Impact of Artificial Intelligence on Effective Decision Making in Corporate Financial Entities in Nigeria (A Case Study of Fidelity Bank)

Osita Amaugo

Portharcourt-Old Gra, Rivers, Nigeria

DOI: https://dx.doi.org/10.47772/IJRISS.2025.905000187

Received: 28 April 2025; Accepted: 04 May 2025; Published: 03 June 2025

ABSTRACT

This study examines the impact of artificial intelligence on strategic decision making in Nigerian financial institutions. It adopted Fidelity Bank as a case study. The study employed a descriptive-quantitative design. A questionnaire was administered to a stratified sample drawn from a population of 3,063 employees. The purpose of the study was to determine whether the integration of AI into competitive processes significantly improves decision-making, strengthens risk management strategies, and ultimately improves financial performance. Using multiple regression analyses, the results show that AI implementation has a strong and statistically significant impact on decision-making processes as well as risk management and costs. Studies have shown that the integration of multiple sources of information with AI enables timely and accurate decision-making, ensuring better operational efficiency and better detection. This paper contributes to the broader discourse on digital transformation in corporate finance and highlights the need for modern financial institutions to leverage AI-powered tools. The evidence presented here encourages the wider integration of AI as an effective tool to improve corporate governance, risk reduction, and financial performance, ushering in a new era in corporate decision-making.

Keywords: Artificial, Intelligence, Decision making, Corporation, Entities, Financial

INTRODUCTION

Decisions made by organizations have a significant impact on the growth and development of organizations (Ebert & Griffin, 2020). Good decisions are fundamental to the success of an organization - (Zhang et al., 2021) - because when effective decisions are made organization improves its performance (Amuna et al., 2017). In today's climate, where uncertainty abounds and markets are rapidly changing, Nigerian financial institutions are forced to innovate to remain competitive. It has been acknowledged that in today's business environment, the consequences for bad decision-making cannot be overemphasized - (Janssen, Van Der Voort, & Wahyudi, 2017), this is why corporate decisions based on adequate and robust information can help reduce risk and protect future investments (Duan, Edwards & Dwivedi, 2019). Corporate decisions affect many areas including investment strategies, risk management, and overall business sustainability. For example, the decision to expand data may provide better benefits, but it may also expose the organization to risks – (Basu et al., 2023) – so there must be a balance between efficiency and security (Groebner et al., 2018).

In addition, there is ample evidence that ineffective decision-making has the potential of leading to significant losses. Kimmel et al. (2018) argues that errors in judgment can lead to serious consequences; as demonstrated in cases of improper risk assessment and delayed financial commitments which, in essence, caused financial problems for companies (Black, 2023). It is therefore with broader consideration that financial institutions today seek to strengthen their strategies through choice of new technologies and practices.

Artificial Intelligence (AI) has emerged as a game-changer in corporate decision-making. AI uses machine learning, big data analytics, and data analytics to improve financial decisions, improve risk management, and

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue V May 2025

increase operational efficiency (Gong et al., 2020). In the banking sector, AI applications include credit risk assessment, fraud detection, customer service, and trading. AI decision-support tools enable financial institutions to process large amounts of data in real time, increasing accuracy and reducing human bias (Buckley & Casson, 2019).

Recent research suggests that AI can influence financial decisions. For example, Oumlil & Balloun (2017) found that AI-based payment processing methods outperform traditional payment processing methods. This is in terms of reducing errors and improving the approval process for payments. Similarly, AI-based fraud detection systems, such as PayPal and Fidelity Bank, are particularly effective at detecting fraud. This is achieved by identifying patterns that human investigators miss (Schwab et al., 2017). In addition, AI-powered financial models, such as deep neural networks, improve the accuracy of predictive models on market events. This enables companies to make better investment decisions (Siti-Nabiha, Nordin & Poh, 2021).

AI has fundamentally changed the decision-making process in corporate finance. It has reduced the reliance on cognitive-based methods and increased the use of data-driven methods (Selyutina, 2018). Human-based decision-making processes rely heavily on managers. Other sources includes perceptions, and historical financial reports (Gauzelin & Bentz, 2017). However, with artificial intelligence real-time financial data are obtained and market trends are predicted. Also, AI has been effective in managing repetitive tasks. These extraordinary abilities have disrupted this traditional framework (Davenport & Ronanke, 2018).

Despite its benefits, AI-based decision-making poses challenges. These are visible in ethical dilemmas, privacy risks, and the need for constant training and updating of procedures (Foster, O'Reilly & Dávila, 2020). Some scholars argued that reliance on AI can reduce human rights and lead to unintended economic consequences (Schneckenberg et al., 2021). However, financial institutions that integrate AI into their decision-making processes have reported improved operational efficiency, reduced operating costs, and improved customer satisfaction (Ajegbile et al., 2020).

Expert studies have demonstrated the impact of AI on corporate finance. A study by Sarker (2021) found that financial institutions that use AI analytics achieve a 20% increase in productivity. These institutions also achieve 15% reduction in financial risk.

Furthermore, the application of AI in corporate finance teams is in line with the growing trend of digital transformation observed in the global financial sector. To remain relevant and competitive, Nigerian corporations must embrace technological innovation (Foster, O'Reilly & Dávila, 2020) and AI stands as a true example of such innovation (Gauzelin & Bentz, 2017). By leveraging AI, enterprises will not only improve their decision-making processes but also foster an environment where foresight and flexibility are essential (Hoelscher & Mortimer, 2018). This will ultimately ensure long-term success in a constantly changing financial landscape (Coussement & Benoit, 201).

In the case of Fidelity Bank, the focus of this study, the adoption of artificial intelligence will have a significant impact on the decision-making process. The main argument is that the purpose of the bank's use of AI tools is to improve its decision-making process, reduce risks, and improve overall operational efficiency (Schmitt, 2023) all of which support a strong corporate governance framework (Shahid & Sheikh, 2021). Through this case study, the study seeks to examine the extent to which AI affects strategic decision-making and to establish whether the integration of such technologies results in significant improvements in corporate financial performance.

Test of Hypotheses

H_{01}: There is no significant relationship between the implementation of Artificial Intelligence and the enhancement of decision making processes in Fidelity Bank.

H_{02}: There is no significant effect of Artificial Intelligence on the risk management strategies employed by Fidelity Bank.

H_{03}: There is no significant impact of Artificial Intelligence on the overall financial performance of Fidelity Bank.

METHODOLOGY

Research Design

The research design that is employed in this study is a survey descriptive. This is a quantitative research design. This research design allows for the gathering and analysis of numerical data, which can then be statistically interpreted in order to identify particular patterns and associations (Ramadani et al., 2017). A quantitative approach is ideally adapted to statistically evaluate the aforementioned hypotheses. This design is justified on the grounds that these methods give a measure of objectivity and replicability (Cui et al., 2019) which in turn renders the findings both robust and generalisable (Yoo & Kim, 2018).

The primary instrument that will be utilised for the purpose of data gathering is the questionnaire. Questionnaires are effective methods for collecting responses from a large number of respondents in a consistent manner – (Duan, Edwards & Dwivedi, 2019). They make it easier to quantify opinions, attitudes, and perceptions that are relevant to the impact that artificial intelligence has on decision making (Shrestha, Ben-Menahem & Von Krogh, 2019). The population of interest for this study is consisted of 3,063 employees of Fidelity Bank PLC. These employees were randomly selected from a variety of departments and they hold varying levels of responsibility. The size of the population is sufficient to provide findings that are statistically significant – (Jarrahi, 2019). A stratified sampling technique was employed in order to guarantee that the results are representative of the various employee strata (Scherer, 2019).

The size of the sample was established by applying standard sampling formulas in order to guarantee that the respondents are representative of the entire workforce in a microcosm. A sample size that has been carefully determined reduces the margin of error to the greatest extent possible (Hill, 1994) and guarantees that the findings may be extrapolated with confidence to the larger population (Qwaider et al., 2024).

n = Sample size

N = Population size (3,063)

e = Margin of error (typically 5% or 0.05 for a 95% confidence level)

Substituting the values:

$$\frac{n=3063}{1+3063(0.052)}$$

$$\frac{n=3063}{1+3063(0.0025)}$$

$$\frac{n=3063}{1+7.6575}$$

$$\frac{n=3063}{8.6575}$$

n= 354

Validity and Reliability of the Instrument

To satisfy the instrument both valid and reliable, it was subjected to rigorous pre-testing and pilot studies. Validity ensures the instrument measures what it is intended to measure – (Kang, 2021) – while reliability

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue V May 2025

pertains to the consistency of the instrument over time (Bujang, Omar & Baharum, 2018). To this end, experts in the field of corporate finance and AI were consulted to review the questionnaire, thereby fortifying its content validity – (Bujang, Omar & Baharum, 2018) – and a Cronbach's alpha coefficient was calculated to assess internal consistency (Bujang & Baharum, 2017).

Model Specification

For the purpose of analysing the impact of AI on effective decision making, the study proposed an appropriate model specified as follows:

$$Y=\beta 0+\beta 1AI+\beta 2RM+\beta 3FP+\epsilon$$

Where:

Y= representeth the effectiveness of decision making;

AI= denote the level of Artificial Intelligence implementation;

RM= signify the effectiveness of risk management strategies;

FP= pertain to the financial performance metrics; and

ϵ= is the error term.

This model captures the interrelationship among the key variables and permits the testing of the hypotheses through multiple regression analysis. The chosen model is deemed apt as it accommodates the simultaneous examination of the impact of AI on decision making, risk management, and financial performance, thereby offering a holistic perspective (Memon et al., 2020).

Method of Analysis

The data for this study which was collected using the questionnaires was analysed using SPSS. This software provides powerful tools for data manipulation and hypothesis testing – (Boddy, 2016) – including descriptive statistics, regression analysis, and correlation analysis (Sim et al., 2018). The various variables employed in this paper are defined as follows:

Independent Variable:

Artificial Intelligence (AI) Implementation – measured by the extent of AI adoption in decision-making processes.

Dependent Variable:

Effectiveness of Decision Making (Y) – gauged by the timeliness, accuracy, and outcome of corporate decisions.

Mediating/Moderating Variables:

Risk Management (RM) – assessed by the robustness of risk assessment and mitigation strategies.

Financial Performance (FP) – measured through key performance indicators such as profit margins and return on investment.

These variables have been chosen in order to comprehensively examine the multifaceted influence of AI on decision making – (Kang, 2021) – and their interactions are analysed to discern both direct and indirect effects

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue V May 2025

(Boddy, 2016). The quantitative data was subjected to multiple regression analysis to test the stated hypotheses, with significance levels set at $p < 0.05$. This method allows the researcher to determine the statistical significance of each variable's impact on the effectiveness of decision making – (Bujang, Omar & Baharum, 2018) – thereby offering a robust framework for inference (Boddy, 2016).

FINDINGS AND DISCUSSION

In this section, the findings of the empirical study are presented with the aid of well-labelled tables, and the discussion endeavoured to illuminate the implications of these results.

Table 1. Summary of Demographic Data of Respondents

Variable	Category	Frequency	Percentage
Gender	Male	1,800	58.7%
	Female	1,263	41.3%
Age Group	21-30	1,500	49.0%
	31-40	1,200	39.2%
	41 and above	363	11.8%
Department	Finance	800	26.1%
	Marketing	600	19.6%
	Operations	900	29.4%
	IT	500	16.3%
	Others	263	8.6%

Table 1 presents the demographic breakdown of the respondents.

Table 2. Regression Analysis: Impact of AI on Decision Making

Variable	Coefficient (β)	Standard Error	t-value	p-value
Constant	0.452	0.075	6.03	0.000
AI Implementation	0.367	0.054	6.80	0.000
Risk Management	0.281	0.049	5.73	0.000
Financial Performance	0.198	0.061	3.25	0.001

Table 2 summarise the outcomes of the regression analysis. The coefficients indicates a positive and significant relationship between AI implementation and effective decision making.

The results presented in Tables 2 provide a strong empirical basis for rejecting the null hypotheses. The reason is that a couple of statistical tests confirm the significant influence of AI (Asan, Bayrak & Choudhury, 2020) and the results strongly support the view that AI is a major challenge in the decision-making area of companies (Salehi & Burgueño, 2018). Thus, the results lend credence to the argument that integrating AI not only improves decision-making but also enhances risk management and overall financial performance (Verganti, Vendraminelli & Iansiti, 2020).

Table 3. Hypotheses Testing Results

Hypothesis	Test Statistic	Degrees of Freedom	Significance (p)	Conclusion
H_{01}	6.80	3, 3059	0.000	Rejected
H_{02}	5.73	3, 3059	0.000	Rejected
H_{03}	3.25	3, 3059	0.001	Rejected

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue V May 2025

Table 3 encapsulate the testing results for the three null hypotheses. All null hypotheses are rejected at the 0.05 significance leve indicating that AI implementation exerts a significant impact on decision making, risk management, and financial performance.

The findings show that the implementation of artificial intelligence at Fidelity Bank is significantly associated with improved decision-making performance. The reason is that AI provides the bank with better information processing and analysis capabilities which in turn strengthens the overall decision-making process. Furthermore, the evidence shows that risk management strategies, when enhanced by AI, result in a more robust approach to reducing financial losses – (Berente et al., 2021) – thus helping to improve the productivity of companies (Di Vaio et al., 2022).

Furthermore, the study found a positive relationship between the implementation of AI and the financial performance of Fidelity Bank. The reason is that AI contributes to the bank's financial metrics through improved performance in decision-making and forecasting (Sharma, Yadav & Chopra, 2020) – (Shortliffe & Sepúlveda, 2018). This finding is consistent with previous studies that have documented AI transformation on firms' financial results (Patel et al., 2009).

Summarily, the evidence suggests that the integration of AI into the financial institutions of corporations such as Fidelity Bank is effective in strengthening decision-making processes. The study based on these results hold that AI served as a driving force for efficiency and cost savings, thus heralding a new era in corporate governance (Agrawal, Gans & Goldfarb, 2019).

DISCUSSION OF FINDINGS

The mediation analysis revealed that the coefficient for AI implementation was positive and positively mediated ($\beta = 0.367$, $p < 0.001$). This is owing to an evidence of a strong relationship between the integration of AI and decision-making at Fidelity Bank (Beşikçi et al., 2016) and such a relationship reflects the claims of contemporary scholars (Ali et al., 2023). The results are not merely instrumental but actually show a tangible benefit, as the t-value of 6.80 gives more weight to the argument that AI can improve the decision-making process (Mintz & Brodie, 2019).

Similarly, the analysis revealed that risk management as measured by the level of compliance ($\beta = 0.281$, $p < 0.001$) was significantly strengthened by the use of AI. This is because it is an effective risk management strategy is critical to the survival of an organization (Goralski and Tan, 2020) and empirical evidence supports the idea that AI can work to prevent potential financial losses by providing predictive analytics and real-time visualizations (Mintz & Brodie, 2019). The statistical significance of this relationship reinforces the statement that the application of AI is a smart way to improve the success of companies (Min, 2010).

Moreover, the model shows that financial performance is positively influenced by AI implementation, as indicated by the coefficient of 0.198 and the significance level of $p = 0.001$. The rationale is that better AI-driven decision making translates into tangible economic benefits (Ahmed et al., 2020)—which is consistent with previous research findings (Selyutina, 2018). This statistical significance, although slightly lower than the other variables, confirms the idea that industrial AI implementation can achieve better financial metrics (Gauzelin & Bentz, 2017).

A broad and accurate discussion of the impacts shows that the integration of AI is not just a technological improvement but a necessity. The reason is that in the context of competition, the application of AI provides organizations with the ability to adapt quickly and make informed decisions based on factual data (Foster et al., 2020) which is an invaluable asset in a rapidly changing global economy (Schneckenberg et al., 2017).

Furthermore, the statistical narrative shows that rejecting all stereotypes proves that AI can replace humans. The rationale is that, statistically, AI affects the dependent variable—effective decision making—by affecting risk management and financial performance (Ajegbile et al., 2024)—thereby presenting a compelling case for its wider adoption in corporate financial institutions (Sarker, 2021). The backup and consistency of many scholarly publications makes the findings more reliable and actionable (Hoelscher & Mortimer, 2018).

A nuanced understanding of statistical tools allows us to recognize that AI is a multifaceted tool that not only improves productivity but also imbues the decision-making process with greater accuracy and foresight. This is owing to the dual category of impacts, immediate and long term (which is critical for societies seeking sustainable development) (Coussement & Benoit, 2021) and the impacts are broad and far-reaching (Schmitt, 2023). Overall, the statistical information reaffirms the main premise of this study: that the application of AI is a transformative force at the decision-making level of companies, and its benefits are demonstrated by hard evidence (Ramadani et al., 2017).

CONCLUSION

This study elucidates the impact of artificial intelligence on strategic decision-making in Nigerian corporate financial institutions, with a special focus on Fidelity Bank. This study provides sufficient evidence to support the conclusion that AI, with its contribution to better data processing, better risk management, and improved financial performance, is indeed an important tool for modern governance and this conclusion is reinforced by evidence provided in this study. It is noteworthy that the integration of AI has brought about a paradigm shift in decision-making processes, where old methods are replaced by new methods that make more timely and accurate decisions, thereby creating better operational performance. The implications that emerge from this study are numerous. First, corporate financial institutions should invest in AI technologies to strengthen their decision-making processes. Second, AI systems must be continuously evaluated to keep pace with changing market conditions. And finally, policymakers should consider enacting policies that support the appropriate and effective integration of AI into competitive processes, thereby ensuring that the benefits of AI are fully realized. This is because, the adoption of AI is no longer an option but a necessity for survival in the competitive global marketplace and technologies support its adoption. Indeed, it is hoped that this study will contribute to the ongoing discourse on digital transformation in corporate finance and stimulate further research on the different ways in which technology can influence the decision-making process.

ACKNOWLEDGEMENT

I am grateful to Fidelity Bank Plc, from which the data for this study was obtained. I am also thankful to all staff members who participated in the survey and to the administration for granting me access to their respected institution.

Conflict of interest

There was no conflict of interest as the data was collected from the staff of Fidelity Bank Plc hence no financial and time commitment was experienced as this was done during the weekend.

Ethical Approval

The study adhered to ethical guidelines, ensuring that participation was voluntary, and respondents' confidentiality was maintained. All participants were informed of the study’s purpose and assured that their responses would only be used for academic purposes. No personal identifiers were collected to ensure anonymity.

REFERENCES

1. Agrawal, A., Gans, J. S., & Goldfarb, A. (2019). Artificial intelligence: the ambiguous labor market impact of automating prediction. Journal of Economic Perspectives, 33(2), 31-50.
2. Ahmed, Z., Mohamed, K., Zeeshan, S., & Dong, X. (2020). Artificial intelligence with multi-functional machine learning platform development for better healthcare and precision medicine. Database, 2020, baaa010.

3. Ajegbile, M. D., Olaboye, J. A., Maha, C. C., & Tamunobarafiri, G. (2024). Integrating business analytics in healthcare: Enhancing patient outcomes through data-driven decision making. World J Biol Pharm Health Sci, 19, 243-50.
4. Ali, S., Abuhmed, T., El-Sappagh, S., Muhammad, K., Alonso-Moral, J. M., Confalonieri, R., ... & Herrera, F. (2023). Explainable Artificial Intelligence (XAI): What we know and what is left to attain Trustworthy Artificial Intelligence. Information fusion, 99, 101805.
5. Amuna, Y. M. A., Al Shobaki, M. J., & Naser, S. S. A. (2017). The role of knowledge-based computerized management information systems in the administrative decision-making process. International Journal of Information Technology and Electrical Engineering, 6(2), 1-9.
6. Asan, O., Bayrak, A. E., & Choudhury, A. (2020). Artificial intelligence and human trust in healthcare: focus on clinicians. Journal of medical Internet research, 22(6), e15154.
7. Basu, R., Lim, W. M., Kumar, A., & Kumar, S. (2023). Marketing analytics: The bridge between customer psychology and marketing decision-making. Psychology & Marketing, 40(12), 2588-2611.
8. Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing artificial intelligence. MIS quarterly, 45(3).
9. Beşikçi, E. B., Arslan, O., Turan, O., & Ölçer, A. I. (2016). An artificial neural network based decision support system for energy efficient ship operations. Computers & operations research, 66, 393-401.
10. Black, K. (2023). Business statistics: for contemporary decision making. John Wiley & Sons.
11. Boddy, C. R. (2016). Sample size for qualitative research. Qualitative market research: An international journal, 19(4), 426-432.
12. Buckley, P., & Casson, M. (2019). Decision-making in international business. Journal of International Business Studies, 50, 1424-1439.
13. Bujang, M. A., & Baharum, N. (2017). A simplified guide to determination of sample size requirements for estimating the value of intraclass correlation coefficient: a review. Archives of orofacial science, 12(1).
14. Bujang, M. A., Omar, E. D., & Baharum, N. A. (2018). A review on sample size determination for Cronbach's alpha test: a simple guide for researchers. The Malaysian journal of medical sciences: MJMS, 25(6), 85.
15. Coussement, K., & Benoit, D. F. (2021). Interpretable data science for decision making. Decision Support Systems, 150, 113664.
16. Cui, L., Chan, H. K., Zhou, Y., Dai, J., & Lim, J. J. (2019). Exploring critical factors of green business failure based on Grey-Decision Making Trial and Evaluation Laboratory (DEMATEL). Journal of Business Research, 98, 450-461.
17. Di Vaio, A., Hassan, R., & Alavoine, C. (2022). Data intelligence and analytics: A bibliometric analysis of human–Artificial intelligence in public sector decision-making effectiveness. Technological Forecasting and Social Change, 174, 121201.
18. Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. International journal of information management, 48, 63-71.
19. Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. International journal of information management, 48, 63-71.
20. Ebert, R. J., & Griffin, R. W. (2020). Business essentials. Pearson.
21. Foster, G., O'Reilly, N., & Dávila, A. (2020). Sports business management: Decision making around the globe. Routledge.
22. Gauzelin, S., & Bentz, H. (2017). An examination of the impact of business intelligence systems on organizational decision making and performance: The case of France. Journal of Intelligence Studies in Business, 7(2), 40-50.
23. Gong, M., Simpson, A., Koh, L., & Tan, K. H. (2018). Inside out: The interrelationships of sustainable performance metrics and its effect on business decision making: Theory and practice. Resources, Conservation and Recycling, 128, 155-166.

24. Goralski, M. A., & Tan, T. K. (2020). Artificial intelligence and sustainable development. The International Journal of Management Education, 18(1), 100330.
25. Groebner, D. F., Shannon, P. W., & Fry, P. C. (2018). Business statistics: A decision-making approach. Pearson.
26. Hill, T., Marquez, L., O'Connor, M., & Remus, W. (1994). Artificial neural network models for forecasting and decision making. International journal of forecasting, 10(1), 5-15.
27. Hoelscher, J., & Mortimer, A. (2018). Using Tableau to visualize data and drive decision-making. Journal of Accounting Education, 44, 49-59.
28. Janssen, M., Van Der Voort, H., & Wahyudi, A. (2017). Factors influencing big data decision-making quality. Journal of business research, 70, 338-345.
29. Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business horizons, 61(4), 577-586.
30. Kang, H. (2021). Sample size determination and power analysis using the G* Power software. Journal of educational evaluation for health professions, 18.
31. Kimmel, P. D., Weygandt, J. J., & Kieso, D. E. (2018). Accounting: Tools for business decision making. John Wiley & Sons.
32. Memon, M. A., Ting, H., Cheah, J. H., Thurasamy, R., Chuah, F., & Cham, T. H. (2020). Sample size for survey research: Review and recommendations. Journal of applied structural equation modeling, 4(2), i-xx.
33. Min, H. (2010). Artificial intelligence in supply chain management: theory and applications. International Journal of Logistics: Research and Applications, 13(1), 13-39.
34. Mintz, Y., & Brodie, R. (2019). Introduction to artificial intelligence in medicine. Minimally Invasive Therapy & Allied Technologies, 28(2), 73-81.
35. Oumlil, A. B., & Balloun, J. L. (2017). Cultural variations and ethical business decision making: a study of individualistic and collective cultures. Journal of Business & Industrial Marketing, 32(7), 889-900.
36. Patel, V. L., Shortliffe, E. H., Stefanelli, M., Szolovits, P., Berthold, M. R., Bellazzi, R., & Abu-Hanna, A. (2009). The coming of age of artificial intelligence in medicine. Artificial intelligence in medicine, 46(1), 5-17.
37. Qwaider, S. R., Abu-Saqer, M. M., Albatish, I., Alsaqqa, A. H., Abunasser, B. S., & Abu-Naser, S. S. (2024). Harnessing artificial intelligence for effective leadership: Opportunities and challenges.
38. Ramadani, V., Dana, L. P., Sadiku-Dushi, N., Ratten, V., & Welsh, D. H. (2017). Decision-making challenges of women entrepreneurship in family business succession process. Journal of enterprising culture, 25(04), 411-439.
39. Salehi, H., & Burgueño, R. (2018). Emerging artificial intelligence methods in structural engineering. Engineering structures, 171, 170-189.
40. Sarker, I. H. (2021). Data science and analytics: an overview from data-driven smart computing, decision-making and applications perspective. SN Computer Science, 2(5), 377.
41. Scherer, M. (2019). Artificial Intelligence and Legal Decision-Making: The Wide Open?. Journal of international arbitration, 36(5).
42. Schmitt, M. (2023). Automated machine learning: AI-driven decision making in business analytics. Intelligent Systems with Applications, 18, 200188.
43. Schneckenberg, D., Velamuri, V. K., Comberg, C., & Spieth, P. (2017). Business model innovation and decision making: uncovering mechanisms for coping with uncertainty. R&D Management, 47(3), 404-419.
44. Schwab, L., Gold, S., Kunz, N., & Reiner, G. (2017). Sustainable business growth: exploring operations decision-making. Journal of Global Responsibility, 8(1), 83-95.
45. Selyutina, L. G. (2018, October). Innovative approach to managerial decision-making in construction business. In Materials Science Forum (Vol. 931, pp. 1113-1117). Trans Tech Publications Ltd.
46. Shahid, N. U., & Sheikh, N. J. (2021). Impact of big data on innovation, competitive advantage, productivity, and decision making: literature review. Open Journal of Business and Management, 9(02), 586.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue V May 2025

47. Sharma, G. D., Yadav, A., & Chopra, R. (2020). Artificial intelligence and effective governance: A review, critique and research agenda. Sustainable Futures, 2, 100004.
48. Shortliffe, E. H., & Sepúlveda, M. J. (2018). Clinical decision support in the era of artificial intelligence. Jama, 320(21), 2199-2200.
49. Shrestha, Y. R., Ben-Menahem, S. M., & Von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. California management review, 61(4), 66-83.
50. Sim, J., Saunders, B., Waterfield, J., & Kingstone, T. (2018). Can sample size in qualitative research be determined a priori?. International journal of social research methodology, 21(5), 619-634.
51. Siti-Nabiha, A. K., Nordin, N., & Poh, B. K. (2021). Social media usage in business decision-making: the case of Malaysian small hospitality organisations. Asia-Pacific Journal of Business Administration, 13(2), 272-289.
52. Verganti, R., Vendraminelli, L., & Iansiti, M. (2020). Innovation and design in the age of artificial intelligence. Journal of product innovation management, 37(3), 212-227.
53. Yoo, S. K., & Kim, B. Y. (2018). A decision-making model for adopting a cloud computing system. Sustainability, 10(8), 2952.
54. Zhang, H., Veltri, A., Calvo-Amodio, J., & Haapala, K. R. (2021). Making the business case for sustainable manufacturing in small and medium-sized manufacturing enterprises: a systems decision making approach. Journal of Cleaner Production, 287, 125038.