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A Comprehensive Review on Applications of Artificial Intelligence in Stock Analysis, Credit Risk and Portfolio Management: Advancements, Challenges and Future Directions

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ABSTRACT:

Artificial Intelligence (AI) has emerged as a transformative force in financial modelling, revolutionizing the way financial institutions analyse data, make decisions, and manage risks. This comprehensive review manuscript examines the state-of-the-art applications, advancements, challenges and future directions of AI in financial modelling across stock analysis, credit risk and portfolio management. The review starts with an overview of AI technologies relevant to financial modelling, including machine learning and deep learning. AI has its applications in financial modelling, such as stock market prediction, credit risk assessment, algorithmic trading, fraud detection, portfolio optimization, and regulatory compliance. The manuscript discusses the importance of AI in enhancing decision-making processes, improving efficiency, and mitigating risks in the dynamic and complex landscape of finance. Furthermore, it addresses the challenges and limitations associated with the use of AI in financial modelling, such as data quality issues, interpretability concerns, regulatory constraints, and ethical considerations. Finally, the manuscript outlines future directions and emerging trends in AI-enabled financial modelling, highlighting opportunities for innovation, collaboration, and responsible AI governance. Finally, this review provides valuable insights and recommendations for practitioners, researchers, and policymakers interested in harnessing the potential of AI to drive advancements in financial modelling and shape the future of finance.

Keywords: Financial modelling, Artificial intelligence, Stock market, Risk assessment, Portfolio management

INTRODUCTION:

Artificial Intelligence (AI) is a branch of computer science focused on creating systems that can perform tasks that typically require human intelligence. These tasks include learning from data, recognizing patterns, making decisions, and solving problems [1]. AI encompasses a wide range of techniques and approaches, including machine learning, deep learning, natural language processing, and robotics [2]. In recent years, AI has experienced rapid advancements, driven by improvements in computational power, availability of big data, and breakthroughs in algorithms. AI technologies are increasingly being integrated into various industries, revolutionizing processes, enhancing productivity, and enabling new capabilities[3].

Financial modelling involves creating mathematical representations of financial situations or scenarios to analyse and make informed decisions. It encompasses a broad range of techniques and methodologies used to forecast future financial performance, evaluate investment opportunities, assess risk, and optimize strategies[4]. Financial models can be simple or complex, depending on the scope and complexity of the analysis. They are utilized by financial professionals, analysts, investors, and decision-makers across different sectors, including banking, investment management, insurance, and corporate finance[5]. Effective financial modelling requires a deep understanding of financial concepts, proficiency in quantitative methods, and the ability to interpret and communicate results accurately[6]. In today's dynamic and complex financial landscape, the role of financial modelling is increasingly important for guiding strategic decisions, managing risks, and maximizing value creation[7].

IMPORTANCE OF AI IN FINANCIAL MODELLING:

The importance of AI in financial decision-making stems from its ability to analyse vast amounts of data, identify patterns, and derive actionable insights in real-time (Figure 1). Here are several key reasons why AI plays a crucial role in financial decision-making:

Enhanced Data Analysis:

AI algorithms can process large volumes of structured and unstructured data from various sources, including financial markets, economic indicators, news articles, social media, and customer transactions. By analysing this data, AI systems can uncover hidden trends, correlations, and market signals that human analysts may overlook[8].

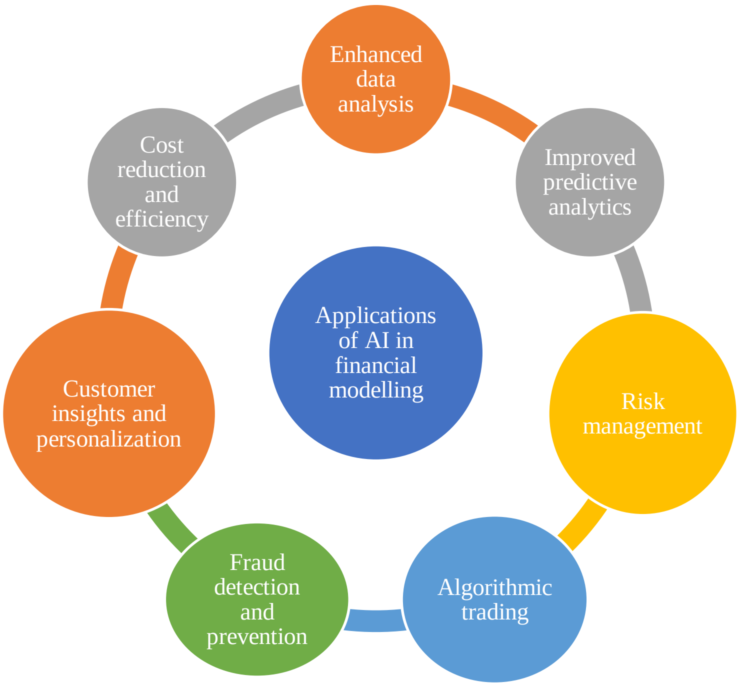

Figure 1. Applications of AI in financial modelling

Improved Predictive Analytics:

AI-powered predictive models can forecast future market trends, asset prices, and financial performance with greater accuracy than traditional methods[9]. By leveraging machine learning algorithms, AI systems can continuously learn from new data and adapt their predictions to changing market conditions, helping investors make more informed decisions[10].

Risk Management:

AI enables financial institutions to better assess and manage risks across different areas, including credit risk, market risk, operational risk, and regulatory compliance[11]. AI algorithms can identify potential risks and anomalies in real-time, enabling proactive risk mitigation strategies and reducing the likelihood of financial losses[12].

Algorithmic Trading:

AI-driven algorithmic trading systems can execute trades at high speeds and frequencies based on predefined rules or predictive models. These systems can capitalize on market inefficiencies, arbitrage opportunities, and price fluctuations, leading to improved trading performance and enhanced portfolio returns[13].

Fraud Detection and Prevention:

AI-powered fraud detection systems can analyse transactional data and identify suspicious patterns or anomalies indicative of fraudulent activity. By detecting fraudulent transactions in real-time, AI helps financial institutions minimize losses, protect customer assets, and maintain trust and confidence in the financial system [14].

Customer Insights and Personalization:

AI enables financial institutions to gain deeper insights into customer behaviours, preferences, and needs through data analysis and predictive modelling. By understanding customer segments and individual preferences, AI can facilitate personalized recommendations, targeted marketing campaigns, and tailored financial products and services[15].

Cost Reduction and Efficiency:

AI automation can streamline and optimize various financial processes, reducing manual effort, minimizing errors, and lowering operational costs. Tasks such as data entry, document processing, compliance checks, and customer support can be automated using AI technologies, freeing up human resources to focus on more strategic activities[16].

AI plays a critical role in financial decision-making by providing valuable insights, improving accuracy and efficiency, mitigating risks, and enhancing customer experiences[17]. As AI technologies continue to evolve, their impact on financial markets and institutions is expected to grow, shaping the future of finance in profound ways[18].

The research objectives are as follows:

- To provide an overview of the current state-of-the-art in artificial intelligence (AI) technologies relevant to financial modelling.
- To explore the diverse range of applications of AI in financial modelling across different domains, including stock market analysis, credit risk assessment, and portfolio optimization.
- To discuss the challenges and limitations associated with the use of AI in financial modelling, such as data quality issues, interpretability concerns, regulatory constraints, and ethical considerations.
- To identify emerging trends and future directions in the field of AI-enabled financial modelling, including advances in deep learning techniques, integration with traditional models, explainable AI approaches, and regulatory frameworks.

FOUNDATIONS OF ARTIFICIAL INTELLIGENCE:

Machine learning:

Machine learning is a subset of artificial intelligence (AI) that focuses on enabling systems to learn from data and improve their performance over time without being explicitly programmed. At its core, machine learning involves the development of algorithms that can identify patterns, make predictions, or derive insights from data [19].

There are several types of machine learning algorithms (Figure 2), including:

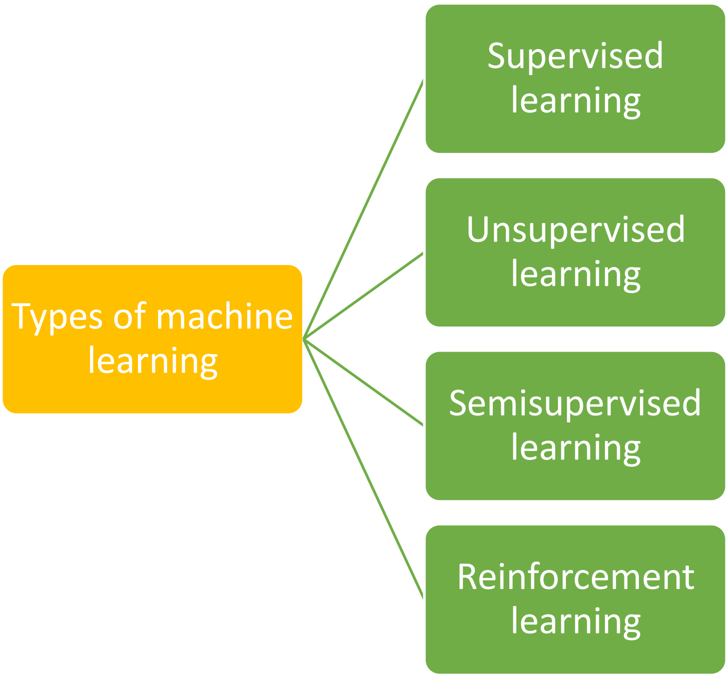

Figure 2. Types of machine learning

1. **Supervised Learning**: In supervised learning, algorithms are trained on labelled data, where each example is associated with a target output. The goal is to learn a mapping from inputs to outputs, enabling the algorithm to make predictions on new, unseen data[20].
2. **Unsupervised Learning**: Unsupervised learning involves training algorithms on unlabelled data, where the goal is to discover underlying patterns or structures within the data. This can include tasks such as clustering, dimensionality reduction, or anomaly detection [21].
3. **Semi-supervised Learning**: Semi-supervised learning combines elements of supervised and unsupervised learning, where algorithms are trained on a mix of labelled and unlabelled data. This approach is particularly useful when labelled data is scarce or expensive to obtain[22].
4. **Reinforcement Learning**: Reinforcement learning is a type of machine learning where algorithms learn to make sequential decisions by interacting with an environment. The algorithm receives feedback in the form of rewards or penalties based on its actions, allowing it to learn optimal strategies over time[23].

Machine learning algorithms can be further categorized based on their complexity and structure. For example, shallow learning algorithms, such as logistic regression or decision trees, are simple and interpretable but may have limited capacity to capture complex relationships in data[24]. In contrast, deep learning algorithms, such as neural networks, are capable of learning hierarchical representations of data through multiple layers of abstraction, making them well-suited for tasks involving large amounts of data or high-dimensional inputs[25].

Machine learning has numerous applications across various domains (Figure 3), including:

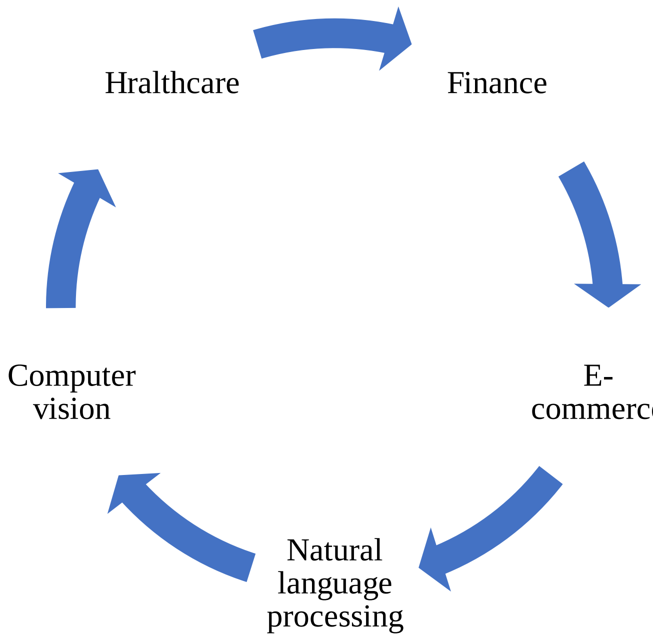

Figure 3. General applications of machine learning

- **Finance**: Machine learning algorithms are utilized for tasks such as stock market prediction, credit risk assessment, algorithmic trading, fraud detection, and portfolio optimization[26].
- **E-commerce**: Machine learning powers recommendation systems, personalized marketing, customer segmentation, and fraud detection in online transactions[27].
- **Natural Language Processing**: Machine learning algorithms are used for tasks such as text classification, sentiment analysis, machine translation, and speech recognition[28].
- **Computer Vision**: Machine learning techniques enable the development of systems capable of tasks such as object detection, image classification, and facial recognition[29].
- **Healthcare**: Machine learning is applied in medical imaging, disease diagnosis, drug discovery, personalized medicine, and health monitoring[30].

Overall, machine learning is a powerful tool for extracting knowledge and insights from data, enabling automation, personalization, and decision-making across a wide range of applications and industries[31].

Deep learning and neural networks:

Deep learning is a subfield of machine learning that focuses on training algorithms known as neural networks to learn from data[32]. Neural networks are computational models inspired by the structure and function of the human brain, consisting of interconnected nodes organized into layers[33]. Deep learning algorithms leverage these neural networks with multiple layers (hence the term "deep"), enabling them to learn hierarchical representations of data through successive layers of abstraction[34].

Neural networks are composed of several key components (Figure 4):

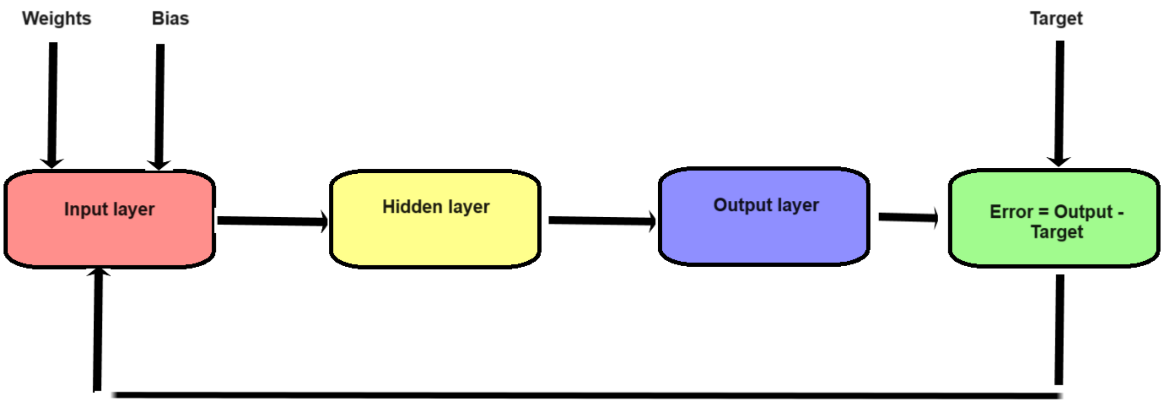

Figure 4. Components of articifal neural network

- **Input Layer**: The input layer receives raw data or features as input to the neural network. Each node in the input layer represents a feature or attribute of the data[35].
- **Hidden Layers**: Hidden layers are intermediate layers between the input and output layers. Each node in a hidden layer receives inputs from the previous layer, performs a weighted sum of the inputs, applies an activation function, and passes the result to the next layer[36].
- **Output Layer**: The output layer produces the final output or prediction of the neural network. The number of nodes in the output layer depends on the task, such as regression (single node for continuous output) or classification (multiple nodes for categorical output)[37].
- **Weights and Biases**: Neural networks learn from data by adjusting the weights and biases associated with each connection between nodes. During the training process, the network learns to update these parameters to minimize a loss function, thereby improving its predictive performance[38].

Deep learning has several advantages over traditional machine learning techniques:

- **Hierarchical Feature Learning**: Deep neural networks can automatically learn hierarchical representations of data, capturing complex patterns and relationships across multiple levels of abstraction[39].
- **Scalability**: Deep learning algorithms can scale effectively with large datasets and high-dimensional inputs, making them well-suited for tasks involving images, text, audio, and video data[40].
- **Feature Engineering**: Deep learning eliminates the need for manual feature engineering, as neural networks can learn relevant features directly from the data, reducing the burden on domain experts[41].

Deep learning has revolutionized various fields, including:

- **Computer Vision**: Deep convolutional neural networks (CNNs) have achieved remarkable performance in tasks such as image classification, object detection, and image segmentation[42].
- **Natural Language Processing**: Recurrent neural networks (RNNs) and transformer-based models like the Transformer architecture and its variants (e.g., BERT, GPT) have significantly advanced tasks such as language translation, sentiment analysis, and text generation[43].
- **Speech Recognition**: Deep learning models, particularly recurrent neural networks (RNNs) and convolutional neural networks (CNNs), have led to substantial improvements in speech recognition systems, enabling applications such as virtual assistants and speech-to-text transcription[44].

Overall, deep learning and neural networks have emerged as powerful tools for solving complex problems across a wide range of domains, driving advancements in artificial intelligence and machine learning[45].

APPLICATIONS OF AI IN FINANCIAL MODELLING:

Stock market prediction and analysis:

Artificial Intelligence (AI) has numerous applications in stock prediction, leveraging its ability to analyse vast amounts of data, identify patterns, and make predictions[46]. Some common applications include:

- ♦ **Time Series Analysis**: AI algorithms, such as recurrent neural networks (RNNs) and long short-term memory networks (LSTMs), are used to analyse historical stock price data and identify patterns and trends over time. These algorithms can capture temporal dependencies in the data and make predictions about future price movements[47].
- ♦ **Technical Analysis**: AI techniques, such as machine learning classifiers and clustering algorithms, are applied to analyse technical indicators derived from stock price and volume data. These indicators include moving averages, relative strength index (RSI), and Bollinger Bands. By identifying patterns in these indicators, AI models can make predictions about future price movements[48].
- ♦ **Sentiment Analysis**: AI-powered natural language processing (NLP) algorithms are used to analyse news articles, social media posts, and other textual data to gauge investor sentiment and market sentiment. By analysing the sentiment of news articles and social media discussions related to specific stocks or sectors, AI models can predict how these sentiments may influence stock prices[49].
- ♦ **Fundamental Analysis**: AI algorithms can analyse fundamental financial data, such as earnings reports, balance sheets, and income statements, to assess the financial health and performance of companies. By identifying key financial metrics and trends, AI models can make predictions about future stock prices based on fundamental factors[50].
- ♦ **Market Microstructure Analysis**: AI techniques, such as reinforcement learning, are used to analyse market microstructure data, including order book data and trade execution data[51]. By modelling the interactions between market participants and the dynamics of order flow, AI models can make predictions about short-term price movements and market liquidity[52].
- ♦ **Algorithmic Trading**: AI-powered algorithmic trading systems use machine learning algorithms to execute trades automatically based on predefined rules or predictive models. These systems can analyse market data in real-time,

identify trading opportunities, and execute trades at high speeds, taking advantage of short-term inefficiencies in the market[53].

- **Portfolio Optimization**: AI algorithms are used to optimize investment portfolios by identifying the optimal allocation of assets based on factors such as risk tolerance, return objectives, and market conditions[54]. By analysing historical market data and asset correlations, AI models can construct diversified portfolios that maximize returns while minimizing risk[55].

Overall, AI has the potential to enhance stock prediction by leveraging advanced data analysis techniques and machine learning algorithms to extract valuable insights from data and make informed predictions about future price movements. However, it's important to note that stock prediction is inherently uncertain, and AI models may not always accurately predict future stock prices[56]

Credit risk assessment and management:

Credit risk assessment and management are crucial tasks for financial institutions to evaluate the creditworthiness of borrowers and minimize the risk of default. Artificial Intelligence (AI) has various applications in credit risk assessment and management, enhancing accuracy, efficiency, and risk mitigation strategies[57]. Some key applications include:

- **Credit Scoring Models**: AI algorithms, such as machine learning classifiers (e.g., logistic regression, decision trees, random forests) and neural networks, are used to develop credit scoring models. These models analyse borrower data, including credit history, income, employment status, and demographic information, to assess the likelihood of default and assign a credit risk score[58].
- **Behavioural Analysis**: AI-powered analytics platforms analyse historical borrower behaviour, transaction data, and spending patterns to identify early warning signs of financial distress or default. By detecting changes in behaviour or financial circumstances, financial institutions can proactively manage credit risk and take appropriate risk mitigation measures[59].
- **Fraud Detection**: AI techniques, such as anomaly detection algorithms and pattern recognition models, are used to detect fraudulent applications and transactions. By analysing patterns in transaction data, AI models can identify suspicious activities, fraudulent behaviours, and potential indicators of identity theft or fraud[60].
- **Stress Testing**: AI-based stress testing models simulate adverse scenarios and evaluate the impact of economic downturns, interest rate fluctuations, and other risk factors on credit portfolios. By stress testing credit portfolios under different scenarios, financial institutions can assess their resilience to potential risks and develop contingency plans to mitigate losses[61].
- **Portfolio Management**: AI algorithms are used to optimize credit portfolios by balancing risk and return objectives. Portfolio management models analyse the risk characteristics of individual loans or assets and optimize the allocation of capital across different segments or categories to maximize returns while minimizing credit risk[62].
- **Loan Origination and Underwriting**: AI-powered underwriting systems automate the loan origination process by analysing borrower data, assessing creditworthiness, and making lending decisions in real-time. By streamlining the underwriting process and reducing manual intervention, AI helps financial institutions improve efficiency, reduce costs, and accelerate loan approvals[63].
- **Regulatory Compliance**: AI technologies assist financial institutions in complying with regulatory requirements, such as anti-money laundering (AML) regulations and know your customer (KYC) requirements. AI-powered compliance

systems analyse transaction data, customer profiles, and other information to identify potential compliance risks and ensure adherence to regulatory standards[64].

Overall, AI has significant potential to transform credit risk assessment and management practices by leveraging advanced analytics, machine learning algorithms, and big data technologies to enhance decision-making, improve efficiency, and mitigate risks in lending operations[65].

Portfolio management and optimization:

Artificial Intelligence (AI) offers numerous applications in portfolio management and optimization, enabling investors to construct diversified portfolios, maximize returns, and manage risks effectively[66]. Some key applications include:

- ♦ Asset Allocation Strategies: AI algorithms analyse historical market data, economic indicators, and asset correlations to identify optimal asset allocation strategies. By dynamically adjusting portfolio weights based on market conditions and risk factors, AI models aim to maximize returns while minimizing volatility and downside risk[67].
- ♦ Risk Management: AI-powered risk management systems assess the risk characteristics of individual assets and the overall portfolio. By analysing factors such as volatility, correlation, and downside potential, AI models help investors manage risk exposures, set risk limits, and implement risk mitigation strategies to protect against adverse market movements[68].
- ♦ Factor-Based Investing: AI techniques, such as machine learning algorithms and factor models, are used to identify and exploit factors that drive asset returns, such as value, momentum, quality, and size. By systematically incorporating factor-based strategies into portfolio construction, investors seek to enhance returns and diversify risk across multiple sources of alpha[69].
- ♦ Portfolio Rebalancing: AI-powered portfolio management platforms automate the process of portfolio rebalancing by analysing current portfolio holdings, target asset allocations, and market conditions. By dynamically adjusting portfolio weights and realigning asset allocations, AI models help investors maintain optimal portfolio risk-return profiles over time[70].
- ♦ Predictive Analytics: AI algorithms analyse market data, economic indicators, and alternative data sources to make predictions about future asset returns, volatility, and correlations. By leveraging predictive analytics, investors can identify investment opportunities, anticipate market trends, and make informed decisions about portfolio allocations and adjustments[71].
- ♦ Multi-Objective Optimization: AI optimization algorithms solve complex multi-objective optimization problems, considering multiple conflicting objectives such as risk, return, liquidity, and transaction costs. By finding Pareto-optimal solutions that balance trade-offs between different objectives, AI models help investors design portfolios that meet their specific investment goals and constraints[72].
- ♦ Dynamic Asset Allocation: AI-driven dynamic asset allocation models adapt portfolio allocations in response to changing market conditions, macroeconomic factors, and investor preferences. By incorporating real-time data and market signals, these models aim to exploit short-term opportunities and mitigate risks in volatile market environments[73].

Overall, AI plays a crucial role in portfolio management and optimization by providing sophisticated analytics, predictive insights, and optimization capabilities to investors, asset managers, and financial institutions. By leveraging AI technologies, investors can make more informed decisions, construct robust portfolios, and achieve their investment objectives more effectively in dynamic and uncertain market environments[74].

CHALLENGES AND LIMITATIONS:

While Artificial Intelligence (AI) has brought significant advancements to financial modelling, it also poses several challenges and limitations:

- Data Quality and Availability: AI models heavily rely on high-quality, reliable data for training and decision-making[75]. However, financial data can be noisy, incomplete, or subject to errors, which can affect the performance of AI models. Additionally, obtaining access to relevant data sources, especially alternative data, can be challenging and may require significant resources[76].
- Interpretability and Explainability: Many AI algorithms, such as deep learning neural networks, are often considered black-box models, meaning their internal workings are not easily interpretable by humans. This lack of interpretability can hinder understanding of model decisions and raise concerns about accountability, especially in regulated industries like finance where explainability is crucial for compliance and risk management[77].
- Overfitting and Generalization: AI models trained on historical data may suffer from overfitting, where they memorize noise or idiosyncrasies in the training data rather than capturing underlying patterns. Overfitted models may perform well on historical data but generalize poorly to new, unseen data. Achieving robust and generalizable models requires careful regularization, validation, and testing procedures[78].
- Regulatory and Ethical Considerations: The use of AI in financial modelling raises regulatory and ethical considerations related to privacy, fairness, transparency, and bias. Regulators may impose restrictions on the use of AI models, especially in critical applications such as credit risk assessment and algorithmic trading, to ensure compliance with legal and ethical standards and protect consumers from harm[79].
- Model Robustness and Adversarial Attacks: AI models, particularly deep learning models, are vulnerable to adversarial attacks, where malicious actors manipulate input data to deceive or sabotage model predictions. Adversarial attacks can compromise the integrity and reliability of AI systems, especially in security-sensitive applications such as fraud detection and cybersecurity[80].
- Computational Complexity and Resource Requirements: Training and deploying complex AI models can be computationally intensive and require significant computational resources, including high-performance computing infrastructure and specialized hardware accelerators (e.g., GPUs). Managing computational complexity and resource requirements can be challenging, especially for smaller firms with limited budgets and technical expertise[81].
- Human Expertise and Domain Knowledge: While AI algorithms excel at data-driven tasks, they may lack the domain expertise and intuition of human experts. Financial modelling often requires understanding complex financial concepts, market dynamics, and regulatory frameworks, which AI models may struggle to capture without human guidance and supervision[82].

Addressing these challenges and limitations requires a multidisciplinary approach that combines expertise in AI, finance, statistics, and ethics[83]. By developing robust methodologies, adopting best practices, and fostering collaboration between domain experts and data scientists, organizations can harness the full potential of AI in financial modelling while mitigating risks and ensuring responsible and ethical use[84].

FUTURE DIRECTIONS:

The prospects of using Artificial Intelligence (AI) in financial modelling are promising, with continued advancements expected in several key areas:

- Advanced Analytics and Predictive Modelling: AI algorithms will continue to evolve to oversee increasingly complex financial datasets and improve predictive accuracy. Advancements in deep learning techniques, such as recurrent neural networks (RNNs) and transformers, will enable more accurate forecasting of financial market trends, asset prices, and economic indicators[85].
- Explainable AI (XAI): There will be a growing emphasis on developing explainable AI models in financial modelling to enhance transparency, interpretability, and trustworthiness. Explainable AI techniques will enable users to understand and interpret model decisions, identify key drivers of predictions, and assess model reliability and robustness[86].
- Integration with Traditional Models: AI techniques will be integrated with traditional financial models to enhance their predictive power and effectiveness. Hybrid models combining AI algorithms with econometric models, time-series analysis, and risk models will provide more comprehensive and accurate assessments of financial markets, investment opportunities, and risk exposures[87].
- Alternative Data and Unstructured Data Analysis: There will be increased adoption of alternative data sources, such as satellite imagery, social media feeds, and sensor data, in financial modelling. AI algorithms will be used to analyse unstructured data and extract valuable insights to inform investment decisions, assess credit risk, and identify market opportunities[88].
- Ethical AI and Responsible AI Governance: There will be greater emphasis on ethical AI practices and responsible AI governance in financial modelling. Financial institutions will implement frameworks and guidelines to ensure the ethical use of AI, mitigate biases and discrimination, and promote fairness, transparency, and accountability in AI-driven decision-making processes[89].
- Personalized Financial Services: AI-powered personalization techniques will enable financial institutions to offer tailored financial products and services to individual customers based on their preferences, risk profiles, and financial goals. Personalized investment advice, automated wealth management, and customized insurance products will become more widespread[90].
- Regulatory Compliance and Risk Management: AI technologies will play a critical role in regulatory compliance and risk management in the financial industry. AI-powered compliance systems will help financial institutions monitor transactions, detect fraudulent activities, and ensure adherence to regulatory requirements, while AI-based risk management systems will assess and mitigate risks across various domains, including credit risk, market risk, and operational risk[91].

Overall, the future of AI in financial modelling holds immense potential to revolutionize the way financial institutions analyse data, make decisions, and deliver value to customers[92]. By leveraging AI technologies effectively and responsibly, organizations can gain competitive advantages, enhance decision-making processes, and drive innovation in the rapidly evolving landscape of finance[93].

CONCLUSION:

The integration of Artificial Intelligence (AI) into financial modelling has ushered in a new era of innovation, efficiency, and risk management in the financial industry. Throughout this review manuscript, we have explored the myriad applications, advancements, challenges, future directions of AI in financial modelling, spanning from stock market prediction to credit risk assessment, and portfolio optimization. Despite the remarkable progress made in leveraging AI technologies to enhance decision-making processes and drive value creation in finance, significant challenges remain. Issues such as data quality, interpretability, regulatory compliance, and ethical considerations underscore the importance of adopting responsible AI practices and governance frameworks. Moreover, the need for collaboration between domain experts, data scientists, and policymakers is essential to address these challenges effectively and ensure the ethical and equitable deployment of AI in financial modelling. Looking ahead, the future of AI in financial modelling holds immense promise. Continued advancements in AI algorithms, data analytics, and computational capabilities will enable financial institutions to develop more sophisticated models, make more accurate predictions, and deliver personalized financial services to customers. Moreover, the integration of AI with traditional financial models, coupled with advancements in explainable AI and ethical AI governance, will further enhance transparency, accountability, and trust in AI-driven decision-making processes. In conclusion, while the journey towards harnessing the full potential of AI in financial modelling may present challenges, the opportunities for innovation, collaboration, and positive impact are vast. By embracing responsible AI practices, fostering interdisciplinary collaboration, and prioritizing ethical considerations, we can unlock the transformative power of AI to drive advancements in financial modelling and shape the future of finance for the better.

CONFLICT OF INTEREST

Authors declare no conflict of interest.

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