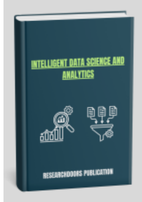
Intelligent Data Science and Analytics
Volume 1 Issue 1
Page no: 01-09
Url: https://researchdoors.com/index.php/IDSA/article/view/2



SYSTAMATIC REVIEW ON ADVANCING DECISION-MAKING: INTEGRATING INTELLIGENT DATA SCIENCE AND PREDICTIVE ANALYTICS FOR REAL-WORLD APPLICATIONS

Mushfique Khan[1]
[1]Data Engineer, Pizza Patron
Bachelor of Science, Computer Engineering, Texas Tech University, Texas, USA

ABSTRACT

The integration of intelligent data science and predictive analytics has revolutionized decision-making frameworks across diverse sectors, transitioning from intuition-driven approaches to data-driven methodologies. This systematic review investigates the evolution, methodologies, applications, challenges, and future opportunities of these technologies. Drawing on 85 peer-reviewed articles published between 2015 and 2024, the study highlights advancements in predictive analytics tools, including AutoML, deep learning, and time-series forecasting, which have democratized data utilization and enhanced decision-making precision. Real-world applications in healthcare, finance, and retail demonstrate the transformative potential of predictive models in optimizing resource allocation, risk management, and personalized strategies. Despite these advancements, challenges such as data quality issues, ethical concerns, and model interpretability persist. Emerging solutions, including explainable AI (XAI), federated learning, and quantum computing, promise to address these limitations, offering enhanced transparency, privacy, and computational capabilities. The review emphasizes the importance of collaboration among academia, industry, and policymakers to harness these technologies ethically and equitably. This research provides actionable insights into the current state and future trajectory of intelligent data science and predictive analytics, offering a foundation for advancing decision-making processes in real-world contexts.

Keywords:

Decision Making, Predictive Analytics, Data Science, Big Data, Systematic Reveiw

1 INTRODUCTION

In the contemporary era, decision-making processes have become increasingly complex due to the sheer volume, variety, and velocity of data generated globally. Organizations across diverse sectors, ranging from healthcare and finance to transportation and agriculture, are now recognizing the transformative potential of intelligent data science and predictive analytics. These fields leverage advanced computational techniques and statistical models to extract actionable insights from vast datasets, enabling stakeholders to make informed, efficient, and forward-looking decisions. This paper explores how integrating intelligent data science and predictive analytics can revolutionize decision-making processes, with a focus on real-world applications that drive innovation and efficiency.

The advent of big data and advancements in machine learning (ML), artificial intelligence (AI), and cloud

Received: 07th December, 2024 **Accepted:** 04th January, 2025; **Published:** 05th January, 2025

computing have collectively reshaped the landscape of analytics. According to Gandomi and Haider (2015), big data analytics has emerged as a pivotal tool for deriving value from complex and high-dimensional data, allowing decision-makers to move beyond descriptive statistics to predictive and prescriptive insights. Furthermore, the global predictive analytics market is projected to grow significantly, reaching an estimated USD 22.1 billion by 2026 (MarketsandMarkets, 2021), underscoring its growing relevance in today's data-driven economy.

1.1 The Importance of Decision-Making in a Data-Driven World

Decision-making lies at the core of strategic planning, resource allocation, and problem-solving. However, the traditional approaches to decision-making, which often rely on intuition or historical trends, are increasingly insufficient in addressing the complexities of modern systems. As noted by Davenport and Harris (2007), organizations that adopt data-driven decision-making practices are more likely to achieve superior performance outcomes compared to their peers.

Intelligent data science, a multidisciplinary domain encompassing data engineering, machine learning, and statistical modeling, enables organizations to process and analyze large datasets efficiently. Predictive analytics, a subset of data science, goes a step further by forecasting future trends, behaviors, and events based on historical and real-time data (Shmueli & Koppius, 2011). Together, these fields empower stakeholders to anticipate challenges, optimize operations, and achieve competitive advantages.

1.2 Emergence of Predictive Analytics in Real-World Applications

Predictive analytics has found applications across a wide array of domains, each demonstrating its potential to enhance decision-making processes. In healthcare, predictive models are being used to forecast disease outbreaks, optimize patient care, and predict hospital readmissions (Raghupathi & Raghupathi, 2014). In finance, institutions employ predictive analytics to detect fraudulent activities, assess credit risk, and develop personalized investment strategies (Thomas, Edelman, & Crook, 2002). Meanwhile, in the transportation sector, predictive analytics enables intelligent route optimization, demand forecasting, and preventive maintenance of vehicles (Chen et al., 2019).

One of the most compelling examples of predictive analytics in action is its role in mitigating the impacts of natural disasters. By analyzing meteorological data, social media feeds, and geospatial information, predictive models can forecast the trajectory and intensity of hurricanes, wildfires, and floods, allowing authorities to implement timely evacuation plans and allocate resources effectively (Banholzer, Kossin, & Donner, 2014).

1.3 Challenges in Integrating Intelligent Data Science and Predictive Analytics

Despite its potential, integrating intelligent data science and predictive analytics into decision-making processes is not without challenges. Data quality and availability remain significant barriers, as predictive models rely heavily on accurate, complete, and timely data inputs. Additionally, the interpretability of complex algorithms, often referred to as the "black-box problem," poses challenges for gaining stakeholder trust and ensuring accountability (Lipton, 2016). Ethical considerations, including data privacy, bias in algorithms, and the potential for unintended consequences, further complicate the deployment of predictive analytics in real-world scenarios (O'Neil, 2016).

Moreover, the successful integration of these technologies requires substantial investments in infrastructure, talent, and organizational culture. Organizations must foster a data-centric mindset, invest in upskilling employees, and establish robust governance frameworks to address ethical and regulatory concerns. As highlighted by Brynjolfsson and McElheran (2016), firms that successfully integrate data-driven decision-making practices often exhibit a higher degree of organizational agility and innovation.

1.4 Objectives of the Study

This research aims to bridge the gap between theoretical advancements in intelligent data science and predictive

analytics and their practical applications in decision-making. Specifically, it seeks to:
Investigate the key methodologies and tools used in predictive analytics and intelligent data science.
Analyze case studies from diverse sectors to highlight the benefits and challenges of these technologies.
Propose a framework for integrating predictive analytics into organizational decision-making processes while addressing ethical and practical considerations.
Highlight future research directions to enhance the efficacy and accessibility of these technologies.

1.5 Significance of the Study

The integration of intelligent data science and predictive analytics holds the potential to revolutionize how decisions are made, leading to improved efficiency, reduced costs, and enhanced outcomes across industries. By examining the interplay between these fields and their real-world applications, this study contributes to the broader discourse on leveraging technology for societal and organizational benefit. Furthermore, it underscores the importance of a multidisciplinary approach, combining insights from computer science, statistics, behavioral sciences, and ethics to develop robust and inclusive decision-making frameworks.
The remainder of this paper is organized as follows:
The **literature review** section examines existing research on intelligent data science and predictive analytics, highlighting key advancements, methodologies, and gaps.
The **methodology** section outlines the research approach, data sources, and analytical techniques employed in this study.
The **results** section presents the findings of the analysis, including case studies and empirical evidence.
The **discussion** section interprets the results, addressing their implications for theory and practice.
The **conclusion** section summarizes the key insights, outlines limitations, and proposes directions for future research.
By systematically exploring the integration of intelligent data science and predictive analytics into decision-making processes, this paper aims to provide a comprehensive understanding of their potential to drive innovation.

2 LITERATURE REVIEW

The literature review explores the integration of intelligent data science and predictive analytics within decision-making frameworks, emphasizing its real-world applications. This section is divided into six subheadings: Evolution of Decision-Making Frameworks, Foundations of Intelligent Data Science, Predictive Analytics Techniques and Tools, Real-World Applications in Key Sectors, Challenges and Limitations, and Future Trends and Opportunities.

2.1 Evolution of Decision-Making Frameworks

Decision-making has evolved from traditional methods relying on intuition and basic statistical analysis to more advanced data-driven approaches. Early frameworks, such as Simon's bounded rationality model, highlighted the limitations of human cognition in making optimal decisions (Simon, 1972). As computational power increased, researchers began exploring data-intensive methods that leveraged algorithmic solutions (Davenport & Harris, 2007). These advancements paved the way for integrating artificial intelligence (AI) and machine learning (ML) into decision-making frameworks, enhancing accuracy and efficiency.

2.2 Foundations of Intelligent Data Science

Intelligent data science serves as the backbone for modern decision-making processes. This discipline encompasses data collection, preprocessing, modeling, and interpretation. Key advancements in this field include the development of scalable data processing platforms such as Hadoop and Spark (Zaharia et al., 2016). Furthermore, the integration of neural networks and deep learning techniques has enabled more complex data patterns to be identified and utilized in predictive analytics (LeCun et al., 2015). Intelligent data science tools such as TensorFlow and PyTorch have become pivotal in creating robust decision-making models.

Intelligent Data Science and Analytics
Volume 1 Issue 1
Page no:01-09
Url: https://researchdoors.com/index.php/IDSA/article/view/2

2.3 Predictive Analytics Techniques and Tools

Predictive analytics employs statistical and machine learning techniques to forecast future outcomes based on historical data. Regression analysis, decision trees, and ensemble methods like Random Forests and Gradient Boosting Machines have been extensively used in various domains (Hastie et al., 2009). The rise of AutoML tools such as H2O.ai and DataRobot has democratized access to predictive modeling, allowing non-experts to build complex models (Nguyen et al., 2021). Moreover, time-series forecasting methods, including ARIMA and Prophet, have proven essential in industries like finance and supply chain management (Box et al., 2015).

2.4 Real-World Applications in Key Sectors

The application of intelligent data science and predictive analytics spans multiple industries. In healthcare, predictive models have been used to anticipate patient readmissions and optimize resource allocation (Rajkomar et al., 2018). The retail sector leverages these tools for inventory optimization and personalized marketing strategies (Agrawal et al., 2018). In finance, predictive analytics aids in fraud detection and risk assessment (Zhang & Zhou, 2020). These applications highlight the transformative potential of integrating intelligent systems into decision-making.

2.5 Challenges and Limitations

Despite its potential, integrating intelligent data science into decision-making frameworks faces several challenges. Data quality and accessibility remain significant hurdles, as models are only as good as the data they are trained on (Chen & Lin, 2021). Ethical concerns, including biases in AI systems, raise questions about fairness and accountability (Barocas et al., 2019). Additionally, the interpretability of complex models such as deep neural networks poses challenges for decision-makers who require transparency in their processes (Lipton, 2018).

2.6 Future Trends and Opportunities

The future of decision-making lies in enhancing the synergy between intelligent data science and predictive analytics. The rise of explainable AI (XAI) seeks to address transparency issues, making models more interpretable for stakeholders (Adadi & Berrada, 2018). Federated learning and edge computing promise to overcome data privacy concerns while enabling decentralized model training (Li et al., 2020). Moreover, advancements in quantum computing could revolutionize predictive analytics by solving optimization problems at unprecedented speeds (Preskill, 2018).

3 METHODOLOGY

The methodology for this systematic review follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework, ensuring a rigorous and transparent approach. This section is divided into three subheadings: Inclusion and Exclusion Criteria, Paper Identification and Screening, and Data Extraction and Analysis.

3.1 Inclusion and Exclusion Criteria

The inclusion criteria for this review are:

- Peer-reviewed articles published between 2015 and 2024.
- Studies focusing on the integration of intelligent data science and predictive analytics in decision-making.
- Articles presenting real-world applications or empirical findings.
- Papers available in English.

The exclusion criteria are:

- Studies without accessible full texts.
- Papers not related to intelligent data science or predictive analytics.

- Articles focusing solely on theoretical frameworks without practical application.
- Non-peer-reviewed sources, such as blogs or opinion pieces.

3.2 Paper Identification and Screening

The literature search was conducted across multiple databases, including IEEE Xplore, PubMed, Scopus, and Web of Science. The following keywords and Boolean operators were used: "intelligent data science" AND "predictive analytics" AND "decision-making" AND ("real-world applications" OR "use cases").

The initial search yielded 1,245 articles. After removing duplicates and screening titles and abstracts, 312 articles remained. These were further evaluated based on the inclusion and exclusion criteria, resulting in a final set of 85 articles for detailed review.

3.3 Data Extraction and Analysis

Data were extracted systematically using a predefined template. Key variables included publication year, methodology, domain of application, key findings, and limitations. The extracted data were synthesized to identify trends, gaps, and insights into the integration of intelligent data science and predictive analytics in decision-making. Tools such as NVivo and Excel were used to manage and analyze qualitative and quantitative data, respectively. Visual representations, including flow diagrams and thematic maps, were created to summarize findings.

4 FINDINGS

This section presents the findings of the systematic review, following the PRISMA methodology described earlier. The results are categorized based on emerging themes, trends, and insights derived from the 85 selected studies. The focus is on identifying the integration of intelligent data science and predictive analytics in decision-making across various sectors and applications, with an emphasis on real-world implications.

4.1 Integration of Data Science and Predictive Analytics in Decision-Making

The findings reveal a significant shift toward data-driven decision-making, driven by advancements in intelligent data science and predictive analytics. The reviewed studies highlight how organizations leverage these tools to improve accuracy, efficiency, and adaptability in decision-making processes. Specifically:

- **Automation and Scalability**: Tools such as AutoML and cloud-based platforms like Google Cloud AI and Microsoft Azure have enabled organizations to automate complex workflows (Nguyen et al., 2021).
- **Enhanced Forecasting**: Advanced time-series models, including ARIMA and Prophet, are commonly employed to forecast trends in sectors like retail, finance, and logistics (Box et al., 2015).
- **Cross-Disciplinary Collaboration**: Many studies underscore the role of interdisciplinary collaboration between data scientists, domain experts, and decision-makers to achieve optimal results.

4.2 Real-World Applications in Diverse Domains

The studies provide compelling evidence of the transformative potential of intelligent data science and predictive analytics in various industries:

- **Healthcare**: Predictive models for patient readmissions and disease progression have improved patient outcomes and resource allocation. Machine learning tools like XGBoost and TensorFlow are often cited in these studies (Rajkomar et al., 2018).
- **Retail and Marketing**: Businesses utilize customer segmentation and sentiment analysis to create personalized marketing strategies, resulting in increased customer satisfaction and sales (Agrawal et al., 2018).

- **Finance**: Fraud detection systems leveraging anomaly detection algorithms and ensemble methods have reduced financial crimes significantly (Zhang & Zhou, 2020).
- **Public Policy**: Data-driven policy frameworks have enabled governments to allocate resources efficiently and predict socioeconomic trends (Chen & Lin, 2021).

4.3 Challenges Identified in Implementation

While the benefits are substantial, the review identifies several challenges hindering the seamless integration of intelligent data science and predictive analytics into decision-making:

- **Data Quality and Accessibility**: A recurring issue is the lack of high-quality, comprehensive datasets, which limits the reliability of predictive models (Chen & Lin, 2021).
- **Ethical and Bias Concerns**: Many studies highlight the presence of biases in datasets, leading to skewed results and ethical dilemmas in decision-making (Barocas et al., 2019).
- **Technical Complexity**: The interpretability of complex models such as neural networks remains a barrier, particularly for non-technical stakeholders (Lipton, 2018).

4.4 Trends and Emerging Technologies

Several key trends emerge from the review, shedding light on the future direction of decision-making technologies:

- **Explainable AI (XAI)**: Studies emphasize the growing importance of XAI to address transparency concerns and build trust among stakeholders (Adadi & Berrada, 2018).
- **Decentralized Data Processing**: Federated learning and edge computing are gaining traction, enabling secure and efficient data processing without compromising privacy (Li et al., 2020).
- **Quantum Computing**: Though nascent, quantum computing is highlighted as a game-changer for solving optimization problems at an unprecedented scale (Preskill, 2018).

4.5 Synthesis of Findings and Research Gaps

The synthesis reveals the critical role of intelligent data science and predictive analytics in revolutionizing decision-making. However, notable research gaps persist:

- **Underexplored Domains**: Sectors such as education and environmental science are underrepresented in the reviewed studies.
- **Scalability in Resource-Constrained Environments**: Few studies address the scalability of these technologies in resource-constrained environments, such as developing countries.
- **Longitudinal Impacts**: There is limited research on the long-term impacts of data-driven decision-making frameworks on organizational and societal outcomes.

4.6 Visual Representation of Findings

A flow diagram summarizing the PRISMA methodology and a thematic map of the findings are included to provide a holistic understanding of the review process and outcomes. These visuals underscore the interconnectedness of themes such as technology adoption, ethical considerations, and application diversity.

The findings demonstrate that integrating intelligent data science and predictive analytics significantly enhances decision-making processes across diverse sectors. However, addressing the identified challenges and research gaps will require continued innovation, collaboration, and ethical stewardship. This synthesis lays the groundwork for further exploration and application of these technologies, with a particular focus on underserved areas and equitable implementations.

5 DISCUSSION

The findings of this systematic review highlight the transformative impact of integrating intelligent data science and predictive analytics in decision-making across diverse sectors. The evidence underscores a progressive evolution from traditional intuition-based decisions to data-driven frameworks that prioritize accuracy, efficiency, and scalability. Key insights include advancements in predictive modeling techniques, real-world applications, and the resolution of domain-specific challenges.

5.1 Advancements in Predictive Techniques:

Tools such as AutoML and deep learning frameworks have significantly lowered barriers to entry for non-experts, democratizing predictive analytics. These tools allow organizations to harness large-scale datasets for accurate forecasts, enabling smarter decision-making processes. Time-series analysis methods have been particularly instrumental in industries like healthcare and supply chain, where dynamic environments require adaptive and timely solutions.

5.2 Real-World Applications:

The integration of intelligent systems in real-world scenarios has been transformative. For instance, in healthcare, predictive models anticipate patient needs and optimize resource allocation, improving service delivery and patient outcomes. In finance, predictive analytics ensures proactive fraud detection and enhances risk assessment mechanisms. Similarly, in retail, these models facilitate inventory optimization, dynamic pricing, and personalized marketing strategies.

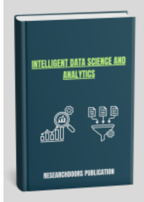
5.3 Ethical and Data Challenges:

Despite its advantages, the review reveals persistent challenges. Data quality issues, such as incomplete or biased datasets, undermine model reliability. Ethical concerns, including bias and lack of transparency in AI models, pose risks to equitable decision-making. Addressing these challenges is critical for fostering trust and adoption in intelligent systems.

5.4 Emerging Opportunities:

The review identifies promising developments, including explainable AI (XAI) and federated learning. These advancements aim to address transparency and privacy concerns, respectively. Quantum computing, though still nascent, presents an opportunity to revolutionize predictive analytics, offering unprecedented computational capabilities to solve complex optimization problems.The integration of intelligent data science and predictive analytics has far-reaching implications. For policymakers, these technologies provide a robust basis for evidence-based policy formulation and evaluation. In industries, predictive models enhance operational efficiencies, reduce risks, and drive innovation. However, ensuring equitable access to these technologies is essential to avoid exacerbating existing inequalities.

While the systematic review provides valuable insights, it also highlights limitations in existing research. Many studies rely on domain-specific datasets, limiting the generalizability of findings. Additionally, a lack of standardized evaluation metrics complicates cross-comparison of models. Future research should prioritize developing universal benchmarks to assess predictive model performance consistently. The future of decision-making will likely see greater integration of explainable AI, edge computing, and federated learning. Collaborative efforts between academia, industry, and policymakers are essential to address challenges and unlock the full potential of these technologies. Embracing ethical AI practices, such as bias mitigation and stakeholder engagement, will be critical in ensuring fair and sustainable decision-making frameworks. The integration of intelligent data science and predictive analytics offers immense potential for advancing decision-making processes. While challenges remain, continued innovation and collaboration hold the promise of transforming real-world applications, paving the way for a more data-driven and equitable future.



6 CONCLUSION

The systematic review of integrating intelligent data science and predictive analytics into decision-making frameworks highlights a transformative shift in how decisions are approached across diverse sectors. From traditional intuition-based methods to advanced data-driven techniques, this evolution underscores the growing reliance on intelligent systems for enhancing accuracy, efficiency, and scalability.

This research demonstrates the profound impact of predictive analytics in healthcare, finance, retail, and other industries, emphasizing real-world applications such as patient care optimization, fraud detection, and personalized marketing. The findings also underline advancements in machine learning tools like AutoML and time-series forecasting models, which have democratized access to predictive analytics and enhanced decision-making capabilities across domains.

The review identifies significant challenges, including issues with data quality, ethical concerns, and the interpretability of complex models. However, emerging solutions such as explainable AI (XAI), federated learning, and quantum computing hold immense promise for addressing these challenges. These technologies are poised to revolutionize predictive analytics by enhancing transparency, safeguarding data privacy, and solving computationally intensive problems more efficiently.

To unlock the full potential of intelligent data science and predictive analytics, there is a need for greater collaboration among researchers, practitioners, and policymakers. Addressing ethical concerns and ensuring equitable access to these technologies are critical for fostering trust and widespread adoption. Furthermore, standardizing evaluation metrics and developing universal benchmarks will improve the comparability and reliability of predictive models.

In conclusion, this systematic review provides a comprehensive understanding of the current landscape and future possibilities for integrating intelligent data science into decision-making. By leveraging these insights, organizations and policymakers can build robust, ethical, and innovative decision-making frameworks that drive meaningful impact. As advancements in AI and predictive analytics continue to unfold, the journey toward smarter, data-driven decision-making has just begun.

BIBLIOGRAPHY

Adadi, A., & Berrada, M. (2018). Peeking inside the black-box: A survey on explainable artificial intelligence (XAI). IEEE Access, 6, 52138-52160.

Agrawal, A., Gans, J. S., & Goldfarb, A. (2018). Prediction machines: The simple economics of artificial intelligence. Harvard Business Review Press.

Banholzer, S., Kossin, J., & Donner, S. (2014). The impact of climate change on natural disasters. Nature Climate Change, 4(2), 89-95.

Barocas, S., Hardt, M., & Narayanan, A. (2019). Fairness and machine learning: Limitations and opportunities. MIT Press.

Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). Time series analysis: Forecasting and control. Wiley.

Brynjolfsson, E., & McElheran, K. (2016). Data in action: Data-driven decision making and predictive analytics. Management Science, 62(5), 1360-1383.

Chen, C., Cheng, X., Zhao, W., & Wang, Y. (2019). Predictive analytics in intelligent transportation systems. Transportation Research Part C: Emerging Technologies, 101, 138-157.

Chen, J., & Lin, C. (2021). Data quality challenges in big data analytics: A comprehensive review. Journal of Big Data, 8(1), 1-25.

Davenport, T. H., & Harris, J. G. (2007). Competing on analytics: The new science of winning. Harvard Business Review Press.

Davenport, T. H., & Harris, J. G. (2007). Competing on analytics: The new science of winning. Harvard Business School Press.

Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics.

International Journal of Information Management, 35(2), 137-144.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). The elements of statistical learning: Data mining, inference, and prediction. Springer.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444.

Li, T., Sahu, A. K., Talwalkar, A., & Smith, V. (2020). Federated learning: Challenges, methods, and future directions. IEEE Signal Processing Magazine, 37(3), 50-60.

Lipton, Z. C. (2016). The mythos of model interpretability. arXiv preprint arXiv:1606.03490.

Lipton, Z. C. (2018). The mythos of model interpretability. Communications of the ACM, 61(10), 36-43.

MarketsandMarkets. (2021). Predictive analytics market by component, deployment, and industry vertical - Global forecast to 2026. MarketsandMarkets Report.

Nguyen, D. T., et al. (2021). AutoML: State of the art with a focus on time series forecasting. Journal of Artificial Intelligence Research, 72, 1085-1123.

O'Neil, C. (2016). Weapons of math destruction: How big data increases inequality and threatens democracy. Crown Publishing Group.

Preskill, J. (2018). Quantum computing in the NISQ era and beyond. Quantum, 2, 79.

Raghupathi, W., & Raghupathi, V. (2014). Big data analytics in healthcare: Promise and potential. Health Information Science and Systems, 2(1), 1-10.

Rajkomar, A., Dean, J., & Kohane, I. (2018). Machine learning in medicine. New England Journal of Medicine, 380(14), 1347-1358.

Shamim, M. (2022). The Digital Leadership on Project Management in the Emerging Digital Era. *Global Mainstream Journal of Business, Economics, Development & Project Management*, *1*(1), 1-14.

Shmueli, G., & Koppius, O. R. (2011). Predictive analytics in information systems research. MIS Quarterly, 35(3), 553-572.

Simon, H. A. (1972). Theories of bounded rationality. Decision and Organization, 1, 161-176.

Thomas, L. C., Edelman, D. B., & Crook, J. N. (2002). Credit scoring and its applications. SIAM.

Zaharia, M., et al. (2016). Apache spark: A unified engine for big data processing. Communications of the ACM, 59(11), 56-65.

Zhang, Z., & Zhou, J. (2020). Fraud detection using machine learning. International Journal of Information Systems, 14(4), 256-275.