The Impact of Large Language Models (LLMs) in Finance: The benefits and risks of LLM applications on financial decisions

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Introduction

Language plays an integral role in human communication and serves as a bridge between humans and machines in artificial intelligence (AI). The demand for machines to handle complex language tasks has driven the rapid development of advanced language models (Naveed et al., 2023). Zhao et al. (2023) explain how language modelling has evolved from traditional statistical methods to sophisticated neural networks. Modern pre-trained models, particularly those built using transformer architectures, have revolutionised natural language processing (NLP), unlocking applications across various industries (Hadi et al., 2024). The financial sector, in particular, has embraced large language models (LLMs) due to their ability to process and analyse vast amounts of unstructured data. LLMs are reshaping decision-making processes in finance, enabling institutions to gain insights from complex datasets, enhance market predictions, and gain a competitive advantage. However, integrating LLMs into finance is not without challenges. Ethical concerns surrounding data privacy, transparency, and bias in AI models remain significant barriers. Furthermore, regulatory compliance presents a complex issue, as financial institutions must ensure that LLMs adhere to existing legal frameworks. These factors make it crucial to examine both the opportunities and risks associated with the application of LLMs in financial decision-making.

Overview of LLMs' Benefits and Challenges

Artificial intelligence (AI) has sparked significant debate in the financial sector. Some researchers praise its efficiency, highlighting AI-driven services' potential to save time and streamline operations. Others, however, raise ethical concerns, particularly around automation and privacy invasion. Despite these contrasting perspectives, the literature remains underexplored regarding viable solutions to these challenges (Sheth et al., 2022). In particular, research on LLMs in finance showcases their versatility, with applications ranging from decision-making and customer support to risk management, fraud detection, market analysis, and compliance automation. LLMs are appreciated for their ability to process vast datasets and generate actionable insights. Yet, a notable gap persists in understanding their broader influence on financial decisions and the associated risks. This review aims to address this gap by examining the transformative role of LLMs in financial decision-making. It delves into the technical, ethical, and regulatory challenges surrounding their adoption, offering a detailed analysis of their impact on the financial sector. By providing this analysis, the review seeks to contribute to a more informed and balanced discourse on integrating LLMs into finance.

One of the primary advantages of LLMs is their ability to make financial decisions by analysing large datasets, automating reporting, predicting market trends, assessing public sentiment, and providing portfolio management recommendations to optimise investment strategies (Goldberg, 2024). For example, Li et al. (2023) point out that LLMs can analyse large datasets more accurately and quickly than human analysts, enabling financial institutions to make more informed decisions. This is especially important for tasks that require real-time analysis, such as trading or market trend forecasting, where the speed and accuracy of decision-making are critical to success. Zhao et al. (2024) highlight that LLMs can perform such tasks with remarkable precision, reducing the risk of human error while increasing productivity and accuracy. In financial trading, for example, LLMs can assist in identifying emerging trends and market opportunities by analysing historical market data, social media sentiment, and news articles in real-time (Kim et al., 2024). This has significant implications for trading strategies, as LLMs can help institutions react swiftly to market changes, ultimately leading to more effective decision-making and a competitive advantage.

Furthermore, using LLMs like ChatGPT in customer support decisions has proven transformative, enhancing operational efficiency and personalisation in financial services. By automating routine tasks such as answering customer enquiries, tracking account balances, and providing updates on financial products, LLM-powered chatbots significantly reduce the workload on human support teams while improving customer experiences. These chatbots utilise advanced natural language processing to understand complex queries and deliver tailored responses in real-time, offering personalised financial advice and investment strategies (Udeh et al., 2024; Ali & Aysan, 2023). LLMs have further extended their utility by offering sophisticated services, such as financial planning and generating insights based on client-specific data. Models like ChatGPT-4 have surpassed traditional advisory models in some cases, enabling financial institutions to scale their services effectively while maintaining a high degree of customisation and satisfaction (Cheng et al., 2024). Furthermore, compared to FinBERT, a reputable sentiment analysis model for financial texts, ChatGPT 3.5 has shown significant potential to enhance sentiment analysis, particularly in forecasting market patterns in the foreign exchange market (Fatouros et al., 2023). These advancements provide actionable insights into customer preferences, market sentiment, and investment behaviours, significantly enhancing decision-making related to customer engagement. Moreover, LLM chatbots have demonstrated their broader economic potential by predicting stock price movements using news headlines. By analysing such data, these models produce actionable insights that improve market efficiency, particularly for smaller stocks or during periods of negative news. This predictive capability complements human decision-making, reshaping market dynamics by aligning stock prices more closely with underlying fundamentals (Lopez-Lira & Tang, 2023). However, it is essential to recognise that human experts still play a critical role in investment decisions to ensure the accuracy and reliability of the information provided by chatbots (Ko & Lee, 2024).

On the other hand, the rapid development of domain-specific LLMs tailored for the finance sector complements the capabilities of general-purpose models like ChatGPT. These specialised models address the unique challenges of financial decision-making, offering more precise and efficient processes. A prominent example is BloombergGPT, which is designed to analyse financial data, such as market trends and risk assessments. Trained with financial terminology, it enhances the interpretation of complex data, improving accuracy and relevance for professionals (Wu et al., 2023). However, the large parameter sizes of such models result in high training costs. To mitigate this, FinGPT adopts a data-centric approach, using low-rank adaptation techniques to reduce computational costs and improve efficiency, providing cost-effective solutions for decision-makers in a rapidly changing financial environment (Chen et al., 2023). FinGPT demonstrates significant potential for diverse applications, including personalised robo-advisory, quantitative trading, portfolio optimisation, and financial education, offering a holistic, AI-driven approach to decision-making in finance (Yang et al., 2024).

Similarly, Liu et al. (2024) introduced the DeLLMa framework, leveraging LLMs to improve decision-making under uncertainty by integrating key financial indicators like interest rates and market volatility. This model supports decision-makers in navigating fluctuating market conditions. Another framework, Strux, enhances decision-making by structuring LLM outputs into clear, understandable explanations, which is crucial in complex tasks such as stock investment forecasting (Lu et al., 2024).

In addition to their applications in customer support, risk management, and trading, LLMs are increasingly valuable in enhancing credit scoring and fraud detection processes, with their influence being indirect but still significant. Feng et al. (2023) highlight that LLMs can improve credit scoring by analysing both traditional data, like credit history, and alternative data, such as social media activity or transaction patterns. This leads to more accurate creditworthiness assessments, benefiting both lenders and borrowers. Similarly, in fraud detection, LLMs can identify unusual patterns in financial transactions, helping institutions detect fraudulent activities more quickly and efficiently (Guven, 2024). Although LLMs do not make decisions directly in these areas, their ability to process and analyse complex data significantly enhances the decision-making processes within financial institutions involved in credit scoring and fraud detection. By providing deeper insights and improving the accuracy of risk assessments, LLMs ultimately influence the broader decision-making landscape in financial services, helping institutions make more informed, data-driven decisions.

The adoption of LLMs in the financial sector presents significant potential for enhancing decision-making processes. However, to fully realise these benefits, several challenges must be addressed, including concerns about data privacy, model transparency, algorithmic bias, misinformation, and accuracy. One of the most pressing challenges is ensuring data privacy and security. The financial sector is subject to stringent regulations, such as the General Data Protection Regulation (GDPR), the Dodd-Frank Act, and the Basel Accords, which set high standards for data protection and privacy (Paul et al., 2023). However, as LLMs handle and generate large volumes of sensitive data, the risk of unauthorised access and data misuse increases significantly. This vulnerability can result in privacy breaches, exposing private financial data and potentially causing harm to individuals and institutions (Yan et al., 2024). Another critical issue is algorithmic bias, which remains a significant challenge in deploying LLMs for financial decision-making. Like any AI system, LLMs can unintentionally perpetuate biases present in the data they are trained on. This can lead to discriminatory outcomes in sensitive applications, and to mitigate this, implementing clear guidelines for fairness and transparency in AI decision-making processes is essential. These measures can help address bias and promote equitable outcomes in financial applications (Dhake et al., 2024).

While LLMs possess vast knowledge bases and advanced reasoning capabilities, they remain susceptible to misuse, raising significant concerns in the financial sector, where precision is critical. As Chen and Shu (2024) warn, deploying LLMs to generate financial market content may unintentionally spread misinformation. This risk is heightened by the tendency of financial large language models (FinLLMs) to hallucinate—producing plausible but inaccurate outputs, such as misleading financial forecasts or market interpretations, which can lead to monetary losses and erode trust in financial systems (Kang & Liu, 2023). Additionally, while LLMs hold promise for financial sentiment analysis, they struggle with the intricate, context-dependent language of financial texts. Zhang et al. (2023) note that inadequate contextual information often causes misclassification, particularly when models are not fine-tuned for the financial domain. This limitation diminishes their utility in critical decision-making scenarios requiring nuanced analysis.

High costs and logistical challenges further complicate LLM integration in finance. Updating these models to reflect evolving regulations, market changes, and economic data is resource-intensive, making it difficult to maintain their long-term accuracy and effectiveness in a dynamic landscape (Yang et al., 2024). Finally, in applications like peer-to-peer lending, models such as BERT have demonstrated potential by providing accurate credit risk assessments from loan descriptions. However, issues like model opacity and inherent bias underscore the need for robust regulatory frameworks to ensure transparency and accountability in AI-driven decision-making processes (Sanz-Guerrero & Arroyo, 2024). Addressing these challenges is essential to unlock the full potential of LLMs in finance without compromising trust or accuracy.

Bale et al. (2024) propose several solutions to address the challenges of LLMs in finance, grouped into three main themes: promoting openness in AI development, educating users about AI-generated content, and fostering collaboration among developers, regulators, and users. These strategies, combined with robust regulatory frameworks, are essential for mitigating the ethical risks associated with AI in financial decision-making. However, uncertainties remain, even with these mitigation efforts. While LLMs offer significant benefits, such as automating repetitive tasks, reducing reliance on low-skilled labour, and improving employee efficiency, accurately quantifying their long-term impact on bank profitability is challenging. This difficulty stems from the limited availability of data on the prolonged effects of AI in the financial sector (Kaya et al., 2019).

Conclusion

In conclusion, LLMs are transforming the financial sector by offering substantial advantages in decision-making. These models enable financial institutions to process and analyse vast amounts of data, providing insights that facilitate more informed, efficient, and timely decisions. However, challenges remain, particularly concerning the accuracy of LLM predictions and addressing concerns related to transparency, accountability, and the ethical implications of their use. It is essential to navigate these challenges and ensure that LLMs are integrated responsibly into the financial decision-making process to maximise their potential.

Future research should prioritise enhancing model interpretability and transparency to build user trust and confidence in these systems. Long-term studies are also needed to assess the broader impacts of LLMs on market dynamics, while robust ethical frameworks must be developed to mitigate risks such as bias, misinformation, and data privacy violations. By addressing these issues, the financial sector can unlock the full potential of LLMs, fostering innovation while maintaining accountability and trust.

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