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AI-driven decision-making in financial management

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Abstract

The financial management of registered accounting firms in Lagos State, Nigeria, is assessed in this study using AI-driven decision-making. Specifically, the study aimed to determine how AI-driven financial planning enhances the reliability and effectiveness of organisational operations. The study employed a survey research design because data were collected directly from the respondents. The results indicate that AI-driven decision-making with machine learning, expert systems and natural language has a considerably significant relationship with financial management because its usage in organisational management will assist in enhancing the operation of financial management practice by 19.5% which will enable the financial management to gain more efficient and effective operation. Managing the complex interactions between regulatory frameworks and technological advancements. The study added to the body of knowledge already available on utilising AI-driven decision-making in financial management within registered accounting firms in Lagos State, Nigeria. Based on dialogue between technology developers and regulators that create adaptive frameworks in keeping pace with the rapid advancements in AI, this recommends the successful integration of innovative solutions into financial management.

Keywords: Financial management, natural language, expert systems, machine learning, and artificial intelligence. JEL: O30, L80, L86, L68, L63

Introduction

Financial management is central to economic stability and development worldwide, in both the developed as well as developing world. In the developed economies, an advanced financial management culture has become indispensable for surviving complicated financial markets and inflation posed "regulatory scheme" (Piroska et al., 2021). Likewise, countries use sophisticated financial instruments to build economic flexibility (Aluko et al. 2024). On the other hand, LDVCs have limited financial infrastructure and are more susceptible to economic shocks, hence there is a need for adapted financial management which promotes sustainable development.

Market volatility, regulatory changes, and sustainable finance are the key challenges to financial management (Zamfiroiu & Pinzaru, 2021). Furthermore, global economic uncertainty, technological disruptions and changing consumer behaviour add further complexity in financial decision-making processes (Aluko et al. 2024). Similarly, new approaches are required to optimise placements of capital and risk management, and to make of the investment in the pursuit of financial stability and long-term growth (Bui et al., 2020). But in an organisation, poor financial management means undeveloped productivity instead of profitable growth. As such, the challenge of economic management is to effectively manage these interdependent and multifaceted dimensions to maintain financial performance and robustness in a dynamic context.

Recently, a lot of research has focused on financial management. For instance, Addy et al. (2024) look into how AI-driven analysis is changing financial planning. They point out that while AI can boost efficiency in ways we haven't seen before, it can also bring about new challenges. This emphasises the importance of having a balanced approach when integrating AI into financial practices. Also, Thakur and Sharma (2024) and Schmitt (2023) analysed the role of automated machine learning in enhancing AI-driven decision-making within business analytics, and the study stated that it is a significant step toward automated decision-making in business for financial management analytics. Consequently, with the effort to tackle these issues, the menace of financial management persists.

Above mentioned studies were conducted in different countries, at different periods, with different variables of Artificial Intelligence on the approach to accounting functions, while very little attention has been given to financial management. However, this nature will not enable us to adopt the general and universal results of past studies. The study specifically aimed to determine how AI-powered decision-making contributes to bridging the gap in financial management and how the efficiency of accounting practices' participation in more activities is linked to the enhancement and reliable operation of an organization when it has transformed financial planning (Addy et al 2024). Moreover, providing real-time analysis, predictive modelling, and risk assessment based on vast amounts of data, and this enables more accurate forecasting, minimizing human errors, and identifying potential opportunities or threats that might otherwise be overlooked (Schmitt 2023). Ultimately, AI empowers financial management by offering insights that can lead to more informed, data-driven decisions enhancing efficiency and potentially maximizing returns.

This study focuses on the ongoing challenges that businesses in Lagos State, Nigeria, face when it comes to managing their finances effectively. It highlights the important roles of machine learning, expert systems, and natural language processing in fostering better decision-making powered by AI. These advancements in AI can greatly impact financial management, making it possible to make more precise predictions, assess risks more effectively, and gain strategic understanding from large and complex sets of data. Using AI algorithms and advanced analysis can reveal patterns and trends that might go unnoticed by people, which helps make smart decisions quickly. Moreover, AI can take over routine jobs, making processes run smoother and cutting down on human mistakes. Overall, AI helps financial organisations improve their investment plans, handle risks better, follow regulations more easily, and tailor experiences for their customers. Financial environments use more data and change quickly. Artificial intelligence (AI) can help make decisions. This offers new chances and reduces possible dangers. AI is important for making financial management last (Owoeye et al. 2024).

Consequently, this study's goal differs significantly from the previous one, as it aims to examine AI-driven decision-making of financial management with a particular focus on 35 registered accounting firms in Lagos State, Nigeria southwest. To accomplish this goal, the study will examine the predictive power of machine learning, expert systems, and natural language as sub-components of artificial intelligence (AI).

The remaining sections have been structured as follows: The study will involve gathering insights from auditors, chartered accountants, manager directors accounting firms. In contrast to earlier research that concentrated only on enhancing auditing performance, the study will provide a pictorial analysis of the existing body of research on natural language, expert systems, machine learning, AI decision-making, and related theoretical concerns. The methodology of the study will involve collecting data and analyzing it to draw meaningful conclusions. After a thorough discussion of the study's findings, a conclusion will be made.

Literature Review

Conceptual Review

This section will give an explanation of the research's concepts and demonstrate the relationship between AI-driven decision-making in the financial management of registered accounting firms in Nigeria.

Financial Management

Akinadewo et al. (2024) conceptualized financial management as long-term planning, investment decisions, financial policies, and identifying opportunities for growth and expansion. It involves assessing the overall financial health of the organization and making decisions that align with its strategic objectives. Also, Oluwagbade et al. (2024) define financial management as day-to-day financial activities such as budgeting, cash flow management, financial reporting, and ensuring that the organization's financial operations run smoothly and efficiently. It is concerned with the implementation and monitoring of financial processes to support the strategic goals of the organization. However, effective financial management is crucial, as they address different aspects of decision-making and resource allocation within an organization.

Managing finances well is vital for companies because it ensures they can thrive over the long haul, as noted by (Shapiro & Hanouna in 2019). When organisations handle their finances well, they're better equipped to make smart choices about where to invest, how to manage risks, and how to allocate their resources effectively. In the same vein, it helps organisations deal with financial unpredictability, seize chances for growth, and steer through economic hurdles (Bui et al., 2020). Moreover, sticking to smart financial practices ensures that organisations comply with regulations, keep financial reports clear, and remain answerable to their stakeholders.

Financial management is crucial for organisations as it's essential to guarantee their long-term viability and prosperity (Shapiro & Hanouna, 2019). By effectively managing finances, organisations can make informed decisions regarding investments, risk management, and resource allocation. Similarly, enables them to mitigate financial uncertainties, capitalise on growth opportunities, and navigate economic challenges (Bui et al. 2020). Furthermore, compliance is guaranteed by prudent financial management with regulations, transparency in financial reporting, and accountability to stakeholders. One of the most important aspects of financial management is how it boosts operational efficiency, improves profitability, and lays down a strong groundwork for reaching strategic goals and fostering growth in the organisation.

AI-Driven Decision Making

Akinadewo et al. (2024) argued that AI for decision support is a way to present insights and culled recommendations for human decision-makers. It slogs through huge volumes of data, susses out ideas, trends and correlations that humans would miss, and delivers it in a way (sometimes as simple as a visual image) that makes it useful. This enables decision-makers to take the most effective and well-informed decisions possible, thereby enriching and deepening the calibre and reliability of their decisions. Likewise, Kuziemski and Misuraca (2020) indicate that AI-informed decision-making consists of interactive automated decision-making by applying pre-existing rules, algorithms or ML models. AI can quickly process data, evaluate multiple scenarios, and make decisions without human intervention, which is especially helpful for repetitive, rules-based decisions. To avoid biased or unfair results, it's crucial to make sure that these automated decision-making systems are created with ethical considerations and oversight.

Surprisingly, by using these cutting-edge algorithms to evaluate vast amounts of data, AI-driven decision-making critically improves financial management by improving comprehension of consumer behaviour, market trends, and investment opportunities. This capability detects fraudulent activities in real time and strengthens an organisation's strategy (Saravi et al., 2022). With machine learning, expert systems, and natural language, artificial intelligence (AI) also makes automated trading, individualised customer service, and simplified compliance and reporting procedures possible. All of these features eventually help financial managers make more accurate, efficient, and strategic decisions. Through increased operational efficiency, improved customer experiences, and improved financial results, artificial intelligence (AI) has the potential to completely transform financial management.

Machine learning

Machine learning, according to Mahesh (2020), is the capacity of tools to learn from historical data and use that knowledge to forecast or predict future, unseen data. In this way, machine learning (ML) can be viewed as a tool for finding and utilising patterns in complicated datasets, opening up applications like forecasting stock prices, consumer behaviour, or equipment malfunctions. In a similar vein, Jo (2021) believed that machine learning allows systems to automatically adapt to new data and improve their performance. Other financial management tasks, like automating credit scoring procedures, enhancing investment portfolios, or spotting irregularities in financial transactions to detect fraud, can make use of this.

Empowering algorithms to analyse vast volumes of financial data, identify patterns, and produce incredibly precise forecasts, machine learning greatly improves financial management. Financial professionals can use this capability to enhance fraud detection procedures, optimise investment strategies, and improve risk assessment (Jo 2021). Furthermore, machine learning algorithms may automate repetitive tasks like data input and reconciliation, freeing up financial managers' time to focus on strategic decision-making. Additionally, machine learning helps make better decisions by spotting subtle patterns and correlations in financial datasets, which eventually improves financial results and operational efficacy in the financial management industry.

Natural Language

Chowdhary and Chowdhary (2020) conceptualised natural language as a medium for sharing information, engaging in dialogue, and conveying complex concepts through speech, writing, and gestures. Within this framework, natural language is essential for interpersonal communication, literature, storytelling, and the transmission of cultural knowledge. In addition, Fanni et al (2023) and Akinadewo et al. (2024) defined natural language as a structured analysis of language to extract meaning, sentiment, intent, and other relevant information. Applications such as chatbots, emotion analysis, language translation, and information extraction from textual data are made possible by natural language processing techniques, which enable robots to understand and produce human language.

By facilitating more intuitive and effective communication, analysis, and decision-making, natural language can improve financial management. By employing sentiment analysis and natural language processing, financial institutions can gain a great deal from unstructured textual data, such as news articles, social media posts, and customer reviews (Fanni et al., 2023). This can assist in identifying possible risks, tracking market trends, and gauging investor sentiment (Osaloni et al. 2022). Additionally, by enabling users to access and analyze financial data through conversational commands and queries, natural language interfaces can streamline communication with financial management systems. This can simplify procedures like forecasting, budgeting, and reporting, increasing the accessibility and actionability of financial data for both individual customers and professionals. Furthermore, textual content can be automatically generated using natural language generation (NLG) technologies.

Conceptual Framework

The purpose of this study's conceptual framework was to illustrate how the independent and dependent variables relate to one another. The dependent variable is registered accounting firms' financial management. AI-driven decision-making, which uses machine learning (ML), expert systems (ES), and natural language (NL) as proxies, is the independent variable.

AI-driven decision-making in the financial management of registered accounting firms in Nigeria.

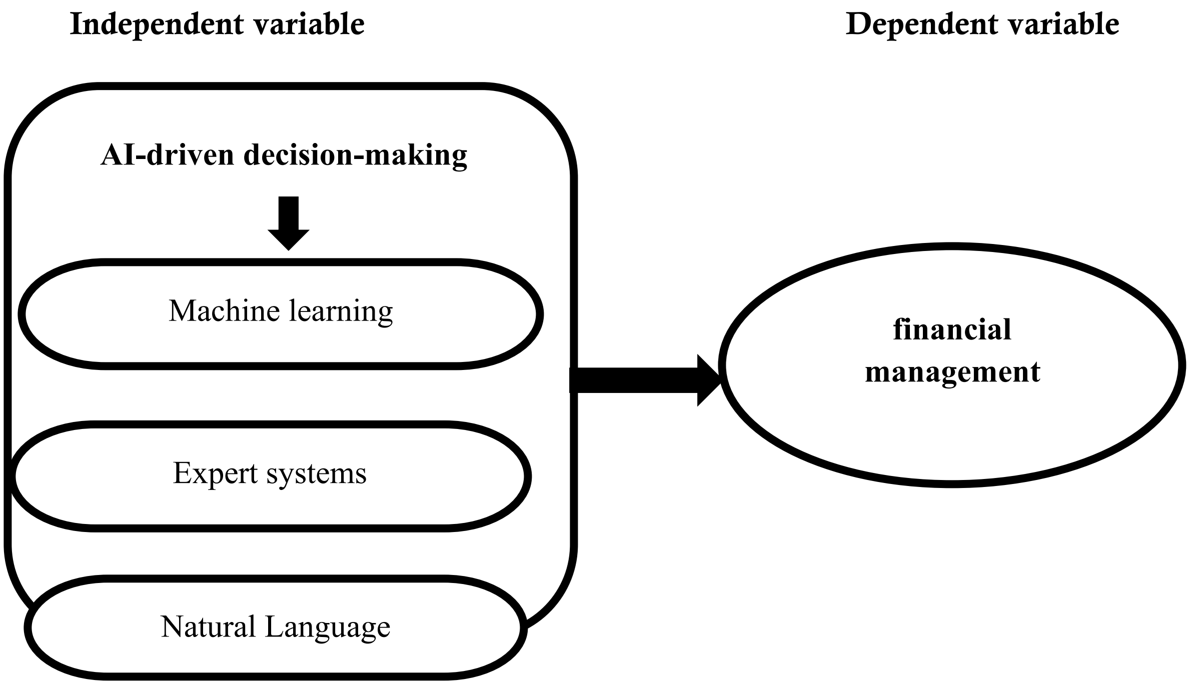

Figure 1: Conceptual framework to show the nexus between Machine learning, Expert systems, Natural Language, and financial management.

Source: ***Authors Computations***

Theoretical Framework

The study was anchored on Decision Theory, which was propounded by Leonard J. Savage (1954). Decision theory is based on several fundamental assumptions. However, it assumes that decision-makers are rational in evaluating available options. Additionally, decision theory operates on the assumption that individuals can assign utilities to outcomes, seeking to maximise expected utility. Furthermore, decision theory often deals with uncertainty, encompassing various forms such as risk and ambiguity.

The Decision Theory has been subject to several critiques by authors such as Nwogugu (2005); and Hillman (1999), primarily concerning its reliance on a rational and logical decision-making framework that may not fully capture the complexities of human decision-making. Critics claim that the traditional Decision Theory fails to sufficiently take into consideration the emotions, biases, and heuristics that frequently influence human decision-making.

The theory is appropriate for this study because it offers solid support and insightful information that can improve AI-driven financial management decision-making by offering a framework for creating sophisticated algorithms that mimic logical decision-making processes. AI systems can be created to evaluate various financial options according to predetermined criteria and goals by integrating the idea of rational evaluation of available options.

The ability of this theory to address financial management issues by allocating utilities to outcomes and optimising expected utility to direct AI algorithms in assessing the risks and possible rewards connected to different financial decisions is what makes it relevant to this study. The need for AI tools to handle and assess sensitive financial data to make well-informed predictions and risk assessments is also in line with addressing uncertainty and various types of risk. Last but not least, the autonomy of option assessment fits in with AI systems' modularity and adaptability, which enable them to take into account and assess several variables and scenarios at once. These basic tenets of decision theory can ultimately guide the creation of AI-powered financial management decision-making procedures, resulting in increasingly complex and potent instruments for maximising financial outcomes and strategies.

Literature Review and Hypothesis Development

Machine learning

Al Ayub Ahmed et al. (2022) Analyse information mining and machine learning to assess contemporary financial management strategies. It focuses on researching and developing methods that work well with evaluation tools. The study illustrates the substantial advantages of financial management institutions utilising financial data to improve performance and ensure precise management of consumer data, thereby identifying defaulters, reducing equipment failures, processing transactions quickly and efficiently, minimising incorrect judgments, categorising potential customers, and minimising financial organisation waste. This is also significantly positively supported by the findings of Warin and Stojkov (2021), who examined the present status of scholarly investigations into financial ideas in a metadata-based systematic review of the literature on financial machine learning.

Mashrur et al. (2020) undertook research on offering a methodical overview of the quickly expanding body of knowledge on machine learning for financial risk management; nonetheless, the article fills this void by analysing machine learning for finance. Based on the findings, a taxonomy of financial risk management jobs with notable publications during the last ten years is presented. This correlated with the China study by Yubo (2021), who investigated the real-world and theoretical aspects that influence the planning of routes and budget management mode selection. The study reveals the positive significance of instrument value in managing financing, which has significantly raised its standing in corporate management, particularly in artificial intelligence. This correlated with the findings of a study by Mahesh (2020) on the connection between machine learning and regularisation in financial management with improved efficiency.

Likewise, Noviandy et al (2023) explore how to use XGBoost-driven machine learning and data augmentation techniques to detect credit card fraud for modern financial management. Demonstrate that the alignment improves credit card fraud detection when paired with data augmentation techniques. The study shows that methods are significantly positive in addressing unbalanced datasets and enhancing the accuracy of fraud detection.

Similarly, El Hajj and Hammoud (2023), A thorough examination of AI applications in trading, risk management, and financial operations reveals the impact of AI and machine learning on financial markets. The results of the study, which employed quantitative research, show how the most common uses of AI and ML in financial institutions, such as algorithmic trading, risk management, fraud detection, credit scoring, and customer service, have seen a sharp increase in use.

However, empirical review from the past studies of authors such as Al Ayub Ahmed et al (2022); Warin and Stojkov (2021), and Mashrur et al. (2020) indicates a positively and significant conetion of Machine Learning and financial management. Similarly, Yubo (2021); Mahesh (2020); Noviandy et al (2023), and El Hajj and Hammoud (2023) also showed a positive nexsus of machine Learning and financial management.

H_{01}: *There is a significant positive relationship between Machine Learning and financial management.*

Expert systems

Kit and Ghani (2023) analyse software for personal financial management on the implementation of artificial intelligence. In order to support users in reaching their financial objectives, the study employed a rule-based expert system technique to provide useful alignment. The results reveal significant satisfaction. The study's findings give users useful, well-informed financial choices to help them achieve their financial goals. In the same vein, thus aligning with the study of scholars in China, Güneysu (2023) who examines the effect of financial management expert systems and artificial intelligence. And demonstrate a strong, positively significant connection with financial management and machine learning.

Er and Güneysu (2023) X-trayed the working capital management emergency using an expert system application in small and medium-sized businesses in Turkey. The study analysed data from 283 businesses listed in the BIST between 2012 and 2020. The result of the study showed that expert systems substantial impact on small and medium-sized businesses working capital management in Turkey.

Myachin et al (2021) investigate the effect of building a fuzzy expert system on the financial and economic security of telecommunications enterprises. The research is based on primary and secondary accessible statistical and financial reporting data, as well as economic process modelling both domestically and internationally. The result has a significant positive effect of the fuzzy expert system on the financial-economic security of telecommunications enterprises.

Qhal (2023) studied the use of smart systems and expert robotics to improve knowledge of financial management in libraries. Both expressive and contented review approaches were used to carry out the study. While indicating a negatively significant effect of both expert systems robots and Smart systems due to large numbers of datasets of financial management in Libraries.

However, authors such as Güneysu (2023), Kit and Ghani (2023), Er, and Güneysu (2023) and Myachin et al (2021) show a positively significant relationship between expert systems in financial management. While only Qhal (2023) indicate that expert systems have no significant relationship with financial management.

H_{02}: *There is a significant positive effect of expert systems and financial management.*

Natural Language

Oyewole et al. (2024) explore how natural language could revolutionise accounting disclosures. The study meticulously employs a qualitative research design. The study reveals a significantly positive reporting efficiency and accuracy through the use of natural language in financial disclosures. The findings justify the result of the survey by Guo and Yang (2023) on the evaluation of natural language Models in financial management.

Xiao et al. (2024) analyse the effect of natural language sentiment and Transparency on Financial Reporting. The study used *Ex-Post facto* research. The study indicates the positive significance of natural language on financial management, enriching traditional financial analysis methods. The findings correlate the study of Ukraine by Prikhno et al (2021) on the application of Technology to financial management with positively significant.

Li et al. (2022) investigated natural language tone on earnings management behaviour. While a qualitative research design was used on 20-F filings of Chinese firms listed from 2002–2014. Results are positively significant to corporate management, adjusting the narrative of their financial reports in order to manipulate earnings. This confirms findings of UK researchers Mosteanu and Faccia (2020) who analysed natural language digital systems on financial management. And finding show a positive significance of natural language digital systems on financial management reducing the risk of error.

Similarly, the empirical evidence of authors such as Oyewole et al. (2024); Guo and Yang (2023), Xiao et al. (2024), and Prikhno et al. (2021) indicates that a relationship exists between natural language in financial management. This is also supported by (Li et al. 2022; and Mosteanu and Faccia 2020).

H_{03}: *There is a significant positive relationship between natural language and financial management.*

Data and Methods

Information was gathered directly from the respondents, and the study used the method of survey research. All 35 of Lagos State, Nigeria's recognised accounting organisations made up the study's population. The study used a census sampling technique to determine the sample size, which was 100% of the population. Based on the relative size of the population, five respondents are chosen from each accounting company, for a total of 175 respondents.91.4 % of the sample size, constitutes 153 answers, were obtained for the study. The Cronbach's Alpha reliability test was used to assess the validity and reliability of the research tool. Both descriptive statistics, regression analysis were employed to analyse the collected data.

Reliability

The instrument's reliability was assessed using the Cronbach Alpha test. For machine learning, expert systems, natural language, and financial management, the results show Cronbach Alpha values of 91.4%, 91.3%, 91.4%, and 91.3%, respectively. Consequently, a thorough analysis of this result reveals that every item accurately reflects the variables included in the model, which is over 70%. The research tool is deemed credible as, on average, all of the variables have Cronbach Alpha values of 89.6%, indicating that they are at a threshold of 0.7 criteria.

Table 1: Reliability Test

Item	Variables Cronbach Alpha	Model Cronbach Alpha
Machine Learning (ML)	91.4%	
Expert System (ES)	91.3%	
Natural Language (NL)	91.4%	
Financial Management (FM)	91.3%	89.6%

Source: *Authors' Computation (2024)*

Model Specification

The study's model aligned with Nigerian research by Oluwagbade et al. (2024) on issues that arise from Artificial Intelligence implementation Practices of Auditing in Nigerian Accounting Firms. However, the below is the model:

$FM_t = \beta O + \beta 1ML_t + \beta 2ES_t + \beta 3NL_t + \in$
$t \ldots \ldots \ldots \ldots \ldots . eqe(1)$

Where:
FM=Financial Management
ML= Machine Learning
ES= Expert System
NL= Natural Language
t = Period of the survey (1 year, 2024)
βO = When all other independent variables are maintained constant, the parameter to be estimated is the rate at which the dependent variable increases when the independent variable increases by one unit.

$\beta 1$, $\beta 2$, $\beta 3$= Coefficient of slope or gradient of the independent variables.

∑t= Errior term

***A-Priori expectation* =** $\beta 1>0$, $\beta 2>0$, $\beta 3>0$

Table 2: Descriptive Statistics

Variable	FA	ML	ES	NL
Mean	4.1488	4.1750	4.1343	4.42232
Maximum	5.0000	5.0000	5.0000	5.0000
Minimun	2.67	3.14	3.30	3.17
Std. Dev	0.43697	0.45475	0.40770	0.42659
Skewness	0.093	-0.330	0.327	0.325
Kurtosis	0.093	-0.330	0.327	0.325
Observations	153	153	153	153

Source: *Authors' Computation (2024)*

Data Analysis and Discussion of Findings

Descriptive Statistics

The study's descriptive statistics are displayed in Table 2 above. These statistics are used to assess the variable's series characteristics and assess how well the sample data distribution matches the normal distribution. A mean of 4.1488 and a standard deviation of 0.43697 are shown in financial management, which presents that the financial management mean is low and skewed positively at 0.093 value, while the value of the variable is normally distributed, as indicated by the kurtosis of 0.523. With a standard deviation of 0.45475 and an average value of 4.1750, machine learning indicates that the deviation is likewise minimal. With a kurtosis value of 0.142 and a skewness value of -0.330, the variable is clearly negatively skewed.

Likewise, the expert system presented the value of the mean at 4.1343, with the standard deviation of the disparity evidence being 0.40770, and the mean's deviation rate is also low. Hence, given that the kurtosis value of 0.108 is less than 3, indicating a leptokurtic distribution, the expert system is positively and significantly skewed, according to the skewness value of 0.327. Similarly, Natural Language showed a modest departure from its mean value, with an average of 4.2232 and a standard deviation of 0.42649. Finally, the Natural Language shows a positively skewed distribution with a value of 0.325 and a kurtosis value of -0.561, which indicates a leptokurtic distribution because it is less than 3.

Test of Variables

Normality Test

All of the independent variables were shown to have a linear association with one another. (natural language, machine learning, and expert systems) and the dependent variable (financial management). This was demonstrated by the residuals' variance, which is constant across levels of projected values, as shown by the Normal P-P plot of the standard residual plot in Figure 1.

Linearity Test

Table 3 presents a correlation of both Financial Management, Machine Learning as being positively significant, with a coefficient value of 0.536. However, this suggests that a rise in AI-driven decision-making usage through Nigerian licensed financial management will be improved through machine learning. Also, with a coefficient of 0.644 and P-value of 0.000, the Expert system and Financial Management both have a positive and significant association, indicating that more Expert system use of AI-driven decision-making usage will also enhance the Financial Management of registered accounting firms in Nigeria. Similarly, Natural Language has a value of significantly positively correlated of 0.695 and a P-value of 0.000 with the Financial Management of registered accounting firms in Nigeria. This indicates that an increase in the Natural Language of AI-driven decision-making usage will enhance the Nigerian financial management of registered accounting firms by 69.5%.

Table 3. Correlation Analysis of the Variables

	FM	ML	ES	NL

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FM	1.0000			
ML	0.536** (0.000)	1.0000		
ES	0.644** (0.000)	0.608** (0.000)	1.0000	
NL	0.695** (0.000)	0.413** (0.000)	0.621* (0.000)	1.000

Source: ***authors' Computations (2024)***

Multicollinearity Test of Variables

Table 4 below, is the result of multicollinearity statistics which demonstrate that the variables in the model used to calculate the Tolerance and Variance Inflation Factor (VIF) do not exhibit multicollinearity. However, this finding showed that the tolerance level that measures the amount of variance not captured by the other independent variables for Natural Language, Expert System, and Machine Learning is 0.612, 0.465, and 0.629, respectively. Additionally, the results of the Variance Inflation Factor (VIF) indicate that the values for Machine Learning, Expert Systems, and Natural Language are 1.590, 2.149, and 1.634, respectively. Since the values lie between 0 and of tolerance level, multicollinearity is absent, and the values are inside the limit and 1, and the VIF values are less than 10 and more than 0. Similar to this, Durbin Watson was used to do the autocorrelation test, and the results fell between 1.5 to 2.5, which is an acceptable range.

Table 4a: Tolerance and VIF Value

Variable	Tolerance	VIF	1/VIF
ML	0.629	1.590	0.629
ES	0.465	2.149	0.465
NL	0.612	1.634	0.612
Mean VIF		1.791	

Source: ***authors Computations, (2024)***

Table 4b: Post Estimations Test Result

Durbin Watson

Null Hypothesis		**Probability**
There is no Serial Correlation (P>0.05)		1.869
Tolerance and VIF Value		
Null Hypothesis	**VIF**	**1/VIF**

Absence of Multicollinearity among the variables (1/VIF>0.10)

Source: ***authors' Computations (2024)***

Evaluation of the effect of AI-driven decision-making in the financial management of registered accounting firms in Nigeria.

The results of the ordinary least squares analysis are shown in Table 5, on AI-driven decision-making in the financial management of registered accounting firms in Nigeria. The table showed that the corrected value of the coefficient of determination, which is 0.578, is 0.582. The outcome shows that the independent variable explains around 58.2% of the variance in the dependent variable, with error factors that are not included in the model accounting for the remaining 47.8%. The model's probability is 0.000, with the F-statistic value of 132.220. Given that the P-value is significant at 5%, this explains why the model's whole set of variables is well-fitted.

The model's coefficients for each parameter also show that machine learning and financial management in Nigeria have a positively significant correlation of 0.195 units at P=0.000<0.05. According to the results, Nigerian financial management would improve by 19.5% for every unit improvement in machine learning. When it comes to financial management in Nigeria, the expert system has a significant positive coefficient of 0.247 units at P=0.000<0.05. This shows that Nigerian financial management practices will improve by 24.7% for every unit increase in expert system implementation. In a similar vein, Nigerian financial management practices and natural language have a strong, favourable correlation of 47.9%. According to this finding, Nigerian financial management practices rise in natural language.

Table 5: OLS Regression Analysis on the AI-driven decision-making in the financial management of registered accounting firms in Nigeria.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.291	0.196	1.485	0.139
ML	0.195	10.046	4.201	0.000
ES	0.247	0.060	4.097	0.000
NL	0.479	0.050	9.557	0.000
R-Squared	0.582			
Adjusted R-Squared	0.582			
F-Statistic	132.220			
Prob (F-Statistic)				

Source: ***authors' Computations, (2024)***

Discussion of Findings

According to the findings, machine learning and financial management in Nigeria are significantly correlated, as their application in organisational management can help in enhancing the operation of financial management in Nigeria by 19.5% which allows registered accounting firms' financial management to operate more effectively and efficiently**.** This is consistent with the results of Al Ayub Ahmed et al. (2022), Warin and Stojkov (2021), and Mashrur et al. (2020), who researched Machine Learning Analysis for Financial Risk Management. By offering a thorough analysis of the rapidly expanding body of knowledge on machine learning for financial risk management, the study fills this gap. The findings include an index of financial risk management jobs that have been published in the last ten years. This correlated with the China study by Yubo (2021), who looked into the theoretical and practical factors that affect route planning and financial management mode selection. The survey indicates that financial management's position as one of the main value-added tools in business management has been greatly improved by artificial intelligence (AI). This correlated with the findings of a study by Mahesh (2020) on the connection between regularising financial management with increased efficiency and machine learning.

However, the result of the expert system also has a considerable significant relationship with financial management in enhancing the operation by 19.5% which will enable the financial management of registered accounting firms to gain more efficient and effective operation**.** This similarly aligns with the findings of studies such as Güneysu (2023) who examine artificial intelligence and expert systems in financial management with positive significance. In addition, Kit and Ghani (2023); and Er, and Güneysu (2023who also examined the application of the expert system on working capital management in small and medium-sized businesses (SMEs) in Turkey and found a strong positive correlation between financial management and the expert system. Similarly, Myachin et al. (2021) show a positively significant relationship between expert systems in financial management. While only the study of Qhal (2023) indicates that expert systems have no significant relationship with financial management.

On the other hand, Oyewole et al. (2024) investigated NLP's potential in the context of financial disclosures while negotiating the complex interactions between regulatory frameworks and technological advancements. And other authors such as Guo and Yang (2023), Xiao et al. (2024), and Prikhno et al. (2021) that lend credence to the relationship that exists between natural language in financial management in Ukraine. This is also supported by the U.S. and the U.K. by Li et al. (2022) and Mosteanu and Faccia (2020), with a positively significant relationship between NL and financial management.

Recommendations and Conclusion

It was uncovered by the study a lack of statistical and empirical evidence on the effect of AI-driven decision-making in financial management in Nigeria. Similarly, the research offered emerging empirical statistical proof that machine learning (ML), Expert system (ES), and Natural language positively affect the financial management of registered accounting firms in Nigeria. These variables were regressed on financial management. The regression and correlation analyses that were used demonstrated that the explanatory variables significantly and favourably explained the explained variable. The conclusion drawn from the study's findings is that AI-driven decision-making raises financial management's degree of productivity. In financial management, the application of AI-driven decision-making demonstrates effectiveness through enhanced insights into consumer behaviour, market trends, and investment opportunities. Regarding the research findings, the study suggested that:

(1) Implement machine learning to identify anomalies in financial transactions on historical transaction data, to help the organization detect unusual patterns that may indicate fraud or errors. Regularly update your models to improve their accuracy and responsiveness to new types of fraud.

(2) Develop expert systems that leverage rules and insights from financial experts to optimize portfolio management decisions to help organizations in analysing market conditions, risk appetite, and investment goals to suggest portfolio adjustments. They can also simulate various scenarios to help inform strategic financial decisions.

(3) Utilize NL tools to analyze and summarize financial reports, and market sentiments by organization in converting unstructured data into actionable insights, financial managers can stay informed about market trends and make better decisions.

Implementing these techniques can significantly enhance decision-making processes in financial management.

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APPENDIX

AFE BABALOLA UNIVERSITY, ADO EKITI
SCHOOL OF SOCIAL AND MANAGEMENT SCIENCES
DEPARTMENT OF ACCOUNTING

Dear Respondent,

REQUEST FOR THE COMPLETION OF QUESTIONNAIRE

This research survey questionnaire aimed at gathering data on " AI-driven decision making in financial management of registered accounting firms in Nigeria''. Your kind and objective responses will significantly contribute to the success of this study. This study will assist organizational management with a more efficient and cost-effective system of operation and reduce the menace in decision-making processes.

Your response shall be treated with high confidentiality and only be used for the study.

Thank you for your cooperation.

Section A

Kindly tick(√) on that which agrees with your opinion.

1. Class of Respondents: Auditors( ), Accountants ( ), Manager Directors ( ).
2. Designated "Department" within the organization: Accounting Dept ( ), Audit Dept ( ), Adimin Dept ().

Section B

This section contains sets of questions asked concerning AI-driven decision-making in the financial management of registered accounting firms in Nigeria.

Please tick (√) as appropriate.

Note: SA= Strongly Agree, A= Agree, UD= Undecided, D= Disagree, SD= Strongly Disagree, NA= Not Applicable.

B(i): Machine Learning

		SA	A	UD	D	SD	NA
1	Do you agree that the introduction of Machine Learning enhances financial data performance better.						
2	Electronic systems will open doors for more consumer data to identify defaulters in the decision-making of financial management.						
3	Does Machine Learning reduce the number of equipment failures associated with decision-making of financial management.						
4	Do you agree that Machine Learning makes it easier to process transactions quickly and efficiently.						
5	Does Machine Learning guarantee data accuracy reduce reduce the number of incorrect judgments.						
6	Machine Learning categorizes potential customers, and minimizes the wastage of financial organizations.						

B(ii). Expert System

1	**expert system technique to provide practical recommendations for financial management**
2	Does the use of an expert system support users in achieving their financial goals.
3	Expert system and the make financial component, and economic security of telecommunications enterprises.
4	Expert systems can automate routine financial decisions using predefined rules and logic based on the knowledge of finance professionals.
5	By leveraging historical data and expert knowledge, these systems can provide detailed analyses and forecasts of risks associated with different investments.
6	Expert systems can analyze past financial performance and current market conditions to support more accurate budgeting and forecasting.

B(iii) Natural Language

1	**Do you agree that natural language can analyze vast amounts of unstructured data from financial reports,**	
2	Natural language can generate financial reports and summaries automatically from raw data, saving analysts time and ensuring consistency in reporting.	
3	NL can provide insights that influence financial strategies and investment decisions.	
4	NL can handle customer inquiries related to financial products, services, or account issues, improving customer satisfaction.	
5	NL can assist in extracting and categorizing expenses from receipts and invoices, streamlining the expense management process.	
6	NLP can analyze text from regulations, policies, and legal documents to ensure compliance in financial reporting and transactions.	

B(iv) Financial management

		SA	A	UD	D	SD	NA
1	AI-driven analysis historical financial data to make accurate forecasts about future performance, cash flow, and market trends.						
2	AI reduces time and also reduces the likelihood of human error, ensuring consistency and accuracy in reporting.						
3	AI helps organizations proactively manage risks before they escalate.						
4	AI can analyze expenditures and operational data to identify areas for cost savings.						
5	With AI financial managers can make actionable insights, and better-informed choices aligned with business goals.						