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Machine Learning for Financial Planning: A Comparative Analysis of Traditional Approaches and New Technologies

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Abstract:- This studyaimed to explain the evolving subject of financial planning by comparing established approaches with the emerging domain of machine learning (ML) technology. For the attainment of this goal, the data was collected from secondary sources and 83 sources were reviewed. It is found that the use of ML in financial planning procedures has emerged as a significant development in the constantly evolving financial environment. This paper undertakes a thorough comparison analysis to clarify the advantages and disadvantages of conventional financial planning and techniques that incorporate ML. The focus is on explaining the potential of machine learning algorithms (MLA) to improve precision, efficiency, and adaptability in the field of financial planning. Moreover, this paper delves into the complex problems and ethical considerations that arise from the integration of ML and the field of finance. The purpose of doing this comparative analysis is to offer significant insights into the evolution of financial planning practices, enabling them to effectively utilise advanced ML technology. The primary objective of this research is to provide valuable insights for professionals, scholars, and policymakers, enabling them to make well-informed choices on the effective incorporation of ML in the domain of financial planning.

Keywords:- *Financial planning, ML , Comparative Analysis, Traditional Approaches, Ethical considerations.*

I. INTRODUCTION

The significance of financial planning cannot be emphasised, as it is critical in assisting individuals, businesses, and organisations in efficiently navigating the obstacles offered by the current economic environment. Because of the numerous financial decisions and issues that individuals confront, such as retirement planning, investment management, risk assessment, and budgeting, the need for good financial management solutions has expanded dramatically (Siami-Namini, Tavakoli and Namin, 2018). Financial insecurity, missed opportunities, and greater exposure to economic uncertainty can all result from poor financial planning. In contrast, competent financial planning promotes the achievement of targeted financial goals for both individuals and organisations. It enables individuals to manage their financial resources, accumulate wealth, and successfully offset potential dangers. Given these repercussions, there is a growing realisation of the importance of dependable and effective financial planning systems. ML has become a valuable tool in the field of financial planning, bringing new options and better functions. The exponential growth of data and advances in computing power have created the possibility for MLA and methodologies to significantly alter conventional financial planning approaches. Using extensive datasets, automation, and sophisticated modelling techniques (Otchere et al., 2021), ML can provide substantial insights and predictions. The algorithms can learn from historical data, adapt to dynamic market conditions, and recognise intricate patterns that conventional methods would overlook. In the administration of extensive and heterogeneous financial data, ML offers several benefits. The aforementioned advantages include increased precision, enhanced operational efficiency, expansion potential, and adaptability. Utilising this technology has the potential to improve financial plans, increase the effectiveness of decision-making (DM) processes, and provide individualised recommendations (Potdar and Pande, 2021). This research holds an aim to carry out of the conventional approaches to financial planning and contemporary technology, specifically ML. The fundamental purpose of this investigation is to carry out a contrastive investigation of the various advantages, limitations, and prospective benefits of ML in comparison to conventional methodologies. This article's goal is to present interesting insights on the topic that will aid professionals and researchers in making informed decisions regarding the incorporation and application of ML techniques. This study aims to investigate the viability, effectiveness, and ethical considerations associated with the use of ML in the field of financial planning. As it relates to financial planning, the corpus of knowledge that already exists in the field of ML will be expanded as a result of this study.

The research objectives that guide this study are as follows:

- To examine the current landscape of traditional approaches in financial planning and identify their strengths and limitations.
- To explore the potential applications of machine learning (ML) in financial planning, including risk assessment, portfolio management, and personalized financial advice.
- To evaluate how well machine learning (ML) techniques perform in comparison to more conventional ways of financial planning.
- To analyse the ethical and regulatory considerations associated with the adoption of ML in financial planning.
- To identify future trends and challenges in the use of machine learning (ML) for financial planning.

These objectives and questions will be addressed throughout the article, providing a comprehensive analysis and contributing to the understanding of ML's role in financial planning.

II. OVERVIEW OF FINANCIAL PLANNING

Financial planning as defined by Abdullah, (2021) is the methodical process of establishing and attaining financial objectives through the effective utilization of financial resources and the application of wise DM. While doing financial planning, it is pivotal to establish quantifiable and specific goals in the initial stages (Amanullah et al., 2020). These goals can be starting a business, buying a house, paying for college, or saving for retirement. It is also crucial to evaluate the present financial situation by carefully examining revenue, expenses, assets, and liabilities. Financial planning includes risk assessment and mitigation as essential components (Ferrag et al., 2020). Understanding and assessing the risks connected to insurance, investments, and unforeseen events enables people and organisations to make wise decisions and safeguard their financial stability. Additionally, Wang et al., (2018) pointed out that proper budgeting and cash flow management guarantee the distribution of money and satisfaction of debt obligations. Financial planning must include investment management. To maximise profits while minimising risks, the process includes assessing various investment possibilities, taking one's risk tolerance into account, diversifying portfolios, and routinely monitoring assets. Financial planning includes estate and tax planning since they allow for the smooth transfer of assets while reducing tax liabilities.

The traditional approaches used in financial planning come with inherent challenges and limitations that demand acknowledgement. The reliance on static models and rule-based systems has a drawback. The DM processes used by conventional techniques frequently rely on pre-established rules or algorithms, which may not adequately reflect the complex and constantlyevolving nature of financial markets (Vineeth, Kusetogullari and Boone, 2020). When attempting to adapt to market conditions that are fast changing, these strategies could run into difficulties and produce less-than-ideal results. Additionally, traditional financial planning approaches frequently rely on historical data and make assumptions based on past results. The dependence on historical data may not sufficiently consider forthcoming unpredictability and uncertainty. Consequently, conventional methods might not yield precise predictions or adequately consider unforeseen risks and potential advantages (Mulvey, Hao and Li, 2018). Another challenge arises from the limitations of traditional approaches in handling extensive and intricate datasets. It is found that recently there has been a considerable expansion both in the quantity and variety of data about the financial sector. This surge poses challenges for traditional approaches in effectively handling and analysing the extensive pool of information. This limitation has the potential to impede the ability to extract significant insights and make prompt, well-informed decisions (Hajek and Henriques, 2017). Furthermore, conventional methods of financial planning may exhibit a deficiency in terms of personalization and customization. The strategies and recommendations often offered lack specificity and fail to consider the unique circumstances, objectives, and preferences of individuals or organisations (Dang, Moreno-García and De la Prieta, 2020). The imposition of this constraint has the potential to diminish both the effectiveness and pertinence of the financial planning process. According to Nikou, Mansourfar and Bagherzadeh, (2019), conventional methodologies for financial planning are extensively employed; however, they encounter difficulties and constraints in accommodating ever-changing market dynamics, integrating intricate data, and delivering tailored recommendations. The aforementioned limitations underscore the importance of employing novel methodologies, such as ML, to address these challenges and potentially enhance the effectiveness of financial planning techniques.

III. TRADITIONAL APPROACHES IN FINANCIAL PLANNING

A. *Rule-based financial planning*

Rule-based systems have been widely adopted in the field of financial planning. The DM processes of these systems are influenced by pre-established rules and algorithms (Atrill, 2017). In the context of financial planning, rule-based systems involve the establishment of explicit guidelines and thresholds to ascertain suitable courses of action. For example, in the case where an individual exhibits a high level of risk tolerance, a rule-based system could propose allocating a specific proportion of their income towards investments in equities (Brüggen et al., 2017). Frequently, these concepts are derived from historical data, known knowledge, or opinions provided by experts. Rule-based systems are developed to enhance uniformity and impartiality in the DM process. Rule-based systems offer a wide range of benefits such as simplicity, accessibility to wider individuals and reduction and consistency in subjectivity (Kapoor et al., 2018). In contrast, rule-based systems possess inherent limitations. A drawback exists when an individual or organisation is unable to effectively respond to dynamic market conditions (Anderson, Baker and Robinson, 2017). Regulations are typically formulated based on historical data, which may not fully encompass emerging patterns or unforeseen market fluctuations. The incorporation of this constraint has the potential to lead to less-than-optimal DM and the overlooking of potential opportunities. Another challenge is in the constrained capacity of rule-based systems to effectively handle intricate and interrelated financial variables. The field of financial planning involves a complex web of interconnected elements and non-linear relationships that may not be well captured by rule-based approaches (Bellomarini, Laurenza and Sallinger, 2020). The incorporation of this constraint can diminish the precision and effectiveness of the DM process.

B. *Statistical modelling in financial planning*

Financial planning specialists frequently use statistical modelling tools to examine historical data, detect patterns, and make forecasts. Statistical modelling approaches such as regression analysis, time series analysis, and Monte Carlo simulations give quantitative frameworks for understanding and predicting financial actions and consequences (George, Walker and Monster, 2019). These approaches employ mathematical and statistical models to determine the relationships between variables and forecast future values based on historical data. As highlighted by Xiang et al. (2021) regression analysis is a statistical tool for identifying relationships between variables such as income, expenses, and savings. This helps financial planners forecast future savings by factoring in anticipated revenue. Statistical modelling approaches have been used in a variety of financial planning scenarios (Lee et al., 2023). Models for assessing risk use statistical techniques to calculate the likelihood that certain events will occur and the potential effects they may have on financial performance. Models for portfolio optimisation use statistical techniques to calculate the best asset allocation while taking risk and return into account. The inherent limitations of statistical modelling tools must be understood, though (Shafizadeh-Moghadam et al., 2018). These models initially place a significant emphasis on historical data, functioning under the presumption that earlier patterns and linkages would persist over time. This presumption might not always be accurate, particularly when the market is experiencing a quick change or when extraordinary occurrences are taking place (Alharbi et al., 2020). Financial planners should use caution when forecasting future results using only previous data. Due to the assumptions and simplifications they make, statistical models have limits. These models frequently incorporate linear relationships, stable processes, and assumptions about the distribution of the underlying data. Any departures from these presumptions may have an impact on the models' accuracy and dependability (Yap, Komalasari and Hadiansah, 2018). The limitations and inherent biases associated with statistical modelling tools must be understood by financial planners. In conclusion, traditional financial planning techniques like statistical modelling and rule-based systems have been widely used. Although structural and quantitative analysis techniques provide insightful information, they are limited in their ability to be flexible, handle complicated variables, and produce precise projections under dynamic conditions. The aforementioned drawbacks emphasise how important it is to run trials with cutting-edge technology like ML to supplement and improve the current financial planning approaches.

IV. INTRODUCTION TO ML

ML is a specialised field within the broader domain of artificial intelligence, wherein computers are equipped with the ability to acquire knowledge and generate predictions or assessments without relying on explicit instructions from human programmers (Greener et al., 2022). The process involves the development of algorithms and models that acquire knowledge of patterns and associations from data, thereby facilitating the enhancement of system performance through iterative learning. MLAsare designed to effectively analyse and comprehend large datasets to extract pertinent insights and generate precise predictions or classifications (Kubat and Kubat, 2017). ML is supported by three essential components: training data, models, and algorithms. The MLalgorithm utilises training data, which comprises labelled examples or historical data, to comprehend patterns and relationships (Zhou, 2021). Mahesh (2020) posits models serve as representations of acquired patterns, whereas algorithms are the computational methodologies that enable the model to acquire knowledge and make predictions. Three primary forms of MLA may be distinguished from one another such as supervisor, unsupervisor and reinforcementlearning.

- For supervised learning (SL) algorithms to function properly, the training data must be labelled. This means that the input data must be linked to the appropriate output labels. These algorithms learn from the labels that are supplied to create predictions or categorise data that has not previously been seen. According to Saravanan and Sujatha (2018), some of the most common types of supervised learning algorithms used in financial planning include neural networks, support vectors, linear regression, and a decision tree..
- Unsupervised learning algorithms, on the other hand, work with unlabeled data and aim to discover patterns or structures within the data. These algorithms identify clusters, associations, or anomalies in the data without explicit guidance. Unsupervised learning techniques, such as clustering algorithms (e.g., k-means clustering) and dimensionality reduction algorithms (e.g., principal component analysis), can be useful in segmenting customers, identifying market trends, or reducing data complexity (Alloghani et al., 2020).
- Algorithms that use reinforcement learning (RL) acquire knowledge by interacting with their surroundings and receive feedback in the form of rewards or punishments according to the actions that they carry out. These algorithms aim to maximize a reward signal by exploring and exploiting different actions. Reinforcement learning has found applications in portfolio management, where algorithms learn to optimize investment strategies based on feedback from market performance (Oh et al., 2020).

ML relies heavily on the phases of feature engineering and data preparation, which have a big impact on the effectiveness and precision of models. Data preparation is the methodical process of cleaning, manipulating, and standardising data to prepare it for further analysis. Addressing problems including missing data, outliers, improper formatting, and data quality are all part of this process (Simeone, 2018). By guaranteeing the quality and uniformity of the input, preprocessing improves the dependability and robustness of ML models. The discipline of carefully choosing and altering significant features or variables from a given dataset to improve the predictive abilities of models is known as feature engineering. The procedure entails the extraction of important data, the development of original features, and dimensionality reduction (Stamp, 2022). The activity of feature engineering has the potential to improve a model's performance by capturing important patterns and deleting unimportant data from the dataset. To assure the precision and dependability of MLmodels, feature engineering and data preparation play a crucial role in financial planning (Bi et al., 2019). Missing values, outliers, and noisy data are frequently found in financial datasets, and any of these can have a considerable bearing on the results obtained by a model. The quality of

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the data used for training and testing purposes improves as a result of the preprocessing techniques' success in addressing these issues. Financial planning is extremely important because feature engineering makes it possible to extract important financial indicators, ratios, or trends from raw data (Mahesh, 2020). This process helps models better capture the critical elements that influence financial outcomes, enabling more accurate predictions or evaluations. According to Simeone, (2018) in the specific branch of AI known as ML, without using explicit programming, these systems are designed to learn from the data they are given and subsequently provide predictions or judgements.. Financial planning has made extensive use of MLtechniques, such as SL, USL, and RL. The ML pipeline is not complete without data preparation and feature engineering because it improves the stability and accuracy of models by resolving issues with data quality and choosing the right features.

V. APPLICATION OF ML IN FINANCIAL PLANNING

A. ML for risk assessment and management

A systematic risk assessment is critical for economic and financial setups. Currently, there is a need for persistent risk assessment, enhancement in learning lessons from the past and definingprocedures to evaluate relevant data, these are to be united with suitableproficiency to cope with unusual events to ensure provision of support for management of risks. There is a growing utilization of ML methods to evaluate and address risks in financial markets (Ma et al., 2018). With the establishment of ML, traditional practices of managing risks have been alleviated and the doors for Artificial Intelligence-based models have been opened up. These systems are found extremely helpful for Internet finance enterprises in opening ML-driven online credit models (Li & Li, 2021). Widely used ML methods comprise K nearest neighbours (KNN), BP neural network and support vector machine (SVM). Moreover, tree models like the basic decision tree model, random forest (RF) and lightGBM for risk assessment are also extensively used.

Table 1: Overview of different ML Models used for Financial Risk Assessment

Common ML models	Utilization in financial risk assessment	References
K nearest neighbours (KNN)	Used for unpretentious reference systems, mining of data, predictions of financial markets and detection of intrusions	Huang et al., 2021
BP neural network	Used to regulate the current economic situation of an enterprise and management of its financial risks accurately. It has a good prediction effect.	Liu et al., 2022
Support vector machine (SVM)	Used for low-variance data and can handle high-dimensional data as well.	Lim, 2021
Random forest (RF)	The financial credit risk data is categorized using the weighted random forest method, an assessment index system is built, and the process of analytical hierarchy is used to determine the financial credit risk level.	Lin et al., 2022
lightGBM	Used for financial ratio predictions and detection accurately	Wang et al., 2022

Based on the analysis Huang et al. (2021) suggested that the modern ML tool RF is more accurate in risk prediction than previously used statistical models. A study conducted on China's financial system proposed the utilization of ML and AI-based risk assessment models such as RF (random forest) algorithm are highly fruitful in getting an early warning of financial risks. According to Lin et al. (2022), technologies like OLAP, Data warehouse, and data mining can aid the departments involved in supervision to familiarize themselves withMLmodels in countries where the dependence on financial experts is to be minimized.

In addition to risk detection, ML has turned out to be a new normal in risk management. It has helped to make quicker decisions in investment, minimized costs for compliance, reduced operational and regulatory budgets and decreased potential losses. The tools such as Long Short Term Memory (LSTM) can help financial institutions to measure the volatility of the future market more effectively. Kou et al. (2019) maintained that natural language processing (NLP) techniques are now progressively utilized to increase financial forecasting enactments. ML has also carved its importance in financial sensitivities calculation.

B. Predictive modelling for credit risk assessment

Financial globalization and fiscal market volatility have made credit risk more protuberant and worthwhile. Credit risk can be defined as the possibility of an economic loss due to the inability of a debtor to return the loan. These risks can be determined more effectively using predictive modelling, which uses statistical tools to predict future behaviour. They use historical data and analyse it to give future outcomes to make informed decisions (Chang et al., 2018). These models help provide an overview of loan limitations and interest rates for certain borrowers. This can assist firms in minimizing their credit risk and supplying credit and loans to clients who are likely to make payments on their bills on time.When estimating the overall probability of default on a credit obligation, it is necessary to take into account both the loss given default and the exposure at default.

Predictive modelsare categorized as supervised. Although both Supervised and unsupervised MLA are being used for modelling credit risk assessment Xia et al. (2018) showed utilization of joint strategy to enhance the results of classification of better performance of credit scoring models.The procedure begins with thorough data collection, which includes an individual's credit history, income sources, length of employment, existing debts, payment practices, and macroeconomic variables. Papouskova and Hajek (2019) highlighted that the extensive dataset will be used to train predictive models. The models cover a wide range of procedures, such as decision trees, logistic regression, ensemble methods such as random forests, and even more complicated techniques like boost gradients and artificial neural networks.

C. Fraud detection using anomaly detection algorithms (ADA)

ADA are used to detect fraud in a variety of areas, including banking and cyber security. It can be discovered using three mathematical approaches: statistics, traditional ML, and deep learning. Machine Learning Anomaly detection, which is the process of discovering patterns in data that deviate greatly from the norm, is a strong tool for spotting fraudulent conduct that is distinct from permitted transactions (Zhu and Zhou, 2019). This method may distinguish fraudulent behaviour from authorised transactions. Anomaly detection methods include the examination of past data to recognise patterns of usual activity. After that, they discover examples that exhibit certain patterns or behaviours by making use of the model that they have just recently learned (Jiang et al., 2019). In the context of fraud detection, these algorithms can automatically recognise transactions, behaviours, or events that are out of the ordinary and may constitute fraudulent activity.

Anomaly detection algorithm involves collecting data, feature extraction, training model, anomaly detection, threshold setting and real-time monitoring.K-nearest neighbours (Knn), one-class SVM, DBSCAN, LOF and isolated forests are common tools which are widely used to detect anomalies (Anandakrishnan et al., 2018). These ML tools are far more erudite, very complex, and easy to deal with unqualified data. They play a crucial role in fraud detection by automating the identification of unusual and potentially fraudulent activities (Pourhabibi et al., 2020). Their ability to adapt to evolving fraud patterns and process data in realtime makes them indispensable tools in maintaining the security and integrity of financial systems and online platforms.

D. Machine Learning for portfolio management

By offering data-driven, dynamic solutions that improve investment DM, ML has transformed portfolio management. Portfolio management has always depended on static models and professional insights, frequently finding it difficult to adjust to the quickly shifting market conditions (Ban, El Karoui and Lim, 2018). On the other hand, ML uses algorithms to examine huge and varied datasets, providing several important advantages. By enabling data-driven, flexible strategies that beat conventional approaches, MLhas revolutionized portfolio management. According to Betancourt and Chen(2021), portfolio managers now have an unprecedented set of tools to improve DM and provide investors with higher returns thanks to ongoing improvements in ML approaches.

To find hidden patterns and connections that guide investing strategies, MLA examines historical market data, economic indicators, news sentiment, and even alternative data sources. The development of predictive models for asset price movements is made possible by ML techniques including time series analysis, regression, and neural networks. These models support trend forecasting in the market and portfolio allocation optimization (Piryonesi and El-Diraby, 2020). It aids in more efficient risk assessment and management. Algorithms can spot potential vulnerabilities and suggest hedging tactics by examining previous market crashes and swings. Modern ML algorithms maximize portfolio allocation by taking into account a variety of variables, such as risk appetite, expected returns, and market conditions (Nevasalmi, 2020). This innovative strategy maximizes portfolio diversification while reducing losses.

By executing established strategies based on real-time market data and automating trading choices, MLAs can react to market movements more quickly than human traders. With the aid of ML-driven sentiment analysis of news stories, social media posts, and market comments, investors may assess market mood and make wise judgments. ML algorithms can provide tailored advice and services on a bigger scale by adapting investment suggestions to specific investor profiles and aspirations (Ren et al., 2021). Chen, Pelger, and Zhu (2023) suggest analysing analytic teams' and portfolio managers' trade data to detect biases. People can then check if these negative tendencies affect their finances. Machine learning (ML) can be used to identify bias during trade executions, portfolio construction, and stock selection to yield the best outcomes.

E. Portfolio optimization and asset allocation using ML

Portfolio optimization is a recognised approach that plays a key role in making decisions related to investmentsin terms of fiscal assets or instruments. It enables the investors to attain diversity, minimize the cost of transactions, and make cognisant investment decisions using a set of models having a range of quantitative tools. ML opens doors for an entirely innovative viewpoint for the optimisation of financial portfolios compared to conventional practices of numerical evaluation and evading mechanisms (Ma et al., 2021). ML has an edge in processing and analysing a large amount of data that cannot be achieved by the mathematical approach being followed traditionally. Secondly, MLcanbuild a non-linear affiliationeasily todecreaseone-dimensional data inclination which is not possiblein any other way. Moreover, MLA are also able to identify and process the multifaceted association between risk and return (Day and Lin, 2019). All such advantages suggest a clear edge of ML models over human beings.

Asset allocation encompasses investment portfolio division among dissimilar categories of assets, likebonds, stocks, and cash. It entirely depends on the individual to choose the process of defining which combination of assets to have in his/her portfolio. Idowu et al. (2021) provided that ML tools offer a lot of chances for active fund management firms to perform exceptionally against market indices and contestants. The investments essentialfor data analysis will be noteworthyto obtainviablebenefitsthat may not be long-term and sustainable (Benhamou et al., 2021).Meanwhile, MLhelpsto analyse large datasets, using its powerful algorithms, to make forecasts against pre-requisite goals. Despite subsequentdirectionsprovided by humans, As additional data is added to the system, machine learning algorithms automatically alter themselves through a process known as trial and error to provide ever more accurate suggestions.

F. Algorithmic trading and market prediction

Trading in the financial markets is complex and chaotic due to the myriad of factors, both economic and psychological, that influence the environment. A typical algorithmic trading system uses ML to provide buy/sell recommendations after successfully analysing multiple data sets from various sources. In algorithmic trading, a transaction is executed by a computer program that is designed to adhere to a specified set of parameters (an algorithm) (Cohen, 2022). As a result of this, a significant number of institutional traders are developing trading platforms that provide them the ability to carry out a high volume of financial transactions in a short amount of time.

ML tools commonly used in algorithm trading include naive Bayesian, SVM, ARIMA, KNN, and RF. These algorithms are found more accurate especially when datasets are large but these algorithms are sometimes greatly subtle to outliers and might not identify anomalies and exceptional cases effectively. Market prediction and future of investment about when to buy or sell would be made more informed using ML algorithm (Salkar et al., 2021).In this way, decisions would be based on facts and figures and not on emotions. Enterprises can make decisions like arbitrage, market making and hedge funds leading to greater profits. Algorithms allow traders to give greater liquidity to the market, judge price differences in different markets, make risky bets and design reward strategies. This has become more common with innovations coming in regularly (Nan, Perumal and Zaiane, 2022). Businesses are now shifting to advances in algorithm trading like cryptocurrency trading, high-frequency trading and quantitative analysis. Trading companies are reliant on algorithm trading for stock market trend analysis as well.

G. Machine learning for personalized financial advice

Thanks to artificial intelligence (AI) and machine learning (ML), the whole financial services sector now has a way to satisfy the demands of customers who want more innovative, user-friendly, and safe means to access, utilise, save, and invest their assets. This is made possible by the fact that AI and ML can learn on their own. In addition to this, artificial intelligence helps the financial industry by speeding up and improving operations linked to quantitative trading, financial risk management, and investment selections (Mahalakshmi et al., 2022). The vast majority of important financial operations, including stock trading, risk assessment, and giving credit to loan applicants, are currently being replaced by AI. Find out of the phrased. as and the as and the phrased. as and the phrased. as and the phrased.As indicated by Pricope (2021) in his study, it could result in more informed and specialized products and services, as well as improved internal procedure productivity, cybersecurity, and risk mitigation. Customer satisfaction increases as a result of the faster reaction time enabled by AI. It is altering the environment by offering outstanding benefits to organisations and customers via improved customer interaction and financial analysis.

Personalization is perilous for modern retail services as well as for the banking sector. Services can be personalized by designing them to meet the specific needs of the consumers. This not only enables them to receive products, services and pieces of advice that are specifically directed to their interests and goals but also aids them in risk tolerance (Osterrieder, 2023).This can help customers make decisions aligned with their long-term financial goals Level of personalization is being improved by financial enterprises by using advanced methods such as a recommender system for sales of various products and services, assessment and evaluation of credit scoring risks and subdivision of consumer-based marketing.

This personalized financial advice can be made more effective by using AI tools like Personal Capital and Mint. There has been an increased use of artificial intelligence in stock trading via the use of ensemble learning, currency recognition through the use of deep learning, stock index efficiency through the use of time-series modelling with feature engineering, and investment portfolio management through the use of reinforcement learning (RL). Moreover, saving improvement, debt payment optimization and cost-saving optimization prospects can be made more personalized. ML is helping individuals in expense characterization and budgeting by helping them understand their transaction patterns and budget allocations (Maree & Omlin, 2022). Some platforms like Wealthfront recommend personalized opinions on successful investments by continuously adjusting portfolios. Across the globe financial institutions like Acorns, Qapital, Clarity Money, Stash and Habito are using ML are personalized financial advice. This ranges from investigating and budgeting to debt management and mortgage assistance. They provide real-time financial advice and answer customer queries as well (Cohen and Qadan, 2022).

H. Recommendation systems for investment strategies

In ML, a recommendation system helps to predict and taper down the options people are looking for. It can be done by using data having a large number of available choices. These recommendations are made based upon the purchases made in past, history of searches, demographics and other similar factors. These systems are very useful to explore products and services that cannot be found by any other means. Several algorithms and tools like collaborative filtering, content filtering and context filtering are available for making recommendations on investments. These algorithms can be used in a hybrid manner, which is a supervised formula used as an amalgamation of both collaborative and content-based filtering approaches. Such systems are more efficient and high-scaled as compared to pure filtering systems (Hernández-Nieves et al., 2020).

Managers are transforming their management strategies based on ML . This can help them in taming their investment processes based on artificial intelligence and its subset. The investment arena has gone through advances like in the near past that have shifted individual investors to ML technology and algorithms. The utilization of robo-advisers has made it easy to get insight into investment strategies with minimal human supervision. They are best suited to make investment decisions using passive indexing strategies. McCreadie et al. (2021) reported that in most developed countries like the UK, the adult population is more focused on sound investments to gain profit from their savings. ML tools can be used effectively in such scenarios to gain expected results.

I. Chatbots and virtual assistants for financial planning

Chatbots and virtual assistants are computer-coded ML tools frequently being used as a means to automate financial tasks. These are providing advice on financial problems and inquiries about users' accounts, bills, and many frequently asked queries. They can keep a record of customer's transactions and create expenses report. Financial institutions like banks often employ virtual assistants to interact with their customers and simplify financial issues for them (Priya & Sharma, 2023). Furthermore, industries are also actively bringing together virtual assistants (VAs) powered by AI technologies to increase their productivity and competitiveness. These VAs are working like personal assistants and are highly beneficial for the financial industries in guiding the customer in financial planning.

Chatbots find their application in digital banking, customer onboarding, refund management and customer services. These are supportive in making financial decisions due to a range of features they support including accessible guidance available all the time, conversational interface, budgeting and expense tracking, investment recommendation, portfolio management, debt management and many more. Several researchers have proposed improved profitability among financial organisations after the use of ML-driven Chatbots and Vas (Ortiz, 2023). Business Insider has reported better financial planning and customer satisfaction with the advent of AI-driven tools.

VI. COMPARATIVE ANALYSIS OF TRADITIONAL APPROACHES AND NEW TECHNOLOGIES

A. Performance evaluation metrics for financial planning

Traditional practices can provide highly personalized responses by taking into consideration individual goals, preferences and life circumstances. They usually involve human-driven financial measures like financial, management and cost accounting. On the other hand,ML-driven systems provide customized recommendations generated through user analysis. Traditional approaches are short-term with greater customer satisfaction, product quality and public responsibility measures when compared to algorithm-based technologies which ensure a lower degree of customer satisfaction (Negri et al., 2021; Betancourt & Chen, 2021). Traditional practices like contribution margin, ROI, RI, net profit, and EPS are mainly concentrated on cost and revenue data rather than process, deal with a limited number of customers and are available during business hours only while ML tools are algorithm-based methods having the capability to deal with a large number of users with an availability of 24 hours (Mahalakshmi et al., 2022; Cohen, 2022). Conventional practices require a greater budget and resources as compared to ML systems which are cost effective and efficient.

B. Case studies comparing traditional approaches and ML techniques

The machine learning (ML) industry is having an increasingly significant influence on the business of providing financial services. The areas of fraud and compliance, credit scoring, the forecast of financial crisis, robo-advising, and algorithmic trading have all been significantly impacted by machine learning. Chang & Park (2018) provided a comparative study in which it is argued that financial institution has shifted to ML, which is achieving near human-level performance. South Korea established the first internet-only banking firm in 2018 and achieved greater customer satisfaction. This swift progress of smart e-form expertise has played a key role in novelty for the financial sector by reducing operational costs. This model also performed very well in the credit scoring market. Chen et al. (2018) studied ML model implementation in Taiwan and found it efficient in terms of financial planning. Munkhdalai et al. (2019) surveyed in the US focused on the performance of the credit scoring system under the random forest method and found its score highly effective against the expert-led system.

The government of the United Kingdom proclaimed plans in 2018 to invest 1.3 billion USD in AL and ML systems to get a return of 814 billion USD added to their economy by 2035 with the financial services sector as one of the leading areas getting this investment. After this initiative, London became an epicentre for AI businesses. Various prominent companies including Swiftkey, DeepMind, and Ravn switched to AI-based methodologies making the London AI foundation twice in size as that of Berlin and Paris combined. A survey was conducted by the Bank of England in 2019 to find out the utilization of ML in financial institutions which indicated that 66% of them were using algorithm-based tools in various areas. Respondents argued that ML has an immense application in fraud and money laundering prevention and customer service situations (Huang et al., 2020). Liebergen et al. (2017) stated that a lot of financial setups are still reliant on an outdated rules-based system that highlights individual communications and unassuming transaction arrangements which is not an erudite tool to identify more complicated transactions .

In 2016, the Lloyds Banking Group collaborated with the artificial intelligence company Pindrop, located in the United States, to combat suspicious financial behaviour and fraud. 'Phoneprinting' is the name given to Pindrop's ML technique. More than 80% of the fraudulent activity in the United States has been uncovered with the use of this method (Buchanan & Wright, 2021). A German e-commerce company used 250, 000 procurements to analyse

10 variables for digital footprints to predict default. According to the findings of the study, digital footprints are a useful addition to the information provided by credit bureaus; they improve access to credit and lower default rates (Berg et al., 2020). Customer satisfaction and buying behaviour can also be increased by using ML techniques. Fintech, a UK-based firm, employed NLP to have greater customer interaction.

VII. STRENGTHS AND LIMITATIONS OF TRADITIONAL APPROACHES VERSUS ML

A. Strengths of traditional approaches versus ML

Table 2: Strengths of traditional approaches over ML (Wang et al., 2022; Mahalakshmi et al., 2022)

Criteria	Traditional Approaches	ML Approaches
Personalized responses	Human experts have a deep understanding and provide tailored advice to clients about their financial planning.	These approaches can only provide responses based on market trends, risks and historical datasets
Emotion handling	These systems can consider emotions while making a decision	No emotion involvement
Expertise	Expertise in such systems may vary depending on demographics	They are expert and logical based on previous datasets

B. Weaknesses of traditional approaches versus ML

Table 3: Weaknesses of traditional approaches compared to ML (Cohen, 2022; Lin et al., 2022)

Criteria	Traditional Approaches	ML Approaches
Subjectivity	Human-based systems show biases and can sometimes show inconsistencies when making decisions	Algorithms can overcome biases present in data
Time and cost	They are time-consuming and require a lot of investment in human resources	Requires limited investment and is time-effective as well.
Flexibility	These systems usually struggle to adapt to changing market scenario	Quickly get Tamed to market trends

C. Key factors to consider when choosing between traditional and ML approaches in financial planning

For the past 20 years, ML has been the unseen driving force behind technological advancement. Before its introduction, only highly skilled human agents could do complex jobs. Many organisations today choose to use digital technologies to streamline and enhance their processes. According to recent studies, AI and ML are the transformative forces that will optimize internal operations and improve customer experiences. The decision between a rule-based and a machine-learning system is driven by organisational requirements. Although ML systems can handle larger, more complicated tasks and environments than rule-based systems, developing effective applications requires more technical competence from teams. It depends on how strict the constraints must be, the criteria for efficiency and training expenses, and whether the rules will be created by a data science team or an algorithm (Xia et al., 2018). When choosing which system to opt for businesses should consider the type of algorithm they want to use and the level of understanding and training required to make it operational and fruitful. Although ML finds its application in fraud detection, stock market, investments and financial planning sometimes customers are more reliant on expert-based systems(Salkar et al., 2021). Automation of system companies should consider the competency of model users, validators and data scientists, data quality and scalability support.

VIII. ETHICAL AND REGULATORY CONSIDERATIONS IN ML FOR FINANCIAL PLANNING

A. Bias and Fairness in Machine Learning Algorithm

ML biases are referred to as the inclination of an algorithm to use and imitate human biases in its output. AI models rely mostly on the data used for their training for the prediction of financial outcomes and planning. In many cases skewed data having inaccurate, imperfect and inapt training results in poor DM by the ML tools. Some of the most common biases include representation bias, historical bias, aggregation bias, evaluation bias, and measurement bias. If the training is done based on such biases, the algorithm will reflect it in its results. There exists past bias for groups of people who were underprivileged like women and poor segments of the society (Mirestean et al., 2021). Scientists sometimes sample a population non-uniformly which creates a dataset resulting in representation bias. Similarly, there exists a difference between the data collection used for training and the one that exists. Bias in evaluation occurs during model iteration and evaluation. When discrete groups or inhabitants are unsuitably united during the construction of an AI model aggregation bias rises, which results in a system that merely does well for the majority. A human reviewer may override a correct model prediction and introduce their own biases when selecting whether to accept or dismiss a model's forecast. This can occur when someone permits their prejudices to influence the algorithm during an evaluation, which can have a major impact on the model's performance.

Such pitfalls can be evaded by careful examination and correction of the systems. A fairer AI model requires superior training datasets with precise, comprehensive, valid, reliable, effective, and unvarying data. Bias extenuation strategies can be employed for the high-quality performance of any ML algorithm. For mitigation of bias, three strategies can be employed. Firstly, the pre-processing of algorithms can be done by altering the weights of the training dataset sample (Alibašić, 2023). Secondly, optimal results can be generated by the data scientists by modification of learning algorithms used for model training. Lastly, Retraining is frequently accomplished by providing fresh data, constructing the model from scratch, or adjusting model parameters. Novel tools like fairness flow can also be established to make ML impartial. Data scientists can identify and address vulnerabilities in data to make the system fair enough to avoid any bias in the financial planning.

B. Privacy and data protection concerns

The financial sector is undergoing huge shifts due to digital conversion, causing supplementary influences and mounting apprehension over protecting data. Digitization of data has raised various privacy concerns in which users are very concerned about whether to provide their data online especially while making online transactions. The major questions that arise are if permission is needed, the time length for which data is kept, processed or stored and the way it is handled. These challenges are growing daily as people are becoming more concerned about their data. Due to this, many financial organisations are reconsidering their privacy policy (Mazurek &Małagocka, 2019). This can be done by execution of an infrastructure that has an intrusion detection and deterrence system, encryption and firewalls. Encryption of the privileged data should be done using efficient data protection mechanisms. Restricted access to sensitive systems, the development of a composed incident response plan and multi-factor authentication can be a tool to protect the privacy of users' data. These measures should be checked regularly to detect and align with emerging threats (Huang et al., 2021). This includes staying well aware of the up-to-date requirements and employing essential controls to secure customer data.

C. Compliance with financial regulations and legal frameworks

The growing use of ML in financial institutions has driven the attention of financial supervisory authorities. ML-associated risks are difficult to undertake by regulatory bodies using conventional practices like external governance. A possible response to AI-centered risks is a licensing condition for ML used in financial enterprises. Another compulsory requirement is an insurance scheme for the AI systems. In 2017, the House of Lords, in the UK made a commotion to establish principles for AI development and treatment in a legal framework (Singh et al., 2021). The regularization process requires the regulators, in conjunction with the institutions, to redevelop new means through which they can disseminate collaboratively compliant information. Early warning systems are a type of collective mechanism that financial organisations like banks have already developed. This mechanism uses artificial intelligence to detect fraudulent activities on common databases. Financial institutions like banks (Ren et al., 2021). Instead of focusing on sharing competitive data, businesses should concentrate on exchanging compliant and fraternal data, also known as collaborative data, to reduce the likelihood of market failure. The sharing of data with competitors will, in most cases, make rent-seeking behaviour worse.

IX. FUTURE TRENDS AND CHALLENGES IN ML FOR FINANCIAL PLANNING

Some of the ML applications that are famous in finance and banking include mobile banking apps and Chatbots. For innovative future applications, MLAs are frequently used with other technological advances. These applications draw out accurate historical data relevant to the customers and predict their futures. The adoption of voice recognition, face recognition, and other types of biometric data along these lines will cause a revolution in the future of security within the sector thanks to the applications of machine learning (Jiang et al., 2019). This will take the level of security to a new and higher level. The use of machine learning models may be of significant aid to businesses in the financial services industry when it comes to assessing current market trends, generating predictions about future developments, and identifying the social media activity of each individual consumer. These chat assistants of the future will be developed with an abundance of finance-specific customer contact tools as well as robust natural language processing engines to enable speedy interaction and querying. In the future, things will turn out like this. The majority of financial companies need to begin by identifying the right set of use cases with an experienced machine-learning services partner (Ortiz, 2023). This is necessary because the partner must be able to not onlhy develop, but also implement the right models to develop and implement the right models.

X. CONCLUSION

Financial institutions have a great opportunity thanks to digitalization, particularly when massive datasets are combined with the right instruments. This article compared and contrasted the use of ML with more conventional approaches to financial planning and analysis. Several facets of ML were discussed to highlight the superiority of AI over more conventional, human-based methods. The research is an attempt to prove that ML has practical applications for the banking industry. ML is at the heart of the AI technique because of the useful skills it provides for data prediction and information inference based on collected data. The use of ML -based technologies also allows for more effective client engagement and faster problem-solving. MLA are used to find better ideas, make data analysis easier, and provide the facts needed to make smarter financial decisions. Strategies for spotting trends, ranking security assessments, and enforcing appropriate countermeasures are standard tools in the hands of management and staff alike. ML methods can help with cost savings, productivity gains, risk reduction, and the promotion of economical purchasing. A further common result of ML algorithms is the generation of personalized reports based on the available data, which deliver information to management at all levels in a streamlined manner, allowing for more educated DM. Insights into how ML could be useful in financial planning are offered to improve DM in the field and promote the use of ML.

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