DECISION TREE MODEL AND ITS RELEVANCE IN FINANCIAL MANAGEMENT

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Abstract: *In today's data-driven financial environment, organizations increasingly rely on analytical tools to make informed decisions under uncertainty. This study examines the relevance and application of decision tree models in financial management, focusing on their capacity to enhance accuracy, interpretability, and efficiency in decision-making. Decision trees provide a transparent and systematic framework for evaluating multiple financial alternatives, quantifying risks, and predicting outcomes. Through a desk review approach, the study synthesizes existing literature and empirical findings on the use of decision trees in budgeting, capital budgeting, portfolio management, fraud detection, and credit decision-making. It further traces the evolution of decision tree algorithms from traditional models such as ID3, C4.5, and CART to modern ensemble techniques like Random Forests and XGBoost, emphasizing improvements in explainability through SHAP and LIME frameworks. Findings show that decision trees offer robustness, flexibility, and high interpretability, making them valuable for regulatory compliance and ethical financial practices. However, challenges such as overfitting, instability, and limited data generalizability persist. The study recommends that financial institutions integrate ensemble-based decision tree methods and invest in high-quality data management systems to improve model performance and reliability. Overall, decision tree models remain indispensable tools for achieving transparency, accountability, and strategic decision-making in modern financial management.*

Keywords: Decision Tree Model, Financial Management, Credit Scoring, Fraud Detection, Machine Learning

I.   Introduction

Making decisions is a normal practice in our everyday life. On numerous occasions, one must make decisions in their personal, and professional life, however, professional decisions influence the entire organization, both in the sense of organizational future and the fulfillment of the established goals. A single wrong move will destroy entire planning and preparation that have been undertaken in achieving the targets. It is the reason why decision making is called as a tedious task. The credit should be given to our hard-working researchers who have researched on some methods to aid in this complex though important task. Decision Tree Analysis is one of such techniques.

One of the decisions that are significant in financial management is investment decision. This ruling is important since those companies or individuals who have intentions to establish or grow business need high capital. Moreover, it is not possible to get returns on investment activities within a short period of time. In case of making a wrong decision then the company may incur enormous losses. To be able to develop a business to satisfy consumer demand, when creating an investment project, a company needs a calculation of the capital budget to decide on investments (Azlika et al, 2023). Decision tree analysis is one of the approaches to the taking of this decision. Pinkasovitch (2025) argues that decision trees are crucial in the financial field and they assist analysts and investors to visualize the choices, risk, and outcomes. Probability models are common in their application in both option pricing and real option analysis, as well as in the analysis of competing projects. There are binomial option pricing models that are based on decision trees as they estimate values of the assets. Decision trees are also useful in corporate analysis as well as financial forecasting but tend to be too complex whenever there is a lot of variables.

Risk analysis, or the decision tree analysis, is a tree-like flow chart where nodes and branches are listed containing all possible outcomes of a decision, which enables you to estimate a probability of every possible outcome, and therefore help you to select between multiple courses of action. The decision trees are predictive models that have been extensively applied in the business world to assists decision-makers to make decisions in a rational manner. There are numerous possible ways of drawing a decision tree, and the aim is to present a graphical illustration of risks, rewards, and values of every decision.

One of the most famous and understandable machine learning algorithms is the Decision Trees. They are also very popular in classification and regression because of their simplicity and the fact that they can be applied on both numerical and categorical information. But the Decision Trees are also subject to overfitting particularly when they are trained on a large data set which has many irrelevant or redundant features. This

overfitting increases the model complexity in addition to lowering the generalizability of the model as well as costing more to compute. Strategic decision making has been the most important in a business environment that is getting more complex to succeed. Decision tree analysis is one of the numerous methods that businesses are using; the method is clear, easy to use, and efficient in terms of dissecting complex decision-making processes into manageable components (Branch, 2024). In addition, decision trees are reputed to be interpretable. The end product tree structure enables users to view and comprehend decision making process with ease. This would be particularly beneficial in areas where transparency and explainability are paramount, and it would be more convenient to trust and justify the findings to the stakeholders (Mienye and Jere, 2024). Decision trees' decision tree algorithms use various tests on a data set to decide how it is going to best predict the dependent variable (Ocal et al., 2015)

The decision tree-based models have been proved useful in the prediction of financial behavior in recent studies. As an example, a decision tree ensemble approach introduced by Sun and colleagues to deal with the problem of class imbalance during enterprise credit assessment combines SMOTE with bagging, showing higher predictive power and resilience in the complex financial environment (Sun et al, 2021). This methodology brings out the efficiency and adaptability of tree based algorithms in modeling investor behaviour particularly in situations where there exist skewed data and non-linear relationships.

With the emergence of machine learning (ML) algorithms, the detection of fraud has been reinvented with advanced tools that can detect and analyze intricate trends in money transactions ML algorithms have shown the aptitude that they are being surprisingly used to redesign the dynamic techniques of fraud. It is to test the effectiveness of it in the detection of fraud in financial transactions (Owoade, 2025). Decision tree is actually a living tool, either virtually or literally, which is utilized in a decision across personal or business and which entails the analysis of both qualitative and quantitative data. The business decisions need aspects of accuracy and addressing of uncertainties resulting in risk-taking that may be of differing degrees and sizes hence the necessity of employing effective tools in the context of deriving the best conclusion cannot be over-stated. Decision trees are part of data science, as such, they may dictate business value to an organization and subsequently relay it to the stakeholders in a highly understandable way (Alao et al., 2021).

This study aimed to:

Assess the history of decision tree model and its relevance in the financial management with a focus on enhancing decision-making.

II.   Literature Review

2.1 Conceptual Review

Wang (2025) claims that a decision tree model is considered to be a recursive sorting system which systematically divides the data set, based on a set of conditional judgments, until it is finally patterned into a tree-like framework. The model chooses the direction of branching in every split by choosing the variables that will most affect the prediction by the importance of the features. Decision Tree is a classification and regression model which is tree-based. The model is the data that is in the form of a tree with defined characteristics. It is believed to be a critical analysis procedure because it assists in realizing how the model predicts and what can be learned about the connections between the characteristics and the target variable (Manorom, 2024).

Decision trees represent one of the potent techniques that are usually applied in different areas, including machine learning, image processing, and pattern recognition. DT are a sequential model that brings together a sequence of the fundamental test in an effective and unified way where a numeric attribute is contrasted with a threshold worth in each test (Jijo & Abdulazeez, 2021). In addition, Mienye and Jere (2024) also held the view that machine learning (ML) has played a significant role in addressing intricate issues and greatly contributing to various spheres of our life. The simplicity and interpretability of decision tree-based algorithms have become extremely popular among the many methods of ML algorithms thanks to their simplicity and interpretability.

Decision trees have wide applications in financial management as they make the sophisticated processes of decision-making easily visible and clear on the tree enabling the financial managers to assess different options and their potential results systematically. They assist in evaluating risks, credit risk, uncertainty in an investment etc by subdividing the decisions into manageable components, and providing probabilities on various situations. The latter enables it to be easier to find the most cost-effective or profitable route, enhancing budgeting, investment planning, and loan approval procedures (Gafsi, 2025).

Besides, decision trees can process numerical and categorical financial data without a lot of preprocessing enabling easy analysis. Their clarity and understandability are especially useful in the world of controlled business such as banking and insurance, where it is necessary to clarify decisions to stakeholders and regulators. In addition, financial processes (e.g., credit scoring and fraud detection) may be automated with the help of decision trees to increase efficiency and consistency. Decision trees help financial managers to make

wise decisions that are based on data, participate in scenario planning, avoid risks, and efficiently prioritize the allocation of resources (Luo, 2025).

Credit scoring is a necessary instrument in the current financial market to quantify the credit risk of the borrower in order to resolve the loan approval, credit limit, and loan interest rate determination, which is considered as a prime credit evaluation index in virtually all operations concerning financial decision-making and is used extensively (Thomas, 2000). The majority of the conventional numeric approaches to credit ratings are founded on statistical models (primarily the logistic regression models), which has been the favored approach due to financial institutions due to their simplicity and ease of interpretation. Nevertheless, due to the rapid growth of the financial market, the volume of accumulated data is growing exponentially, and the properties of the data are becoming more and more sophisticated; the drawbacks of the traditional credit scoring models are becoming evident in the conditions of non-linear and complex data of growing volume, in particular, the accuracy of the prediction does not keep the pace with the modern market requirement of more and more complicated financial affairs (Han et al, 2008).

To solve these problems, more and more financial institutions and scholars have started to adopt machine learning and data science techniques, especially decision tree modelling. Here, we can regard the decision tree model as a "yes" and "no" selection process, it will constantly divide the data into different groups. Each time it groups the data, it relies on only one of the most essential features to make a decision, ultimately resulting in one prediction for each group. In this way, the decision tree model identifies complex connections between the data and automatically filters out the features that impact the outcome most. This feature has led to the widespread use of decision trees in finance, especially in personal credit scoring (Wang, 2025).

2.1.1 Evolution of Decision Tree Model

Decision trees were initially developed in the 1950s and 1960s as a part of the decision theory to model sequential decision-making under uncertainty. Initial uses were primarily manual, as they found use in management science and economics in structuring complex choices. The growth of automatic tree-building algorithms in the 1970s and 1980s saw the growth of decision tree techniques in computer science and artificial intelligence. Another significant advancement was in 1986 when J. Ross Quinlan introduced the ID3 (Iterative Dichotomiser 3) algorithm which enabled machines to construct classification trees based on data using such concepts as the information gain.

This was succeeded by better versions like: C4.5 (early 1990s): supported both categorical and continuous values, introduced the concept of pruning to avoid overfitting. CART (Classification and Regression Trees): CART was created by Breiman et al. during the 1980s, and it was used to perform both classification and regression on binary splits. With simplicity, interpretability and versatility, decision trees became a primary instrument of machine learning by the 2000s. They, however, tended to be particularly easily surpassed by more sophisticated models such as the SVMs or neural networks, until the emergence of multiple decision tree-based methods as ensemble methods, such as the Random Forests (Breiman, 2001), which combine multiple decision trees to enhance accuracy and reduce overfitting. Decision trees, implemented as Gradient Boosting Machines (GBM, XG Boost, Light GBM) with a boosting framework that are based on decision trees to generate state-of-the-art predictive models.

Since the 2010s, decision trees and their ensemble formulations have found broad application in finance, healthcare, marketing, and risk management, and where model interpretability is an important concern. They also act as the foundation in the background of numerous describeable Artificial Intelligent systems. Since prediction is only one of the benefits and decision trees are now used to provide transparency, scenario analysis, automation, and decision support, decision trees are more frequently utilized in regulated industries such as banking and insurance, and in credit scoring, fraud detection, and investment analysis applications.

Molnar (2022), in his book Interpretable Machine Learning: A Guide for Making Black Box Models Explainable, highlights the advantage of decision trees in producing transparent and understandable models. He emphasizes that the structure of decision trees with clearly defined rules and branching paths makes them naturally interpretable, especially compared to black-box models like neural networks.

Similarly, Lundberg and Lee (2017) introduced SHAP (S Hapley Additive ex Planations), a unified framework for interpreting complex machine learning models. While SHAP was designed for black-box models, it has been widely used to explain the output of tree-based algorithms such as XG Boost and Light GBM. Their work demonstrates how even complex ensemble models built from decision trees can maintain a degree of interpretability, enabling clearer insight into how features influence predictions.

Further evidence of decision trees' practical value is provided by Nallakaruppan et al. (2024) in their study Credit Risk Assessment and Financial Decision Support Using Explainable Artificial Intelligence, published in the journal Risks. The authors explore how decision tree models and their ensemble methods are applied in real-world financial decision-making, including credit risk analysis, loan approvals, and automated scoring systems. The study emphasizes the importance of using interpretable models in finance to ensure trust, compliance, and strategic alignment with institutional goals.

2.1.2 Applications of Decision Trees in Financial Management

The application of decision tree models in financial management spans a wide range of areas, including budgeting, financial forecasting, credit analysis, investment decision-making, and risk management. In budgeting, decision trees assist in evaluating multiple expenditure scenarios by outlining various alternatives and their probable financial outcomes. This aids organizations in prioritizing projects based on profitability, cost efficiency, and strategic alignment. By visually mapping decisions, managers can assess the trade-offs between alternative spending paths and understand the implications of each choice under uncertain financial conditions (Thomas, 2000).

In financial forecasting, decision tree models serve as predictive tools for analyzing historical financial data and estimating future performance. They can identify patterns such as revenue fluctuations, market volatility, or customer payment defaults, helping organizations to prepare for diverse market conditions. Unlike static forecasting methods, decision trees incorporate both qualitative and quantitative variables, allowing the analyst to simulate real-world uncertainties and derive probabilistic forecasts (Han et al., 2008).

2.1.2.1 Decision Tree and Fraud Detection

One of the applications of decision tree models in finance with the strongest visibility is fraud detection. With the continued digitization of financial systems, there has been an explosion of the volume and difficulty of transactions, which provide new opportunities in the areas of fraudulent activity. Decision trees are structured in determining anomalies through a classification of the transactions based on quantifiable variables including transaction amount, frequency, location and account behavior. Decision trees can be used to identify the legitimate and suspicious patterns of actions in the dataset by splitting it recursively based on important attributes. To give an example, Classification and Regression Trees (CART) and C4.5 can be used to identify credit card fraud and online banking fraud due to their interpretability and the capability to utilize both discrete and continuous data. In finance, these models are used by financial institutions to automate their fraud monitoring systems so that they can automatically identify abnormal transactions in real-time with minimal false positive alarms (Manorom et al., 2024; Owoade, 2025).

Moreover, the improved ensemble techniques that include Random Forests, XGBoost and Gradient Boosted Trees have facilitated improved accuracy in detecting fraud through the combination of numerous decision trees to include complex, nonlinear relationships between financial variables. The models are capable of analyzing large volumes of transactional data and changing with new fraud patterns based on the historical information thereby enhancing the predictive reliability. In addition to the detection, decision trees can aid post-fraud analysis by indicating the determinants that played a major role in causing the fraudulent act to assist the institutions in enhancing the internal control systems and compliance policies. Being interpretable is another benefit of the tree-based models in regulated financial settings, as it will enable auditors and regulators to track the model decision-making transparently and explain the resultant outcomes within the scope of explainable AI principles (Biana et al., 2023; Kou et al., 2021; Sun et al., 2021).

2.1.2.2 Decision Tree and Capital Budgeting

The decision tree analysis has become an inevitable part of the capital budgeting process since it enables financial managers to address investment projects when they are subjected to risks and uncertainty. Long term financial commitments and uncertain cash flows in the future are common in capital budgeting decisions like whether to invest on new plants, increase production or acquisition of new technology. The decision tree offers a well-structured, graphical way of analyzing these strategic investment options by illustrating a series of decisions, eventualities, and possible payoffs. The branches of the tree hold all the possible paths to the investments taking into consideration costs of the project, future revenues, market dynamics, and the likelihood of success or failure. The visualization is structured so that it allows the manager to compute the Expected Monetary Value (EMV) of each of the project options and compare them in a systematic manner. To illustrate, a firm can consider the decision tree to model a scenario where it is uncertain whether it should launch a new product, therefore the firm may come up with high, moderate, and low market demand with respective probabilities and cash inflows. This analysis is beneficial to rational investment appraisal because it quantifies risk-adjusted returns and offers a clear framework of making decisions (Azlika et al., 2023; Branch, 2024). Decision trees enhance the conventional capital budgeting methods including Net Present Value (NPV), Internal Rate of Return (IRR) and Payback Period by introducing risk and flexibility in the process. Decision trees are used in sensitivity and scenario analysis to give organizations an idea about how the consequences of alterations in the market conditions or input assumptions would influence the results of the project. They are also applied in the real options analysis in modern finance where managers analyze the value of flexibility as the option to delay, expand, or abandon a project depending on emerging information in the market. Decision trees simplify the process of identifying these management options and determining the financial implication of these options. The use of machine learning based decision trees e.g. Classification and Regression Trees (CART) and Gradient Boosted Trees, adds another level of improvement to capital budgeting by using past data to determine the probability of project success, and maximizing the portfolio of investments.

This type of data-driven approach enhances the level of accuracy in forecasting, a better resource allocation, and increased connection between strategic planning and financial performance (Luo, 2025; Nallakaruppan et al., 2024).

2.1.2.3 Decision Tree and Portfolio Management

  Decision tree models are important in the management of portfolio as they offer a systematic model of analyzing investment options in the presence of uncertainty. Portfolio choices in contemporary finance may be based on the balance between risk and reward and are typically motivated by the market volatility, as well as the dependence of assets. The decision trees are useful to visualize investors and portfolio managers the available investment paths, evaluate the effect of different market situations, and choose the best combinations of assets. All the branches in the tree are the possible outcomes like an increase or decrease in the value of assets and the related probabilities and expected returns. This organized visualization enables decision-makers to compare alternative investment policies, approximate the impact of diversification, and know the best portfolio combination that would result in utility optimization with minimum risk exposure (Rad et al., 2025). In that sense, the decision tree analysis is a supplement to the quantitative finance rules like the Modern Portfolio Theory developed by Markowitz (1952), a more intuitive and situation-oriented approach to asset allocation decisions. Decision trees can be used to complement the evaluation of the portfolio performance by incorporating both the financial and behavioural aspects in its evaluation. They are able to include variables including investor risk-taking ability, liquidity choice, and market anticipation with which the model becomes a lot closer to actual decision-making methods in the real world. Practically, the algorithm of the decision tree, such as CART and Random Forests is used to detect the patterns in the historical financial data that determine future portfolio returns or the movement of the asset prices. As an example, an ensemble tree model could be used to categorize investment opportunities as risk-adjusted or predict how an investment will lose in the market in case the market declines. This predictive power helps the active reorganization of portfolios and risk-adjusted investment of capital, which allows investors to be proactive to market shifts (Branch, 2024; Luo, 2025). Decision trees have become a crucial part of decision-making in the modern portfolio management process by providing the balance between the data-oriented science and the strategic decision-making of investment.

2.1.2.4 Decision Tree and Cost Management

  The decision tree models are crucial in management of costs as they assist the financial managers to detect, review, and manage the main determinants of organizational costs in the uncertain environment. Decision trees provide managers with control over alternative cost-control strategies including production scaling, outsourcing, or investing in new technology and determining how much they cost-effectively contribute to the bottom line in various situations because these decision trees are hierarchical and visual in nature. Decision trees enable firms to estimate the expected monetary value by quantifying the probability and outcomes of an event and are useful in choosing cost-effective paths that would not compromise the overall effectiveness of the firm. As an example, the decision trees can be applied to manufacturing and service industries and decide whether to maintain the internal production or to outsource based on the uncertainties of cost, quality, and demand. Liao and Liu (2022) state that decision tree models facilitate the enhancement of the early warning system by detecting repetitive patterns in financial indicators that reflect the possibility of cost overruns or inefficiencies and making decisions in advance and adjusting the budget. The reason is that decision trees can be used to aid in the cost-benefit analysis and maximizing the performance through the combination of qualitative and quantitative data into the evaluation process. Their interpretability enables managers to identify the influence that each variable of the decision, like the price of raw materials, the cost of labor or the efficiency of a given machine, has on the total financial performance. This method facilitates the dynamic cost prediction, sensitivity analysis, and trade-offs between the short-term costs and the long-term savings. Decision trees are also used in strategic financial planning in order to allocate resources by setting priorities of projects or departments based on their estimated cost implication and risk. Adaptability and transparency of the model also allow its effective application in the enterprise financial management systems where decision-makers will have to explain cost-related decisions to the auditors, investors, and to the regulatory authorities (Thomas, 2000; Branch, 2024). Therefore, the decision tree analysis can be dismissed as a powerful analytical tool that will allow reducing financial waste, streamline spending, and help to develop sustainable cost management approaches in the complicated business context.

2.1.2.5 Decision Tree and Credit Decision-Making

  The use of decision tree models in credit decision-making has gained growing importance as it is easily interpretable and can utilize complex data on borrowers. These models are used in the financial institutions to categorize the loan applicants under a wide range of parameters including income, employment history, credit history and outstanding debt. Financial analysts can use determinants of creditworthiness that are the most significant in each node due to the hierarchical structure of decision trees, which simplifies the risk segmentation. An example is a decision tree will initially separate applicants by the credit utilization ratio, then by income stability, and lastly by the debt to income ratio and end up with transparent, rule based decisions that

are both auditable and understandable. This openness is a strong benefit compared to black box systems such as neural networks as regulators are increasingly requiring explainable AI in credit scoring. Wang (2025) says that decision tree models can be used to improve the accuracy of their predictions in the case of personal credit scoring and also helps in improving fairness as it gives a clear indication of the role played by various variables in the ultimate lending decision. Credit decision-making processes have been further enhanced by modern ensemble decision tree methods like the Random Forests and the Gradient Boosting methods. Such models minimize overfitting and increase the reliability of predictions as they use more than one tree to take a single decision. These sophisticated tree-based algorithms are now being used by financial institutions to automatically approve loans, identify the possible defaults at an early stage, and dynamically increase or reduce credit limits depending on the behavior of the borrower (Gan et al., 2025). Moreover, decision tree models will play a key role in integrating behavioral and macroeconomic factors within the models, allowing responsive credit rating systems to change with fluctuating financial conditions. Their explainability is also favourable to the compliance with regulatory requirements including Basel III and fair lending rules, which ensure ethical and responsible credit assessment. Therefore, the contemporary credit decision-making has been transformed by the use of decision tree models, which can be statistically rigorous, transparent, and versatile to reduce risk and enhance financial inclusivity (Nallakaruppan et al., 2024).

2.1.3 Benefits and Limitations of Decision Tree Models

There are a number of advantages that decision tree models have that render them appealing to financial management. Their interpretability and transparency give financial analysts the ability to see the rationale behind every decision and increase accountability and trust (Molnar, 2022). They deal with numerical and categorical variables hence they are applicable in heterogeneous financial data. The decision trees also enable non-parametric analysis i.e. they do not assume anything about the distribution of the data and it is a considerable characteristic when working with a complex financial or economic data. Their visual format encourages the effective communication of the decision-makers, particularly when communicating the options and risks to the non-technical stakeholders. In addition, decision trees are capable of classifying data as well as regression, which means that they can be used in various financial aspects like credit rating, frauds, and investment evaluation (Luo, 2025).

Nonetheless, even despite these capabilities, the decision tree models have limitations. Overfitting is one of the primary problems where the model explains the noise in the training data and not the underlying pattern making the model less generalizable (Mienye & Jere, 2024). This is most frequently experienced when trees are too profound or sophisticated. The mitigation methods include pruning and ensemble-based approaches such as the Random Forests and Gradient Boosting. The other weakness is instability where minor variations in the data can cause greatly different tree structure, which implies inconsistency. Also, decision trees can be ineffective with skewed data, where one of the outcomes is substantially more prevalent than others, like in the case of fraud detection (Sun et al., 2021). Lastly, decision trees are interpretable; however, they are often computationally complex when the dataset size is large and there are many features and paths to take.

2.2 Theoretical Review

Application of decision tree models in financial management has its deep theoretical grounds in the various theoretical bases explaining how individuals and organizations make decisions under risk and uncertainty conditions. Besides the Risk Management Theory, which dwells upon utility, regression, and diversification, immediate related theories that offer conceptual reinforcement of the decision tree approach is the Machine Learning Theory. These two theories explain the reasoning in the process of decision making, human decision making under risk and computation basis that enable decision trees to simulate as well as optimize decisions in complex financial contexts.

2.2.1 Machine Learning Theory

Machine Learning (ML) Theory is the computational framework of the current models of decision trees, especially as they transformed into data-driven predictive algorithms as opposed to manual heuristics. ML Theory is a branch of statistics and computer science that is based on the design of algorithms, which learn through data to enhance predictive performance and the quality of decisions with time (Mienye & Jere, 2024). The core feature of this paradigm is decision trees that are used to build more powerful ensemble models, including Random Forests, Gradient Boosted Trees, CatBoost and XGBoost, which combine a series of trees into a single model to achieve greater strength and reduce overfitting (Breiman, 2001; Gan et al., 2025). Applying the Machine Learning Theory to the concept of financial management, it is understandable that decision trees can be trained using financial data in the past (credit histories, investment returns, and frauds) and predictive information can be obtained by revealing previously hidden connections. As an example, a random forest regressor, which was trained according to previous loan applications, would automatically discover important predictors of default, like the volatility of incomes or default payments. The theoretical explanation of learning through experience concurs well with the data intensive aspect of modern finance whereby models keep up with the new information.

2.2.5 Risk Management Theory

Risk-management theory relies on three fundamental principles namely utility, regression and diversification. The first person to suggest utility method in 1738 was Daniel Bernoulli and the decision-making process was developed where individuals are required to be more concerned with the magnitude of the effects of various results. It is stated in the articles of M. Bulmer and F. Galton (2003). Regression was used starting the end of the XIX century. It was later established that the rule of regression applies in many situations that begin with the determination of the probability of risks and culminating in prediction of business cycles. H. Markowitz has provided mathematical justification of the strategy of diversification of investment portfolio in 1952. He has demonstrated the smart use of investments to reduce the variance of the projected rate of return.

2.3 Empirical Review

This article, Decision Tree Analysis in Project Risk Management: A Systematic Review by Zaku and Uysal (2022) was aimed to find out which project risk management processes the appropriate methods are more commonly used and the gap in the literature. Literature review and bibliometric analysis technique were employed in this context. The findings have shown that there has been an increment in the use of related risk assessment techniques in the past five years. The techniques were commonly applied in the quantitative risk analysis, qualitative risk analysis, and risk identification processes.

In the same way, in their analysis, Gan et al., (2025) are concerned with the application of machine learning methods to credit risk management. Using a credit risk dataset provided at Kaggle (Default of Credit Card Clients Dataset), they compare and contrast the results of logistic regression, decision tree, and random forest with each other on several fronts, such as accuracy, recall rate, and interpretability. The findings indicate that the decision tree model is illustrative in credit default prediction.

In his research, Machine Learning Approaches to credit risk: Comparative evidence on participation and conventional banks in the UK, Gafsi (2025) compared the use of sophisticated machine learning (ML) models to predict credit risks in Islamic (participation) and conventional banks in the United Kingdom in 2010–2023. He used this robust empirical literature to leverage an equally weighted panel dataset in which the stochastic frontier approach (SFA) to Lerner index of market power - was estimated together with current best-practice tree-based ML algorithms (CatBoost, XGBoost, LightGBM, and Random Forest) to predict non-performing loans (NPLs). The findings reveal that the bank level financial performance indicators, especially the loan ratio, profitability and market power, do better than the macroeconomic variables in predicting credit risk. The CatBoost model showed more accuracy and explainability in comparison with the other models tested, which were verified using SHAP-based explainability analysis. The research implication can be applied practically to risk managers, regulators, policymakers, in the respect of appreciating the explanatory power of explainable AI tools in promoting financial management and decision-making in the post-crisis UK banking.

The research conducted by Trung and Vuong (2025) was based on the idea of creating a credit score model of individual customers of Vietnamese banks through machine learning methods. This article also employed a collection of financial and non-financial indicators as the input of different machine learning algorithms including, among others, Logistic Regression, K-nearest neighbor, Decision Tree, Random Forest, LightGBM, and Support Vector Method. The results derived out of these models were critically analyzed and compared in order to make the final decision of the most suitable credit scoring model to adopt by the bank. The analysis is based on Google Colab, which is a cloud-based service, to analyze all the data and create a model, which guarantees a solid and data-oriented method. This research will offer a viable solution to the Vietnamese banks when dealing with credit risk and enhancing their performance in business.

The article by Rad et al. (2025) explores the most important aspects of investment decisions with the focus on the use of decision tree regression, which is based on the behavioral finance theory. This study is able to determine significant predictors of investment outcomes through a thorough set of data including behavioral, demographic and financial variables, i.e., investment attitudes, decision-making behaviors, financial education, age, income and education. Although the model displays average predictive performance ($R2 = 0.185$; MAPE - 172.96%), it has identified hierarchical relationships between behavioral, cognitive, and demographic predictors. These findings point to the difficulty of investment decision-making and the necessity of integrative, behavioral -oriented methods in predictive models. The attitudes towards investments (25.88%), decision-making behaviours (19.53%), and financial education (16.68) prove to be the most significant variables, and more traditional demographic elements, such as income and age, are less influential. The buttered bread layout of the decision tree identifies important patterns of decision making especially when it comes to speculative behaviours and attitudes towards investments. Such results contradict classical rationality theories since they focus on behavioural factors as the overwhelming determinants of investment decisions. This paper is deemed useful in the proposed research towards bridging the gap between computational modelling and financial economics by illustrating the application of decision tree regression in discovering the intricate investor behaviour.

The Relevance of Decision Tree to Organisations in Nigeria by Alao et al (2021), a research that was to investigate the relevance of decision tree as a probable tool to be used in decision making by viable graphical illustrations, measuring and identifying assumptions within the stipulated environmental constraints, and ranking of priorities or options is a tool of the times that can be easily implemented or complicated with statistical chances and the fact that action taken would be all-encompassing and dynamic in nature. This expository study used a Desk review research method. The study observed that decision tree models, despite being an internal decision making model, its usage can be externalised and included in the financial statements and other reports as a part of sensitivity analysis and as an accretion of the financial package, investment decisions, sensitivity analysis, cost analysis and financial ratio analysis, as primary business areas.

2.3.1 Decision Tree and Fraud Detection

Frauds are a big threat to businesses, governments and also to individuals in the ever-changing financial environment. Such illegal activities do not only cost the economy a lot of money but also undermine trust in the economy and risk its stability. With the ever-growing digital transactions, there is a concern to establish effective and precise ways of detecting fraudulent transactions to safeguard the quality of financial systems (Owoade, 2025). Financial fraud is a topic that has gained widespread popularity in the last few years and presents major challenges to financial services, government and private customers. As the digital technology and online transactions swiftly evolved, the fraudulent activity has only been growing stronger, adversely impacting the economy and compromising the trust of consumers towards the economy (Chou et al., 2020).
Traditional methods used to detect fraud such as rule based systems and manual inspections often fail to detect sophisticated and well established fraudulent practices (Ngai et al., 2011). The use of machine learning (ML) models has promising outcomes in terms of overcoming the drawbacks of conventional fraud detection approaches via intricate pattern recognition and adjusting to changing fraud schemes and the application of vast volumes of data (Kou et al., 2021).

Machine learning wise the researches that are available typically address fraud detection as a binary classification task and train prediction models using off-the-shelf supervised machine learning tools including CART, XGBoost and SMOTBoost. Besides them, neural network-based deep learning has been very successful in a variety of applications due to its strong representation learning, and hence, it was also implemented in this area. Despite being demonstrated to promise some benefits, machine learning and particularly deep learning are yet to face no obstacles in the area of fraud detection task (Biana et al, 2023).

III. Methodology

This study adopts a desk review methodology to critically examine the application and relevance of decision tree models in financial management. A desk review, also known as a documentary or secondary data review, involves systematically collecting, analyzing, and synthesizing information from existing academic, institutional, and professional sources rather than generating new primary data. This method is particularly suited for exploratory and analytical studies where the objective is to integrate existing theoretical knowledge, evaluate empirical trends, and establish conceptual linkages across prior research.

3.1 Rationale for Using Desk Review Methodology

Practical and theoretical reasons are the reasons why a desk review methodology was chosen. To begin with, the research aims to comprehend the development, theoretical approach and practice of decision tree models in financial management that is already a field, full of academic literature and practical evidence. It would have been unnecessary and costly in terms of resources to conduct some fieldwork or experiment since much of the necessary data is published (Luo, 2025).

Secondly, decision tree applications cut across various fields that fall under credit scoring and fraud detection to risk management and investment analysis. It would be tricky to have access to first hand data in such wide settings specifically in terms of time and geographical limitations. A desk review enables the researcher to generalize the results of peer-reviewed journals, conference proceedings, technical reports, and institutional publications, which in turn give a holistic view of global and local trends.
Third, a desk review fits the interpretive and evaluative aspects of this research study which is not meant to test a specific hypothesis but evaluate patterns, relationships and theoretical implications of past research. It helps in the triangulation of knowledge collected by various reliable sources hence increasing validity and credibility of conclusions.

3.2 Data Sources

The secondary data used in this study were obtained from a wide range of reputable sources to ensure diversity, accuracy, and academic quality. These sources include:

▪ Peer-reviewed academic journals such as *IEEE Access*, *Frontiers in Artificial Intelligence*, *Journal of Financial Economics*, *International Journal of Information and Communication Sciences*, and *Risks Journal*;

- Online databases like Google Scholar, Scopus, and ResearchGate, where recent research between 2015 and 2025 was accessed to ensure the inclusion of up-to-date developments in decision tree modeling and explainable AI.

The inclusion of diverse sources ensures that the study captures both theoretical perspectives (e.g., decision theory and expected utility) and practical applications (e.g., credit risk scoring and fraud detection) in financial management.

IV. Findings

The review and empirical evidence indicated in the development of the decision tree model have been used broadly in the field of financial management especially in risk assessment, credit scoring, and investment analysis.

The discussion of decision tree models in financial management indicates that it is becoming increasingly applicable and flexible in various financial settings. In the past, decision trees have served as informal tools in simplifying the decision making process involving complex decisions by visualizing potential outcomes, risks and rewards as a structured and visual tool. As the data science and machine learning evolved with time, the use of decision tree models have become more advanced and are now able to help organizations make more accurate financial choices based on the data.

Empirically, it was proven that decision trees are useful to detect and measure project finance risks. The visualization of the risk paths and the aid in the analysis of the scenarios that the model provided was also mentioned as a strength of the model. Results validate that besides making the classification of borrowers by creditworthiness easier, decision trees also add to the predictive power of ensemble techniques such as random forests.

They also discovered that decision tree models can identify the most influential factors in the decision of an investor, that is, market volatility, risk tolerance, and financial goals among other factors in high-uncertainty environments. In spite of infrastructural and data constraints, decision trees are gradually becoming known to be simple, transparent and applicable in any financial planning and resource allocation.

In these works, similar themes can be identified: in these studies, decision trees are praised due to their interpretability, flexibility, and predictive quality. They offer financial managers with the strong justification of decisions made and improve the quality of decisions taken by combining both qualitative and quantitative data together.

V. Conclusion and Recommendations

5.1 Conclusion

The decision tree model also continues to be an important analysis instrument in the contemporary financial management. The fact that it has been developed as a simple heuristic system to an advanced machine learning model highlights how flexible it is in tackling complicated financial issues. The model assists the financial managers in simplifying complex decisions, forecasting risks, and making informed choices in other aspects of credit assessment, investment planning and risk management.

The results of the empirical review confirm the fact that decision trees are not just applicable but also becoming crucial in a data-driven financial environment. The fact that they can be incorporated within the machine learning systems also increases their possibilities, ensuring that it is possible to have scalable and automated systems of decision-making in most sectors and geographical locations.

5.2 Recommendations

It is recommended based on the above finding and conclusion that:

The use of decision tree models in decision-support systems should be given priority by financial institutions and more so those operating in developing markets through their interpretability and helpfulness in the uncertain environment.

The organizations are supposed to study the application of the ensemble methods (e.g., random forests, gradient boosting) which extend the basis decision tree model to achieve a higher prediction accuracy in the credit scoring and risk management.

To aid in the model development and implementation, financial institutions ought to invest in data collection, data management and preprocessing systems. Due to the fact that, Decision tree models are only effective when quality data is available.

Decision tree algorithms will be customized locally to increase their predictability and usefulness. Financial models have to take into consideration regional and institutional differences as it is demonstrated in the case of Vietnam and Nigeria.

To understand the model output more likely to make sound decisions, financial professionals need to be trained in a basic understanding of machine learning, such as how to use decision trees.

Further empiric surveys in different economic contexts are required to comprehend how decision tree models can be optimized to a set of financial uses, specifically in less-studied markets.

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