool but also as a scientific language that enables technology to understand the relationships between variables within a system

The role of mathematics in modern technology has become increasingly evident through the application of generative AI, which has been rapidly evolving since 2023. Various organizations have begun to utilize AI to support processes ranging from document analysis, market demand forecasting, and *fraud detection* to disease diagnosis and strategic decision-making (Russell, 2010). In the healthcare sector, predictive models are used to help medical professionals identify disease risks based on patient histories (Basile et al., 2025). In the financial sector, mathematical algorithms are applied in credit risk assessment, investment analysis, and the detection of anomalous transactions (Abdullah et al., 2026). Meanwhile, the education sector has begun developing adaptive learning systems capable of analyzing student characteristics to provide more personalized learning recommendations (Akintolu & Oyekunle, 2025). These developments demonstrate that the integration of mathematics and technology has become a crucial foundation for supporting faster, more objective, and more accurate decision-making

Nevertheless, the implementation of data-driven decision-making is not without challenges. Poor data quality, algorithmic bias, a lack of transparency in AI models, personal data protection, and limited data literacy are factors that can affect the validity of the resulting decisions. Hakami et al., (2025) explain that the quality of analytical results is heavily influenced by the quality of the data used. Algorithms built using non-representative data have the potential to produce biased and less accountable decisions. Therefore, the development of analytical technology must be balanced with improvements in data governance, the strengthening of AI ethics, and the enhancement of human resource competencies (Rivai et al., 2017).

Research on the use of AI, *big data analytics*, and *machine learning* in decision-making has grown rapidly in recent years. Most research focuses on the implementation of these technologies in specific fields, such as healthcare, manufacturing, education, or business (Mikalef et al., 2019). On the other hand, studies that integrate mathematics as a conceptual foundation with the development of digital technology within the framework of *data-driven decision making* remain relatively limited. Previous research has tended to treat mathematics as part of computational methods, without comprehensively addressing its contribution to the process of transforming data into the basis for decision-making (Romero & Ventura, 2020). This gap highlights the need for a study capable of synthesizing the latest research findings to provide a more comprehensive understanding of the relationship between mathematics, technology, and data-driven decision-making.

Based on this discussion, this study aims to analyze how mathematics and technology integrate to support data-driven decision-making processes through a *literature review* approach. This study is expected to identify current research developments, explain the contribution of mathematical concepts to the development of analytical technologies, and outline the benefits and challenges of their implementation across various sectors. The research findings are expected to provide a conceptual contribution to the development of applied mathematics and data analytics, while also serving as a reference for academics, practitioners, and policymakers in building adaptive, transparent, and sustainable decision-making systems.

LITERATURE REVIEW

Mathematics as the Foundation of Data-Driven Decision Making

Mathematics is a discipline that forms the basis for the development of various data analysis methods and modern decision support systems. Concepts such as statistics, probability, optimization, linear algebra, graph theory, and mathematical modeling are used to construct models capable of describing relationships between variables and generating predictions that can be used in decision-making (Provost & Fawcett, 2013). In the digital age, the role of mathematics has evolved from merely a computational tool to a scientific framework that enables data to be processed systematically to generate meaningful information (Elgendy et al., 2022).

Advances in AI and *machine learning* have further solidified mathematics' position as the foundation of analytical technology. Machine learning algorithms utilize the principles of optimization, objective functions, probability theory, and statistical inference to learn patterns from data (Mourtzis, 2021). Oleh karena itu, kualitas model AI sangat dipengaruhi oleh ketepatan formulasi matematis yang digunakan dalam proses pelatihan maupun evaluasi model. Therefore, the quality of AI models is heavily influenced by the accuracy of the mathematical formulations used in both the training and evaluation processes. Thus, mathematics serves as a bridge connecting raw data to information that can be used as the basis for decision-making.

Data-Driven Decision Making

Data-Driven Decision Making is an approach that places data as the primary foundation for decision-making (Akintolu & Oyekunle, 2025). This approach integrates the processes of data collection, processing, analysis, interpretation, and the formulation of evidence-based recommendations. Elgendy et al., (2022) explain that DDDM is an evolution of traditional decision-making approaches which previously relied more heavily on experience and intuition. Through DDDM, organizations can enhance objectivity, accuracy, and efficiency in the decision-making process, enabling them to respond to environmental changes more adaptively.

Implementing DDDM requires not only adequate technology but also high-quality data and human resources capable of interpreting the results of the analysis. Therefore, the success of DDDM depends on the synergy between mathematical methods, digital technology, data governance, and user competencies (Lagzi et al., 2026).

Big Data Analytics dan Artificial Intelligence

Big Data Analytics is a technology that enables organizations to manage large-scale data characterized by *volume, velocity, variety, veracity,* and *value*. This technology allows for real-time analysis, thereby generating faster and more accurate information to support strategic decisions (Ouyang et al., 2022)

The integration of Big Data with AI results in an analytics system capable of making predictions, classifications, and anomaly detections, as well as providing automated decision recommendations. Hakami et al., (2025) demonstrate that the application *of machine learning* and Big Data Analytics can enhance the effectiveness of decision-making in the business, healthcare, manufacturing, and government sectors. However, the implementation of these technologies also faces challenges related to data quality, algorithmic bias, information security, and privacy protection—issues that must be addressed in the development of data-driven decision-making systems.

Implementation of Data Analysis Across Various Sectors

The application of data analysis based on mathematics and technology has expanded across various fields. In the healthcare sector, predictive models are used to assist in disease diagnosis, estimate patient risk, and support clinical decision-making (Basile et al., 2025). The application of data analysis based on mathematics and technology has expanded across various fields. In the healthcare sector, predictive models are used to assist in disease diagnosis, estimate patient risk, and support clinical decision-making(Maxim et al., 2025). In the industrial sector, predictive analytics are used to improve production efficiency, predict equipment failures (*predictive maintenance*), and optimize supply chains (Bousdekis et al., 2021).

In the field of education, AI and *learning analytics* are beginning to be used to monitor student progress, provide adaptive learning recommendations, and support academic decision-making (Ouyang et al., 2022). Meanwhile Akintolu & Oyekunle, (2025) explain that the use of AI in *learning analytics* can improve the effectiveness of the learning process by identifying learning needs more accurately. These findings demonstrate that the use of data analysis has expanded across disciplines and has become an integral part of modern decision-making.

RESEARCH METHODOLOGY

Type of Research

This study employs a literature review approach, a research method aimed at identifying, examining, comparing, and synthesizing the results of previous studies on the integration of mathematics and technology in *Data-Driven Decision Making* (DDDM) (Hötte et al., 2023). Through this approach, the researcher gains a comprehensive overview of research developments, the approaches used, and the key findings related to the application of mathematical methods and digital technology in supporting data-driven decision-making.

A literature review is a research method that systematically collects and evaluates various scientific publications to generate a deeper understanding of a research topic. This method not only summarizes previous research findings but also identifies research trends, *research gaps*, and opportunities for future research (Enholm et al., 2022).

Data Sources

This study uses secondary data obtained from international scientific articles published in reputable journals. The articles were sourced from scientific databases such as Scopus, ScienceDirect, SpringerLink, IEEE Xplore, MDPI, Emerald Insight, Wiley Online Library, and Taylor & Francis.

The study focused on articles discussing the relationship between mathematical methods, digital technology, and their application in *data-driven decision making* across various fields, such as industry, healthcare, education, finance, manufacturing, and information systems.

Literature Criteria

Articles were selected based on several inclusion criteria, including : the article was published between 2022 and 2026; the article appeared in a reputable international journal and underwent a *peer-review* process; and the article addressed one or more of the following topics*: Data-Driven Decision Making; Artificial Intelligence; Machine Learning; Big Data Analytics; Support Systems; and Multi-Criteria Decision Making* (MCDM). Meanwhile, articles in the form of editorials, short proceedings, opinion pieces, or articles not directly related to the research theme were excluded from the selection process.

Data Collection Methods

Data collection was conducted through a systematic literature search across various scientific databases, including Google Scholar, Scopus, ScienceDirect, SpringerLink, IEEE Xplore, and Taylor & Francis Online, as well as official reports from international organizations such as *the World Economic Forum* (WEF) and the OECD. The search was conducted using a combination of keywords, including *mathematics*, *data-driven decision making*, *Big Data Analytics*, *Artificial Intelligence*, *machine learning*, *predictive analytics*, and *digital transformation*.

All retrieved literature was then screened based on the relevance of the title, abstract, article content, year of publication, and its relevance to the research objectives. Literature meeting the criteria was subsequently organized using reference management software to facilitate the classification and citation process during article preparation.

Data Analysis Techniques

Data analysis was conducted using *content analysis* techniques through several stages. The first stage involved a thorough reading of each piece of literature that met the selection criteria. The second stage involved identifying key information relevant to the research objectives, including the mathematical concepts used, the technologies applied, the areas of implementation, the benefits, and the challenges in data-driven decision-making.

RESULT AND DISCUSION

Selection Result and Charateristics of the Literature

This study reviewed scientific articles discussing the integration of mathematical and technological approaches to support *Data-Driven Decision Making* (DDDM). Based on the process of identifying, screening, and evaluating the literature using a Literature Review approach, a number of articles were identified that met the inclusion criteria and were relevant to the research objectives.

The analyzed literature was sourced from reputable international journals published between 2022 and 2026. These articles covered various fields of study, such as *mathematical optimization*, *artificial intelligence*, *machine learning*, *big data analytics*, *decision support systems*, *fuzzy decision making*, and the application of DDDM in the manufacturing, healthcare, education, and information systems sectors.

Table 1. Characteristics of the Analyzed Literature

No	Author (Year)	Research Focus	Method/Approach	Key Findings
1	(Baardman et al., 2022)	Optimization in DDDM	Mathematical Optimization Review	Improves decision quality through the integration of predictive models and decision s
2	(Basile et al., 2025)	Data analytics in healthcare	Systematic Literature Review	Data analytics supports evidence-based decision-making through the use of AI and statistics
3	(Romero & Ventura, 2020)	Educational Data Mining	Survey Literature	Machine learning and statistical analysis help generate data-driven educational decisions
4	(Abdullah et al., 2026)	Fuzzy Decision Making	Systematic Review	Fuzzy methods are effective in handling uncertainty in the decision-making process
5	(Khan & Kribs, 2026)	Smart Manufacturing Analytics	Literature Review	The integration of IoT, AI, and optimization improves operational efficiency

No	Author (Year)	Research Focus	Method/Approach	Key Findings
6	(Luo et al., 2026)	Human-AI Decision Making	Research Review	Human-AI collaboration leads to more adaptive decisions
7	(Thelen et al., 2022)	Digital Twin Technology	Review Article	Digital twins combine mathematical simulations and digital technology for prediction
8	(Nikçi et al., 2026)	Stages of DDDM	Comparative Review	DDDM consists of processes ranging from data collection to decision evaluation
9	(Chatterjee & Dethlefs, 2021)	AI Predictive Analytics	Scientometric Review	AI can enhance predictive capabilities in decision-making
10	(Simelane & Kittur, 2026)	AI Chatbot Decision Support	Literature Review	Generative AI is emerging as a decision-support tool
11	(Lagzi et al., 2026)	DDDM Trends	Bibliometric Review	DDDM research is advancing through the integration of AI, data analytics, and quantitative methods
12	(Hötte et al., 2023)	Technology and Decision-Making	Systematic Review	Digital technology is transforming organizational decision-making processes

The Role of Mathematical Approaches in *Data-Driven Decision Making*

The results of the study indicate that mathematics plays a fundamental role in building data-driven decision-making systems. Mathematical approaches are not only used as analytical tools but also as mechanisms to optimize decisions derived from available data.

(Baardman et al., 2022) explain that the development of modern DDDM has shifted from a *predictive analytics* approach to a *prescriptive analytics* approach. In this approach, mathematical models are used to determine the best decision alternatives based on predictions obtained through artificial intelligence technology.

One widely used approach is *mathematical optimization*, such as *linear programming*, *integer programming*, and *stochastic optimization*. These methods enable organizations to determine optimal solutions while taking into account various constraints present in the decision-making environment.

In addition to optimization, *Multi-Criteria Decision Making* (MCDM) methods also play a significant role in data-driven decision-making. Abdullah dkk., (2026) decision-making, particularly when the available information is not entirely numerical.

Thus, mathematics serves as an analytical foundation that transforms raw data into strategic information through the processes of modeling, evaluating alternatives, and optimizing decisions.

The Role of Digital Technology in Supporting Data-Driven Decision-Making

Advances in digital technology have brought significant changes to organizational decision-making mechanisms. Based on a review of the literature, technologies such as Artificial Intelligence (AI), Machine Learning (ML), and Big Data Analytics have become key factors in enhancing organizations' ability to process information quickly and accurately.

Lagzi dkk., (2026) Lagzi et al. (2026)indicate that the development of DDDM research in recent years has been heavily influenced by the increasing use of data analytics technologies. Large volumes of data (*big data*) can be processed using machine learning algorithms to identify patterns, make predictions, and provide decision recommendations.

Romero & Ventura (2020)demonstrate that the application of *data mining* and *machine learning* can generate predictive information that helps decision-makers understand behavioral patterns and plan more effectively.

Furthermore, *artificial intelligence* (*AI)* technology has evolved into *decision support* systems *(DSS*) capable of providing automated recommendations. Luo dkk., (2026) Luo et al. (2026)explain that the concept *of human-AI collaboration* has emerged as a new paradigm by combining machines' analytical capabilities with humans' interpretive abilities.

This demonstrates that technology no longer functions merely as a data-processing tool but has evolved into a strategic component of the decision-making process.

Integration of Mathematics and Technology in Data-Driven Decision Making

Based on the literature review, the integration of mathematics and technology is a key element in the development of modern data-driven decision making (DDDM). Technology provides the capability to collect, store, and analyze data on a large scale , while mathematics provides methods for optimization and determining the best decisions.

This concept of integration is evident in the *"predict-and-optimize"* approach—a model that combines machine learning algorithms for prediction with mathematical optimization methods to determine optimal decisions (Baardman et al., 2022).

For example, in the manufacturing sector, (Khan & Kribs, 2026)explain that the combination of IoT, big data analytics, and optimization models can improve production efficiency by predicting machine breakdowns and optimally allocating resources.

In the healthcare sector, Basile et al. (2025) found that the integration of statistical analysis, artificial intelligence, and health information systems enables faster, evidence-based clinical decision-making.

Meanwhile, Thelen et al. (2022) demonstrate that *digital twin* technology is a concrete example of the integration of mathematics and technology, as it combines mathematical simulations with real-time data to predict and evaluate various decision possibilities.

Based on these findings, it can be concluded that mathematics and technology have a complementary relationship. Technology without a mathematical approach merely generates information, whereas mathematics without technological support has limitations in processing large amounts of complex data.

Challenges and Research Gaps in the Implementation of Data-Driven Decision Making

Although the integration of mathematics and technology offers various benefits, several studies indicate that there are still a number of challenges in its implementation. First, data quality issues are a major factor affecting decision accuracy. Incomplete, inconsistent, or biased data can cause analytical models to produce suboptimal decisions.

Second, the complexity of mathematical models and AI algorithms poses a challenge for organizations in understanding the decision-making process. According to Luo et al. (2026), the need for more transparent AI models (*explainable AI*) is increasing because users require an understanding of the reasoning behind a decision recommendation. Third, the integration of technological systems and human capabilities remains a critical issue. The use of technology must take into account human interpretation, ethics, data security, and organizational readiness.

Based on the literature review, future research could focus on developing hybrid models that combine the strengths of AI, mathematical methods, and human capabilities to produce decision-making systems that are more adaptive, transparent, and sustainable.

Synthesis of Research Findings

Overall, the results of the literature review indicate that the integration of mathematics and technology has become the primary paradigm in the development of *Data-Driven Decision Making*. Mathematical approaches play a role in building analytical and optimization models, while digital technology provides the infrastructure for rapid, large-scale data processing. Recent developments indicate a shift from mere data analysis toward the concept *of intelligent decision-making*—systems capable of predicting, providing recommendations, and automatically optimizing decisions.

Thus, the integration of mathematics and technology not only enhances the effectiveness of decision-making but also opens up opportunities for the development of more accurate, adaptive, and evidence-based decision-making systems across various sectors.

CONCLUSION

Based on the results of *a Systematic Literature Review* on the integration of mathematics and technology in *Data-Driven Decision Making* (DDDM), it can be concluded that the combination of mathematical approaches and digital technology plays a crucial role in improving the quality of decision-making to be more accurate, objective, and adaptive. Mathematical methods such as optimization, statistics, and *Multi-Criteria Decision Making* (MCDM) serve as the analytical foundation for generating optimal solutions, while technologies such as *Artificial Intelligence* (AI), *Machine Learning* (ML), and *Big Data Analytics* support more effective data processing and interpretation. The integration of these two elements indicates a paradigm shift from experience-based decision-making toward evidence-based *decision-making*.

In practical terms, this study implies that organizations need to develop decision-making systems that combine mathematical analytical capabilities with digital technology, accompanied by improved data literacy and human resource readiness. However, this study has limitations because it uses only a literature review approach and thus has not tested the direct implementation of the integration of mathematics and technology in specific sectors. Furthermore, the scope of the literature reviewed is still limited to articles available within a specific timeframe and database. Therefore, future research is recommended to employ empirical approaches, *meta-analyses*, or *bibliometric analyses*, as well as to examine the application of DDDM more specifically across various sectors such as industry, healthcare, education, and finance. Future research should also explore the development of AI-based decision-making systems that are more transparent, adaptive, and take ethical considerations into account regarding data utilization.

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BIBLIOGRAPHY

Abdullah, L., Rahim, S. N., & Awang, N. A. (2026). Fuzzy set-based decision-making methods in business management and finance research: a systematic literature review. *Future Business Journal*, *12*(1), 184.

Akintolu, M., & Oyekunle, A. A. (2025). Data-Driven Decision-Making: Utilising AI-Powered Learning Analytics to Make Informed Primary Educators' Decisions. *Journal of Educators Online*, *22*(3), n3.

Baardman, L., Cristian, R., Perakis, G., Singhvi, D., Skali Lami, O., & Thayaparan, L. (2022). *The role of optimization in some recent advances in data-driven decision-making*.

Basile, L. J., Carbonara, N., Panniello, U., & Pellegrino, R. (2025). The exploitation of data to support decision-making in healthcare: A systematic literature review and future research directions. *Management Review Quarterly*, 1–33.

Bousdekis, A., Lepenioti, K., Apostolou, D., & Mentzas, G. (2021). A review of data-driven decision-making methods for industry 4.0 maintenance applications. *Electronics*, *10*(7), 828.

Chatterjee, J., & Dethlefs, N. (2021). Scientometric review of artificial intelligence for operations & maintenance of wind turbines: The past, present and future. *Renewable and Sustainable Energy Reviews*, *144*, 111051.

Davenport, T., & Harris, J. (2017). *Competing on analytics: Updated, with a new introduction: The new science of winning*. Harvard Business Press.

Di Battista, A., Grayling, S., Hasselaar, E., Leopold, T., Li, R., Rayner, M., & Zahidi, S. (2023). Future of jobs report 2023. *World Economic Forum*, 972–978.

Elgendy, N., Elragal, A., & Päivärinta, T. (2022). DECAS: a modern data-driven decision theory for big data and analytics. *Journal of Decision Systems*, *31*(4), 337–373.

Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial intelligence and business value: A literature review. *Information Systems Frontiers*, *24*(5), 1709–1734.

Hakami, T. A., Alginahi, Y. M., & Sabri, O. (2025). Exploring the Evolution of Big Data Technologies: A Systematic Literature Review of Trends, Challenges, and Future Directions. *Future Internet*, *17*(9).

Hötte, K., Somers, M., & Theodorakopoulos, A. (2023). Technology and jobs: A systematic literature review. *Technological Forecasting and Social Change*, *194*, 122750.

Janiesch, C., Zschech, P., & Heinrich, K. (2021). Machine learning and deep learning: C. Janiesch et al. *Electronic Markets*, *31*(3), 685–695.

Khan, C. N., & Kribs, J. D. (2026). Data-Driven Analytics in Smart Manufacturing: A

Review of Methods, Applications, and Adoption Constraints. *The International Journal of Advanced Manufacturing Technology*, 1–16.
Kim, J., Chang, H., & Bell, B. S. (2025). Organizational-level training and performance: A meta-analytic investigation. *Journal of Management*, 01492063251327588.
Lagzi, M. D., Farkhondeh, F., Amoozad Mahdiraji, H., & Sakka, G. (2026). Exploring data-driven decision-making practices: a comprehensive review with bibliometric insights and future directions. *EuroMed Journal of Business*, *21*(2), 728–762.
Luo, Y., Hao, Y., Gong, H., & Li, B. (2026). Applications of human-machine collaborative decision-making: A review of research with recent developments. *IScience*, *29*(6).
Maxim, H., Eni, Y., & Karmawan, I. G. (2025). The Influence of Digital Financial Literacy, Financial Attitudes, and Financial Knowledge on Financial Behavior of Generation Z in Greater Jakarta Through Financial Technology. *Financial Attitudes, and Financial Knowledge on Financial Behavior of Generation Z in Greater Jakarta Through Financial Technology*.
Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big data analytics capabilities and innovation: the mediating role of dynamic capabilities and moderating effect of the environment. *British Journal of Management*, *30*(2), 272–298.
Mourtzis, D. (2021). Towards the 5th industrial revolution: A literature review and a framework for process optimization based on big data analytics and semantics. *Journal of Machine Engineering*, *21*(3), 5–39.
Nikçi, L. L., Ibrahimi, A., Dermaku, A., & Ahmedi, B. (2026). A Comparative Literature Review of Data-Driven Decision-Making Phases in Information Systems: Toward an Integrated Six-Phase Framework. *International Journal of Innovative Technology and Interdisciplinary Sciences*, *9*(2), 942–980.
Ouyang, F., Zheng, L., & Jiao, P. (2022). Artificial intelligence in online higher education: A systematic review of empirical research from 2011 to 2020. *Education and Information Technologies*, *27*(6), 7893–7925.
Provost, F., & Fawcett, T. (2013). *Data Science for Business: What you need to know about data mining and data-analytic thinking*. ‘ O’Reilly Media, Inc.’
Rivai, A., Suharto, D., & Ali, H. (2017). Organizational performance analysis: Loyalty predictors are mediated by work motivation at urban village in Bekasi City. *International Journal of Economic Research*, *14*(3/4), 441–452.
Romero, C., & Ventura, S. (2020). Educational data mining and learning analytics: An updated survey. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *10*(3), e1355.
Russell, S. J. (2010). *Artificial intelligence a modern approach*. Pearson Education, Inc.
Simelane, P. M., & Kittur, J. (2026). Leveraging chatbots for enhanced decision-making: a comprehensive literature review. *Frontiers in Artificial Intelligence*, *9*, 1748544.
Thelen, A., Zhang, X., Fink, O., Lu, Y., Ghosh, S., Youn, B. D., Todd, M. D., Mahadevan, S., Hu, C., & Hu, Z. (2022). A comprehensive review of digital twin—part 1: modeling and twinning enabling technologies. *Structural and Multidisciplinary Optimization*, *65*(12), 354.