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USE OF LARGE LANGUAGE MODELS IN THE ASSET MANAGEMENT INDUSTRY: EVIDENCE REVIEW

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ABSTRACT

Purpose: Large language model (LLM) applications can play a vital role in the asset management (AM) industry, which is a critical sector within finance and investment. For successful implementation of the technology, there must be a match between the challenges of industry and the technological capabilities.

Design/methodology/approach: A review of evidence supported by an LLM-based evidence and review tool was completed to identify key challenges of the industry and current LLM applications within the sector. Content analysis was used to match the key categories of the challenges with the areas of LLM applications.

Findings: The challenges in the AM industry include regulatory and compliance issues, technological disruption, market dynamics, performance measurement, and adaptation to consumer preferences. Despite the scarcity of specific literature on LLMs in AM, the research points to potential applications such as sentiment analysis, market predictions, and regulatory compliance. LLMs can enhance customer interaction, improve risk management, and develop informed investment strategies by processing and analysing large datasets. A matrix of the industry challenges and LLM application is created to indicate well addressed areas and those requiring further development. There is a need for more diverse training datasets, better integration and scalability of LLMs, and improvements in global applicability.

Practical implications: While LLMs hold significant potential for transforming AM by addressing various challenges, further investigation is needed to overcome existing gaps and limitations. Future research should focus on enhancing data diversity, improving model integration, ensuring regulatory compliance, and addressing the environmental impact of LLM technologies.

Originality/value: This study contributes valuable insights into LLM applications, supporting the advancement of automated tools in financial services.

Keywords: LLM, asset and wealth management industry, investment, challenges

Type of paper: JEL classification N20

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INTRODUCTION

The financial system is described as comprising various institutions and markets that perform distinct but interconnected functions, such as managing risk, providing information, and facilitating transactions, which include subsectors like banking, insurance, and asset management (Merton and Bodie, 1995). The financial services industry is characterised by its interconnectedness, where different subsectors contribute to the overall functioning of the financial system by providing liquidity, managing risks, and facilitating transactions (Oshodin *et al.*, 2017).

The AM industry is a subsector of the larger finance and investment industry. It involves managing financial assets on behalf of end investors, both institutional and retail, which is a core activity within the broader finance and investment industry (Walter, 1999; Epstein, 2019). It includes institutions such as mutual funds, pension funds, and private banking, which are integral parts of financial intermediation, linking savers with borrowers and facilitating capital formation (Walter, 1999; Walter and Sisli, 2007). The industry encompasses numerous services such as portfolio management, financial planning, and advisory services (Gârleanu and Pedersen, 2018). Asset managers play a crucial role in mobilising financial assets, investing them, and realising returns, which are fundamental activities of the finance and investment industry (Clark and Dixon, 2024). The AM industry is interconnected with other financial services, including banking, insurance, and investment banking, highlighting its position as a subsector within the larger financial ecosystem (Walter, 1999).

The existing reviews and surveys provide an exploration of the methodologies, applications, challenges, and prospects of LLMs in the financial industry. They cover aspects such as the integration of LLMs into financial tasks, performance comparisons, and the ethical considerations associated with their use (Cao and Feinstein, 2024; Chen *et al.*, 2024). However, given the rapid advancements in AI and LLM technologies, continuous updates and reviews are essential to capture the latest developments, emerging trends, and innovative applications in the financial industry. This includes new models, improved techniques for fine-tuning and prompt engineering, and novel use cases that may not have been covered in the previous reviews.

There is a notable scarcity of scientific literature specifically addressing the adoption and application of LLMs in the AM industry. Most existing research and case studies focus on applications, such as sentiment analysis, market predictions, and regulatory compliance (Li *et al.*, 2023; Luk, 2023; Cao and Feinstein, 2024). Potential applications of LLMs in AM include among others customer interaction (Guo *et al.*, 2023), risk management (Wan *et al.*, 2024) or investment strategy development (Li *et al.*, 2023; Son *et al.*, 2023).

Studying the application of LLMs for AM, specifically checking for relevant applications of digital innovations in other subsectors of the same industry, including banking, insurance, and trading, can bring relevant insights (Britton and Atkinson, 2017; Haberly *et al.*, 2019). Many challenges faced in AM, such as risk management, regulatory compliance, and customer service, are also present in other financial subsectors, making cross-sector insights valuable (Walter and Sisli, 2007; Epstein, 2019; Folqué González-Valerio, Escrig Olmedo and Corzo Santamaría, 2023). Techniques and models that improve efficiency and performance in one subsector, like automated trading in AM, can often be adapted for use in others, such as fraud detection in banking or claims processing in insurance (Britton and Atkinson, 2017). Understanding the regulatory and market dynamics in one subsector can provide insights into similar dynamics in AM, aiding in the development of more robust and compliant LLM applications (Haberly *et al.*, 2019; Clark and Dixon, 2024).

While current reviews (e.g., Callanan *et al.*, 2023; Dowling and Lucey, 2023; Son *et al.*, 2023) provide a solid foundation, fast development of the field requires continuous updates to fully understand the potential and limitations of LLMs in the specific financial context of AM. More granular analysis of the performance and impact of LLMs in different financial applications can provide nuanced insight into the issue.

This research report explores the status of LLM adoption, focusing on the challenges faced by the AM industry as reported in the literature. The primary aim is to review existing evidence, assess the quality of the studies, and identify further research directions to provide an understanding of how advanced LLM models can transform AM practices. This research aims to answer the following research questions: 1) What are the main challenges faced by the AM industry? 2) Which of these challenges can be addressed with LLM use? Analysis of the challenges of the AM industry and exploration of the application of LLMs to address these challenges can lead to advancements in financial management practices, enhance regulatory compliance, and improve overall market stability, thereby contributing to the broader financial ecosystem.

LLMs are being introduced not only in finance, but across many other areas, such as healthcare or science (Telenti *et al.*, 2024). With the increasing use of AI for a range of academic tasks, from education and research to data analysis and synthesis (Ejjami, 2024; Hersh, 2024), developing reliable tools is essential to ensure that the quality of academic work is not compromised by the introduction of this new technology (Dergaa *et al.*, 2023). The secondary aim of this study was to test and validate the usefulness of the Aestima[5] tool, created specifically for supporting research involving textual data, in the process of data extraction, analysis, and synthesis.

THEORETICAL BACKGROUND

Adoption of new technology is a process depending on a range of variables. Behavioural theories highlight the key factors which determine whether it will be implemented and whether the users' behaviour will change in response to it. The Technology Acceptance Model (TAM) (Davis, Bagozzi and Warshaw, 1989; Davis, 1993) highlights personal level factors important for new technology implementation; these are perceived usefulness, perceived ease of use, and attitude towards use. The Task-Technology Fit (T-TF) Model (Goodhue and Thompson, 1995) focuses on the specific tasks which technology can be used for.

Both models have been used to explore LLM implementation, for example in education (Bernabei *et al.*, 2023; Al-Dokhny *et al.*, 2024), software engineering (Russo, 2024), business (Goh, Dai and Yang, 2023), and financial research (Shin, Kim and Shin, 2024; Toumeh, 2024). Compatibility of new technology with existing tools has been a key factor in its adoption (Russo, 2024). Acceptance of LLM technology in medicine was found to be linked to its quality and effectiveness (Poh Soon *et al.*, 2024). A personal level factor, namely optimism towards LLM technology in a group of higher education students, was found to be associated with technology acceptance, and discomfort related

[5] "AESTIMA SuperBot operates on a sophisticated technical framework that integrates several advanced technologies. At its core, it uses ChatGPT, a state-of-the-art language model developed by OpenAI. This technology enables the SuperBot to generate human-like text based on the input it receives, allowing it to interact intelligently with users. In addition to ChatGPT, the Superbot also utilizes LangChain, a Python-based language processing library. LangChain aids in the processing and understanding of natural language, enabling the Superbot to comprehend and respond to complex queries effectively. The Superbot's functionality is further enhanced by its integration with Zotero, a free, easy-to-use tool that helps users collect, organize, cite, and share research. In its current version, the Superbot receives a database of PDF documents, such as articles or books stored in Zotero. It then performs vectorization on these documents, a process that converts the text data into a numerical format that can be processed by machine learning algorithms." https://aestima.io

to technology use led to negative ease-of-use perception (Lemke *et al.*, 2023). Similarly, effort expectancy was found to be negatively associated with T-TF in higher education research (Al-Dokhny *et al.*, 2024). On the other hand, perceived usefulness of LLM is also associated with its acceptance amongst university educators (Ghimire and Edwards, 2024).

Kukafka *et al.* (2003) proposes an integrative framework for technology implementation, which includes these models as well as other theories focusing not only on the personal but also on the wider environmental and organisational context, highlighting the complexity of the implementation process. The model reaffirms the key point that consideration of a range of factors is required to understand any new technology implementation. This framework provides a comprehensive approach to explore issues related to technology implementation.

RESEARCH DESIGN AND METHODOLOGY

Procedure

The following databases and search engines were selected for the literature search: ScienceDirect, Scopus, Google Scholar, and arXiv. The search terms included a) financial asset AND wealth management industry and b) LLMs AND asset and wealth management industry. These terms were selected as they capture the specific focus and operational scope of the asset management (AM) subsector within the broader financial ecosystem (Walter, 1999; Costanzo, 2011). Unlike broader terms such as “investment industry” or “capital asset industry”, which may encompass a wide array of unrelated fields such as venture capital, real estate, or industrial capital goods, “financial asset” and “wealth management industry” directly align with the tangible instruments (e.g., stocks, bonds, mutual funds) managed within AM by the strategic, client-focused activities intrinsic to this subsector, such as personalised portfolio management, financial planning, and advisory services (Stowell, 2010; Amenc *et al.*, 2011).

The inclusion criteria included sources published in English, peer-reviewed journal articles, arXiv and conference proceedings, with PDFs either freely or institutionally (RISEBA) accessible. In the second search, due to the limited number of sources focused specifically on LLMs in the AM industry, the decision was made to consider the broader financial industry’s applications of LLMs. This approach allowed for drawing informed conclusions about their specific applicability and the potential benefits of LLMs for the AM industry due to similarities of LLM-supported tasks in AM and in the financial industry in general.

The following steps were taken to review and synthesise the evidence. Completion of the steps marked with* was supported by the Aestima[6] tool: 1) identification of papers discussing topics of interest, 2) source relevance check*, 3) extraction of relevant information*, 4) content analysis*, 5) validation of the quality of data analysis augmented by LLM.

The subsequent relevance check[7] was performed using the Aestima tool with the following queries:

1. Check if the source discusses challenges facing the financial AM industry.

2. Check if the source discusses applications of LLMs in the financial industry[8].

[6] The Aestima tool, augmented by Open AI models and designed by co-authors, was used for this research.
[7] Performed with the Aestima tool search function augmented by Open AI models.
[8] Expecting a limited number of publications discussing LLM adoption in the asset management industry, the query was designed to provide broader potential coverage of sources without losing their validity.

These checks were conducted by applying queries to the first 4500 tokens of each text, which is about 3375 words for English texts[9].

The first relevance check revealed 470[10] academic papers with accessible PDFs discussing challenges within the AM industry. Based on the automated relevance scoring, 30 articles discussing AM industry challenges with the highest score were selected for further analysis. The second relevance check produced 15 papers discussing LLM applications in the financial industry. All of them were included in further analysis.

The automated relevance scoring in the Aestima tool assigns each source that is judged relevant a score from 1 to 10, with 1 being the least relevant and 10 being the most relevant source for the query (prompt). The scoring system is based on the user's prompt (query) directing the Aestima tool to check the first three chunks of the article and one chunk found by a similarity search from the other chunks. The more relevant the information found in the analysed chunk, defined by the proportion of text answering the query, the higher the score given to a source. The relevance check uses Pincone's cosine similarity[11] to sort the chunks, and when potentially relevant chunks are selected, LLM is used to score source relevance with higher precision. Three additional chunks are checked for each source with instructions on how to perform scoring and output machine-readable text for easy automatic parsing. The lowest score (1) is assigned to sources which do not contain any information answering the question, whereas the highest score (10) is given to sources providing clear and detailed answers to the question. The accuracy of relevance scoring was manually validated by the authors during the Aestima tool development and was proven to be highly reliable.

Analysis

Content analysis allows for interpretation and quantification of the phrases, topics, or concepts in a range of qualitative data (Neuendorf, 2018). It is a valuable method for scientific research in the fields of economics and entrepreneurship. The method was used in studies focusing on a range of industry and entrepreneurship topics such as women entrepreneurs or pathways of SME internationalisation (Moreira *et al.*, 2019; Dabić *et al.*, 2020).

The use of LLMs can improve the process of content analysis by enhancing literature relevance checks and content/data extraction and comprehensive content analysis. LLMs can efficiently sift through vast amounts of academic literature, identifying relevant studies and ensuring a comprehensive review of existing knowledge. This capability reduces the time and effort required for manual literature searches and enhances accuracy in identifying pertinent works. LLMs can also assist in content/data extraction, reasoning, and summarisations by identifying key categories, patterns, and relationships within the text, facilitating a more nuanced and thorough content analysis (Haviv, Berant and Globerson, 2021; Huynh *et al.*, 2023; Polak and Morgan, 2024; Zeng *et al.*, 2024). By leveraging LLMs, researchers can ensure a more systematic, scalable, and precise approach to content analysis, contributing to richer and more reliable insights in the fields of economics and entrepreneurship.

A coding scheme was developed inductively to identify AM industry challenges discussed in the literature, and the final version of the codes was applied to the content of the 30 most relevant articles (scores of 7 and above) as rated by the Aestima tool relevance check logic. The context in

[9] Data extraction was conducted using the Aestima tool search function augmented by GPT-4 Turbo.
[10] Performed with the Zotero duplicate removal plugin.
[11] https://www.pinecone.io/learn/what-is-similarity-search/

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which the challenges appear was explored to understand the nuances of each of them. All codes were discussed within the research team, and any differences in opinion were resolved through reaching a consensus. The challenges were then grouped into 12 key categories and further combined into 3 key categories (described below). A set of 15 papers was reviewed to list reported cases of AI applications in the AM industry and wider area of the financial industry. In the next step, the relationship between the categories and LLM applications was analysed. The key categories of challenges of the AM industry were matched with reported LLM applications. Finally, the papers' content was analysed to identify key issues in discussions on gaps and limitations in applying LLMs in finance.

RESULTS

Content analysis

Based on the content analysis, 150 challenges were identified for each of the 30 articles included in this stage of the analysis. These were later grouped manually into 13 key categories[12]. These categories highlight the multifaceted challenges faced by the AM industry, driven by regulatory pressures, technological advancements, market dynamics, and shifts in investor behaviour and expectations. These 13 categories were next assigned to one of three broader categories: 1) Strategic Challenges, encompassing high-level issues related to compliance, ethical considerations, and long-term sustainability, 2) Operational Challenges, centred on the internal workings of firms, including technology, data management, and the impact of automation on the workforce, or 3) Market Dynamics and Performance, which covers the competitive environment, performance and risk measurement, consumer preferences, and external economic and political factors. This grouping streamlines the complexity of the 13 challenges into more actionable categories, providing a clearer framework for addressing these issues with LLMs. Addressing these challenges requires a comprehensive approach that includes regulatory adaptation, embracing technological innovation, strategic management, and an understanding of behavioural finance and sustainability issues.

Commented [BB1]: Not clear what these refer to.

Strategic Challenges. LLMs like Shai have been developed to handle legal regulation and compliance data analysis, addressing regulatory and compliance challenges by enhancing accuracy and efficiency in compliance processes (Guo *et al.*, 2023). FinBERT, used for environmental, social and governance (ESG) classification in corporate social responsibility reports, helps integrate social and environmental considerations into investment strategies (Huang, Wang and Yang, 2023). The application of LLMs in generating insights and models for strategic financial management during health crises has been highlighted, though specific detailed applications in the cases provided were not mentioned explicitly. The reported LLM applications address regulatory and compliance challenges and ethical and social responsibility. The areas of regulatory compliance and ethical responsibility are well addressed, with room for more focus on health crisis management.

Operational Challenges. LLMs like FinGPT enhance financial data processing and support the development of tools like robo-advisors and algorithmic trading (Yang, Liu, and Wang, 2023), which align with the challenge of technological disruption and integration. LLMs improve data management capabilities, as seen in their applications for financial statement analysis and financial

[12] List of 13 primary categories: Regulatory and Compliance Challenges, Technological Disruption and Integration of Emerging Technologies, Market Dynamics, Concentration and Competition, Performance Measurement and Managerial Skill, Adaptation to Consumer Preferences and Democratisation, Information Asymmetry and Ethical Challenges and Managerial Skill, Economic and Political Uncertainty and Instability, Complexity of Financial Products, Behavioural and Cultural Factors, Cybersecurity and Data Management, Automation and Employment Impact, Ethical and Social Responsibility, Financial Management in Health Crises (Pandemics).

data analysis, ensuring data security and integrity. The use of LLMs in automating back-office functions and providing AI-powered customer service addresses the challenge of balancing automation with human employment (Haberly *et al.*, 2019). LLMs are well-suited to address operational challenges by enhancing technological integration, improving data management, and supporting automation. Their role in balancing automation with human skills is evident, particularly in back-office functions and customer service. This area is thoroughly covered through technological integration, data management, and automation.

Market Dynamics and Performance Challenges. LLMs like FinBERT are used for sentiment analysis to predict stock movements, which addresses the challenges of market dynamics and competition (Huang, Wang and Yang, 2023). The use of LLMs in financial sentiment analysis helps optimise investment strategies, indirectly addressing performance measurement and managerial skill challenges. AI-driven chatbots and advisory services enhance personalised client interactions and democratise access to financial services (Li *et al.*, 2023). LLMs improve transparency and provide accessible information to investors, thereby managing information asymmetry. LLMs analyse economic and political data for risk management, helping firms adapt to external uncertainties (Luk, 2023; Kirtac and Germano, 2024). They can simplify the understanding of complex financial instruments through detailed analysis and educational content (Ling *et al.*, 2023). While LLMs can analyse behavioural data, specific applications focusing on managing emotional and cultural biases were not highlighted in the reported cases. LLMs cover a broad range of market dynamics and performance challenges. This area is broadly addressed with strong emphasis on market analysis, sentiment trading, and consumer adaptation, but less focus on behavioural factors.

Reported cases of LLM adoption in the financial industry

Following the same procedure as described above, the content of the 15 identified articles was analysed using the following queries: 1) Extract a brief description of the reported case. 2) Identify which challenges of the AM industry are addressed. The six most frequently addressed challenges were manually identified through a tagging and grouping process. These challenges comprise risk management, portfolio management and analytics, sentiment analysis, data management, back-office functions, and customer relationships (front office). The full results are presented in Table A of the supplementary materials.

Commented [BB2]: Not clear what this refers to.

The content analysis highlighted that integrating LLMs into the financial industry represents an advancement in addressing complex challenges and enhancing operational efficiencies. The reported cases show that these sophisticated models are utilised across various facets of finance, from portfolio management to risk assessment and regulatory compliance. One example is using LLMs such as FinBERT and others in sentiment analysis (Zhang *et al.*, 2023), in which LLMs are used to parse and interpret sentiments from financial texts, aiding in stock price predictions and investment strategy formulations (Huang, Wang and Yang, 2023; Kirtac and Germano, 2024). This capability enhances portfolio management and contributes to more dynamic and informed trading strategies.

The applications improve the efficiency and accuracy of financial operations, such as due diligence in structured finance, AM, and back-office functions (Luk, 2023; Wan *et al.*, 2024). LLMs are shown to facilitate better risk management by analysing vast amounts of data to detect potential risks and generate insights that can pre-empt financial crises (Guo *et al.*, 2023; Wan *et al.*, 2024; Zhang *et al.*, 2024).

Another significant advancement is the use of LLMs to create more personalised client interactions through AI-driven chatbots and advisory services (Li *et al.*, 2023; Ling *et al.*, 2023). These models

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are trained to understand and generate human-like responses, making them invaluable in customer service and client relationship management.

Additionally, effort is put into developing specific financial LLMs like Shai and FinGPT, which are tailored to meet the unique demands of the financial sector by processing and analysing financial data with high accuracy and speed (Guo *et al.*, 2023; Yang, Liu, and Wang, 2023). These models not only enhance existing financial processes but also pave the way for innovative financial services and solutions.

Overall, the deployment of LLMs in the financial industry is changing how financial entities operate, manage risks, interact with clients, and comply with regulations, thereby promising a more efficient, secure, and customer-oriented future in finance. All instances of LLM application in the financial industry (bolded in column 3 of Table B in the supplementary materials) were used in the subsequent analysis and alignment with industry challenges.

Matching industry challenges and reported cases

In this step, the 3 key challenges categories of the AM industry were matched with the specific applications of LLMs in the financial sector. The objective was to ascertain how current LLM applications address these challenges. The results of the matching exercise are presented in Table 1.

Table 1. Matching challenges from the AM industry analysis with reported cases of LLM applications

Challenges of the asset management industry	**Reported cases of LLM application for the financial industry**														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Strategic Challenges	+	+	+		+	+	+		+	+			+	+	+
Operational Challenges	+	+	+	+	+	+	+	+	+	+	+	+			
Market Dynamics and Performance	+	+	+		+	+	+	+	+				+	+	+

Key: 1 (Zhang *et al.*, 2024), 2 (Wan *et al.*, 2024), 3 (Luk, 2023), 4 (Zhang *et al.*, 2023), 5 (Guo *et al.*, 2023), 6 (Kirtac and Germano, 2024), 7 (Li *et al.*, 2023), 8 (Ling *et al.*, 2023), 9 (Hirano, 2024), 10 (Yang, Liu and Wang, 2023), 11 (Son *et al.*, 2023), 12 (Xie *et al.*, 2023), 13 (Krause, 2023),14 (Pelster and Val, 2024), 15 (Huang, Wang and Yang, 2023)

The table highlights how 15 reported cases of LLM applications align with AM industry challenges. It shows that LLMs can significantly enhance strategic, operational, and market performance aspects in the AM industry by improving compliance, data management, automation, and client interactions, although there is potential for further exploration in some areas such as health crisis management and managing emotional biases.

Limitations in applications of LLMs in finance and AM

In this step, the content analysis limitations in studies of LLM applications within the financial industry were explored. Five broad categories of limitations were identified: 1) training of the model, 2) training data quality, 3) adoption and scalability, 4) regulatory, legal, and privacy, and 5) financial scenario and context (broad industry) generalisability. The detailed results of the analysis are presented in Table C in the supplementary materials.

Several authors highlight various limitations related to model training, such as the in-sample training concern. For example, Zhang *et al.* (2023) mention the use of a procedure that might resemble in-sample training, where prompts and the number of shots is optimised based on preliminary experiments. This could potentially bias the evaluation, favouring models that are better at handling the specific prompts used in the study. Krause (2023) acknowledges that AI models are not tested for their long-term stability and reliability, which is critical for sustained use in financial applications.

One of the primary concerns identified across multiple papers is the issue of training data limitations, such as the predominance of English-language financial documents, lack of data from emerging economies, and lack of diverse financial text types (Guo *et al.*, 2023; Son *et al.*, 2023; Xie *et al.*, 2023). These limitations can severely impact the performance and applicability of LLMs, making them less effective in global or multilingual markets and restricting their ability to understand fully and process varied financial documents (Cao and Feinstein, 2024; Chen *et al.*, 2024).

Another significant challenge is integrating LLMs into existing financial systems, often involving complex and resource-intensive modifications to workflows and data pipelines (Li *et al.*, 2023). Scalability issues compound this, as the high costs associated with advanced LLMs may not be justifiable or feasible for all financial institutions, particularly smaller or resource-constrained entities (Li *et al.*, 2023; Luk, 2023; Hirano, 2024).

Regulatory, legal, and privacy concerns also feature prominently, reflecting the stringent compliance environment of the financial industry (Li *et al.*, 2023; Wan *et al.*, 2024). The potential for LLMs to inadvertently violate financial regulations or compromise sensitive data poses substantial risks (Luk, 2023), necessitating more rigorous evaluations of regulatory compliance and the development of models that can securely handle sensitive information.

Furthermore, technological dependencies and environmental impacts associated with deploying LLMs include the need for substantial computational resources and the environmental cost of energy-intensive model training processes (Luk, 2023; Yang, Liu, and Wang, 2023; Hirano, 2024). These factors could limit the adoption of LLMs and highlight the need for more sustainable AI practices in the financial sector.

Assessing the quality of the studies

Assessing the quality of the studies reported in a scientific article is essential for determining the reliability and validity of the research findings (Belcher *et al.*, 2016; Luchini *et al.*, 2021) and recognising potential bias which could be present in the dataset (Sanderson, Tatt and Higgins, 2007). The 8 criteria discussed below were formulated specifically for this paper and used to assess the quality of the 15 studies reporting LLM use in the financial industry. The quality assessment was completed using the Aestima tool. The full quality assessment is available in the supplementary materials, Table D.

The studies provide a comprehensive and well-defined exploration of the potential of LLMs in various financial applications with clear objectives and many studies including well-articulated hypotheses. On the other hand, in some studies, hypotheses are implied rather than explicitly stated, which could lead to ambiguity and may make it challenging to assess the studies' scientific rigor and the validity of their conclusions. For example, the exploration of LLMs' performance and potential benefits in financial tasks is not always accompanied by clear, testable hypotheses (Li *et* *al.*, 2023; Son *et al.*, 2023). The studies focus heavily on the technical and practical aspects of LLMs but often overlook ethical considerations and potential misuse of AI-generated financial advice.

The methodologies employed are comprehensive, involving detailed processes and robust evaluation frameworks. Using multiple LLMs and domain-specific models enhances the relevance and applicability of the findings. The methodologies are well-detailed, ensuring robustness and reproducibility. Case studies and live experiments ensure practical applicability. However, some studies rely heavily on synthetic data and expert evaluations, which may introduce biases (Son *et al.*, 2023). The resource-intensive nature of continuous pre-training and fine-tuning could limit accessibility.

The studies use high-quality, credible, and well-annotated datasets from reputable sources. The comprehensive market coverage and expert annotation enhance the reliability and relevance of the data (Guo *et al.*, 2023). Continuous training with up-to-date data and external validation further improves accuracy. However, the reliance on synthetic data and lack of specific details about some datasets may introduce biases, affect transparency, and limit real world relevance. As mentioned above, the resource-intensive nature of continuous training and the potential redundancy in large datasets are also concerns. Some studies do not provide details about the datasets used for evaluation (Krause, 2023), which affects transparency.

Most of the studies provide a thorough and comprehensive evaluation of LLMs in financial tasks, employing a wide range of validation methods and metrics such as using diverse sources of data and/or a range of validation methods. The incorporation of transaction costs and alignment with news release timings make the findings more applicable to real-world trading (Kirtac and Germano, 2024). The use of both automated metrics and human evaluations provides a balanced assessment of model performance (Krause, 2023). The implementation of fact-checking mechanisms enhances the reliability of AI-generated information (Krause, 2023). On the other hand, lack of specific details on certain validation techniques and the disparity between automated and human evaluations suggest areas for improvement (Ling *et al.*, 2023).

The comparative analysis provides a detailed overview of the strengths and weaknesses of various LLMs and domain-specific models in financial tasks. While some models excel in specific areas, others offer more general cost-effective and practical solutions. The studies underline the importance of choosing the right model based on the specific requirements and constraints of the task at hand (Li *et al.*, 2023). The papers mostly report comprehensive comparative analysis of various LLMs and domain-specific models, focusing on their performance in financial sentiment analysis and other financial tasks.

The generalisability of LLM applications in the financial industry varies depending on several factors, including language and market specificity, document and dataset types, domain-specific models, and hardware constraints. While some studies demonstrate high levels of generalisability within the finance domain, others highlight the need for further validation and testing across different contexts and tasks (Hirano, 2024). Some studies aim to democratise access to financial language models, making them adaptable to various financial applications such as robo-advising, quantitative trading, and financial sentiment analysis (Yang, Liu, and Wang, 2023). Domain-specific datasets may not generalise well to other domains, limiting the applicability of the findings.

Making code and data publicly accessible via platforms like GitHub enhances reproducibility and transparency (Yang, Liu, and Wang, 2023). Providing detailed descriptions of methodologies, data sources, and parameters supports reproducibility (Yang, Liu, and Wang, 2023). The use of open-source platforms like Hugging Face promotes transparency and accessibility (Kirtac and Germano, 2024). Releasing models, datasets, and benchmarks aligns with open science principles, promoting collaborative development and innovation. Tutorials and detailed examples enhance transparency and allow other researchers to build upon the work (Yang, Liu, and Wang, 2023).

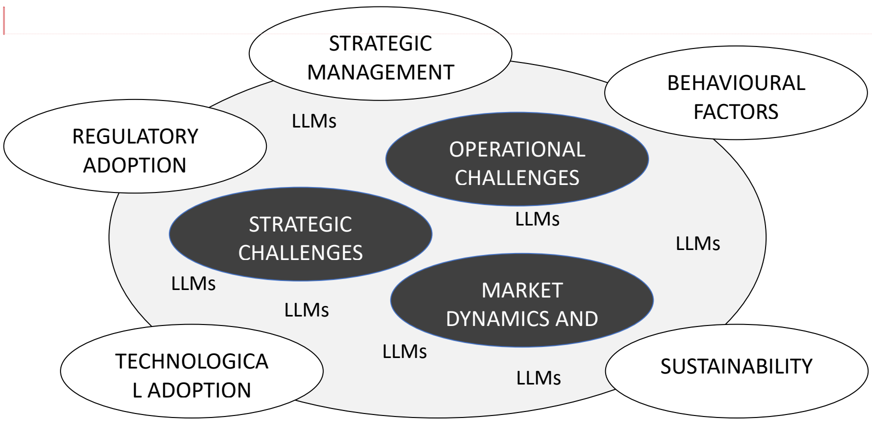
Reproducibility may be limited by the subjective nature of ratings provided by reviewers. The inability to share data due to permission issues, the absence of specific implementation details, and code availability might limit full transparency and independent verification. Using custom applications for data collection may pose challenges for exact replication as may lack of explicit reproducibility guidelines or code repositories (Cao and Feinstein, 2024; Chen *et al.*, 2024).

Current research indicates that refining methodologies and exploring LLMs in diverse languages and domains, enhancing scalability, cost-efficiency, and regulatory frameworks, should be further explored. Other areas worth considering include developing hybrid approaches, meta-learning, and human-in-the-loop systems or integrating macroeconomic and microeconomic data (Ling *et al.*, 2023; Cao and Feinstein, 2024).

DISCUSSION

The research identified a range of key challenges in the AM industry, including regulatory and compliance issues, technological disruption, market dynamics, performance measurement, and adaptation to consumer preferences. LLMs have been applied to tackle some of these challenges effectively. For instance, sentiment analysis using models like FinBERT has been instrumental in predicting stock price movements and informing investment strategies (Liu *et al.*, 2021; Huang, Wang and Yang, 2023). This application directly addresses the need for better market analysis and portfolio management. The key AM industry and financial industry challenge categories, which could be largely addressed by LLMs and the broader issues impacting LLM introduction, are presented in Figure 1.

Figure 1. AM challenges, LLMs and factors impacting their implementation in the industry



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LLMs have enhanced operational efficiencies in back-office functions, risk management, and regulatory compliance. The ability of LLMs to process and analyse vast amounts of financial data quickly and accurately has proven beneficial in due diligence, structured finance, and client relationship management. Specific models like Shai (Guo *et al.*, 2023) and FinGPT (Yang, Liu, and

Wang, 2023) have been developed to cater to the unique demands of the financial sector, offering high accuracy and speed in financial data processing. The studies highlight the transformative potential of LLMs in various financial applications, including sentiment analysis, structured finance auditing, hypothesis generation, financial market prediction, and customer service (Li *et al.*, 2023; Zhang *et al.*, 2023; Kirtac and Germano, 2024). LLMs offer potential efficiency gains, error reduction, and democratisation of financial knowledge. Future research directions are well-defined, focusing on scalability, domain adaptation, and ethical considerations. These findings are in line with the assumptions of the Task-Technology Fit Model (Goodhue and Thompson, 1995), where the demands of specific tasks can be met by new technology.

Despite these advancements, the research highlights several limitations in the current studies on LLM applications in the financial industry. One of the primary concerns is the issue of data limitations. The predominance of English-language financial documents and lack of diverse financial text types restrict the applicability of LLMs in global or multilingual markets (Zhang *et al.*, 2024; Lo and Ross, 2024). This highlights the need for more inclusive and diverse training datasets to improve the performance of LLMs across different financial contexts. Using synthetic data and relying on expert opinions could also introduce bias into data synthesis and analysis. Evidence quality assessment allowed the study team to address this by bringing to their attention the key issues in the analysed sources.

Wider context issues (Kukafka *et al.*, 2003) seem to be the main challenges in LLM implementation in the financial industry. Integration and scalability issues also pose challenges. The resource-intensive nature of LLMs makes it difficult for smaller financial institutions to adopt these technologies. The high costs associated with advanced LLMs and the complexity of integrating them into existing financial systems limit their widespread adoption (Yang, Liu, and Wang, 2023). This calls for more research into cost-effective and scalable solutions that can be easily integrated into various financial workflows (Li *et al.*, 2023; Yang, Liu, and Wang, 2023).

Regulatory, legal, and privacy concerns also need attention (Chen *et al.*, 2024; Lo and Ross, 2024). The financial industry's stringent compliance environment means that LLMs must be rigorously evaluated to ensure they do not inadvertently violate financial regulations or compromise sensitive data (Cao and Feinstein, 2024). Developing models that can securely handle sensitive information while adhering to regulatory standards is crucial for their successful deployment.

The research demonstrated successful inclusion of LLMs into the research process; they were used extensively for both relevance checks and content analysis. All articles were checked for their relevance to the topic using LLMs, ensuring that only the most pertinent studies were included in the analysis. This selection process enhanced the quality and reliability of the research findings. The use of LLMs for content analysis involved extracting statements and analyses from the chosen articles. This approach introduced a new methodological approach by leveraging LLMs for content analysis. This demonstrated the potential of LLMs to streamline the research process, making it more efficient and effective. The quality of the content analysis was validated within the research's boundaries (Gimmelberg et al., forthcoming), providing new evidence on the application of LLMs for research purposes. This validation process ensured that the findings were reliable and could be used as a foundation for future studies, demonstrating LLMs' effectiveness in analyzing large volumes of text and formulating meaningful insights.

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LIMITATIONS

Only papers with available PDFs were included in this review. This was dictated by a pragmatic approach to self-funded research. There are other sources behind paywalls, which could shed more light on the topic. Although the results showed a comprehensive picture of the challenges faced by the AM industry and the LLM applications that could address them, the selection of sources could have introduced some bias. Including only sources written in English limits the generalisability of the results and may introduce bias, favouring this set of publications.

A key challenge in the matching exercise was that the categorisation of challenges was conducted from an industry perspective, whereas the case reports focused on process improvements. Several categories formulated during the case tagging, such as sentiment analysis, portfolio rebalancing, and portfolio risk management, were assigned to the available categories. The matching of challenges of the AM industry and LLM applications in the field revealed some discrepancies between them. This could be explained by a) a potential shortfall in the literature, b) limited case studies being published, or c) a need to refine the coding approach applied in this study.

Practical implementation of the study results may be impacted by research bias, data quality, and market volatility (Li *et al.*, 2023). There is a need for regulatory oversight to manage the risks associated with AI in finance. Future work must address limitations such as the spread of misinformation and the integration of comprehensive economic data (Guo *et al.*, 2023; Son *et al.*, 2023; Chen *et al.*, 2024; Kirtac and Germano, 2024).

Current research indicates that refining methodologies and exploring LLMs in diverse languages and domains, enhancing scalability, cost-efficiency, and regulatory frameworks, should be further explored. Other areas worth considering include developing hybrid approaches, meta-learning, and human-in-the-loop systems or integrating macroeconomic and microeconomic data (Ling *et al.*, 2023; Cao and Feinstein, 2024).

There is a need for a broad approach to future research on LLM use in the financial asset management industry. For example, benchmarking research would help to ensure a more accurate performance evaluation of LLMs in the various AM sub-domains (Li *et al.*, 2023; Hirano, 2024). Regulatory compliance and change are other areas where research is needed to fully understand their implications for LLM-based innovation and use in the AM industry. Another research direction is to understand the potential risks of employing LLMs in various AM subsectors and develop solutions addressing them. Addressing the risk of LLM amplification bias reported in studies exploring LLM performance (Bao *et al.*, 2024; Wang *et al.*, 2024; Xu *et al.*, 2024) also requires attention. Early recognition of bias in the dataset through bias-aware training strategies (Karimi Mahabadi, Belinkov and Henderson, 2020) such as alignment tuning (Zhou *et al.*, 2024) and introducing systematic manual and automated checks could address the issue. Finally, assessing the impact of technological development on competition within AM also needs to be explored.

Enhancing data diversity by incorporating financial texts from different languages and regions will improve the global applicability of LLMs (Krause, 2023; Zhang *et al.*, 2024). Developing more cost-effective and scalable LLM solutions will facilitate their adoption by smaller financial institutions. Additionally, ensuring compliance with regulatory standards and addressing privacy concerns will be critical in gaining the trust of financial entities.

Furthermore, the environmental impact of LLM technologies should not be overlooked (Huang, Wang and Yang, 2023). The substantial computational resources required for training and deploying LLMs raise environmental concerns. Research into more sustainable AI practices will be essential in mitigating this technology’s environmental footprint.

While LLMs offer potential in transforming the financial AM industry, addressing the identified limitations and gaps through targeted research will be crucial in realising their full potential. Future research can lead to more effective and widespread adoption of LLMs in AM by focusing on data diversity, scalability, regulatory compliance, and sustainability.

This review suggests potential gaps in literature and case studies, limiting the overview of the full picture of potential LLM applications in the AM industry and in financial services in general. More process-related challenges need to be incorporated into the list of industry challenges. These should include aspects like portfolio management and rebalancing, risk management, sentiment analysis, and specialised content generation (such as analysis and reporting), among others.

CONCLUSIONS AND RECOMMENDATIONS

This review of the application of LLMs in the AM industry contributes to the field, offering new insights and methodologies. The review included 30 papers to pinpoint key challenges in the AM industry and 15 of the most up-to-date papers on LLM applications in finance. The primary challenges faced by the AM industry were identified, and various applications of LLMs in finance, including sentiment analysis, market predictions, and automated document processing, were highlighted. This comprehensive approach provided a robust foundation for understanding how LLMs can address the specific challenges in the AM industry.

Adopting LLMs in the financial AM industry has shown promising potential in addressing various challenges. Yet, it also reveals significant gaps and limitations that warrant further investigation. Overall, the conducted analysis underscores the necessity for ongoing research to address the evidence limitations, with a focus on enhancing data diversity, improving model integration and scalability, ensuring compliance with regulatory standards, and reducing the environmental impact of LLM technologies. This will be crucial for realising the full potential of LLMs in transforming financial services and operations. It can also inform the development of regulatory frameworks that accommodate technological advancements, ensuring that the benefits of LLMs are maximised while mitigating associated risks.

Declarations. The manuscript has not been previously published, submitted, or uploaded to any archive or pre-print server. We have not plagiarised or self-plagiarised any previous sources. Any tables or figures displayed in the manuscript are of our own creation, and we hold the copyright for these materials. The authors are investors (DG, AB) and paid contributors (MG) in the development of the Aestima tool used in the data analysis.

Authors' contributions. Authors 1 and 2 conducted research, Author 4 was involved in the research design and structuring, and Author 3 reviewed the manuscript, providing valuable reflections.

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REFERENCES

Al-Dokhny, A. *et al.* (2024), “Can Multimodal Large Language Models Enhance Performance Benefits Among Higher Education Students? An Investigation Based on the Task–Technology Fit Theory and the Artificial Intelligence Device Use Acceptance Model”, *Sustainability*, Vol. 16, No. 23, Art. 10780, doi: 10.3390/su162310780.

Amenc, N. *et al.* (2011), “Exploiting Asset-Liability Management Concepts in Private Wealth Management”, pp. 443–468, doi: 10.1057/9780230307230_18.

Bao, K. *et al.* (2024), “Decoding matters: Addressing amplification bias and homogeneity issue for LLM-based recommendation”, *arXiv* [Preprint], available at: https://doi.org/10.48550/arXiv.2406.14900

Belcher, B. M. *et al.* (2016), “Defining and assessing research quality in a transdisciplinary context”, *Research Evaluation*, Vol. 25, No. 1, pp. 1–17, doi: 10.1093/reseval/rvv025.

Bernabei, M. *et al.* (2023), “Students’ use of large language models in engineering education: A case study on technology acceptance, perceptions, efficacy, and detection chances”, *Computers and Education: Artificial Intelligence*, Vol. 5, Art. 100172, doi: 10.1016/j.caeai.2023.100172.

Britton, B. L., Atkinson, D. G. (2017), “An investigation into the significant impacts of automation in asset management”, *Economics World*, Vol. 5, No. 5, pp. 418–428.

Callanan, E. *et al.* (2023), “Can GPT Models Be Financial Analysts? An Evaluation of ChatGPT and GPT-4 on Mock CFA Exams”, *arXiv*, doi: 10.48550/arXiv.2310.08678.

Cao, Z., Feinstein, Z. (2024), “Large Language Model in Financial Regulatory Interpretation”, *arXiv*, available at: http://arxiv.org/abs/2405.06808 (accessed 16 May 2024).

Chen, Z. Z. *et al.* (2024), “A Survey on Large Language Models for Critical Societal Domains: Finance, Healthcare, and Law”, *arXiv*, available at: http://arxiv.org/abs/2405.01769 (accessed 9 May 2024).

Clark, G. L., Dixon, A. D. (2024), “Legitimacy and the extraordinary growth of ESG measures and metrics in the global investment management industry”, *Environment and Planning A: Economy and Space*, Vol. 56, No. 2, pp. 645–661, doi: 10.1177/0308518X231155484.

Costanzo, G. (2011), “The Contribution of the Asset Management Industry to Long-term Growth”, *OECD Journal: Financial Market Trends*, pp. 87–96, doi: 10.1787/FMT-2011-5KG55QW1N6F7.

Dabić, M. *et al.* (2020), “Pathways of SME internationalization: A bibliometric and systematic review”, *Small Business Economics*, Vol. 55, pp. 705–725, doi: 10.1007/s11187-019-00181-6.

Davis, F. D. (1993), “User acceptance of information technology: system characteristics, user perceptions and behavioral impacts”, *International Journal of Man-Machine Studies*, Vol. 38, No. 3, pp. 475–487, doi: 10.1006/imms.1993.1022.

Davis, F. D., Bagozzi, R. and Warshaw, P. (1989), “User Acceptance of Computer Technology: A Comparison of Two Theoretical Models”, *Management Science*, Vol. 35, No. 8, pp. 982–1003.

Dergaa, I. *et al.* (2023), “From human writing to artificial intelligence generated text: examining the prospects and potential threats of ChatGPT in academic writing”, *Biology of Sport*, Vol. 40, No. 2, pp. 615–622, doi: 10.5114/biolsport.2023.125623.

Dowling, M., Lucey, B. (2023), “ChatGPT for (Finance) Research: The Bananarama Conjecture”, *Finance Research Letters*, Vol. 53, Art. 103662, doi: 10.1016/j.frl.2023.103662.

Commented [BB5]: Please provide the doi or URL.

Ejjami, R. (2024), “Revolutionizing Knowledge Synthesis: Introducing AI-Enhanced Collaborative Theory (AIECT)”, *IJFMR – International Journal For Multidisciplinary Research*, Vol. 6, No. 5, doi: 10.36948/ijfmr.2024.v06i05.28203.

Epstein, G. (2019), “The asset management industry in the United States” *Financing for Development series*, No. 271 (LC/TS.2019/81), Santiago, Economic Commission for Latin America and the Caribbean (ECLAC), https://peri.umass.edu/wp-content/uploads/joomla/images/publication

Folqué González-Valerio, M., Escrig Olmedo, E. and Corzo Santamaría, M. T. (2023), “Contribution of sustainable investment to sustainable development within the framework of the SDGS: the role of the asset management industry”, *Sustainability Accounting, Management and Policy Journal*, Vol. 14 No. 5, pp. 1075-1100, https://doi.org/10.1108/SAMPJ-01-2022-0044

Gârleanu, N., Pedersen, L. H. (2018), “Efficiently inefficient markets for assets and asset management”, *The Journal of Finance*, Vol. 73, No. 4, pp. 1663–1712, doi: 10.1111/jofi.12696.

Ghimire, A., Edwards, J. (2024), “Generative AI Adoption in Classroom in Context of Technology Acceptance Model (TAM) and the Innovation Diffusion Theory (IDT)”, *arXiv* [Preprint], https://doi.org/10.48550/arXiv.2406.15360

Goh, T.-T., Dai, X. and Yang, Y. (2023), “Benchmarking ChatGPT for prototyping theories: Experimental studies using the technology acceptance model”, *BenchCouncil Transactions on Benchmarks, Standards and Evaluations*, Vol. 3, No. 4, Art. 100153, doi: 10.1016/j.tbench.2024.100153.

Goodhue, D. L., Thompson, R. L. (1995), “Task-technology fit and individual performance”, *MIS Quarterly*, pp. 213–236, doi: 10.2307/249689.

Guo, Z. *et al.* (2023), “Shai: A large language model for asset management”, *arXiv*, available at: http://arxiv.org/abs/2312.14203 (accessed 11 May 2024).

Haberly, D. *et al.* (2019), “Asset management as a digital platform industry: A global financial network perspective”, *Geoforum*, Vol. 106, pp. 167–181, doi: 10.1016/j.geoforum.2019.08.009.

Haviv, A., Berant, J. and Globerson, A. (2021), “BERTese: Learning to Speak to BERT”, in Merlo P., Tiedemann, J. and Tsarfaty, R. (Eds.), *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, Association for Computational Linguistics, pp. 3618–3623, doi: 10.18653/v1/2021.eacl-main.316.

Hersh, W. (2024), “Search still matters: information retrieval in the era of generative AI”, *Journal of the American Medical Informatics Association*, Vol. 31, No. 9, pp. 2159–2161, doi: 10.1093/jamia/ocae014.

Hirano, M. (2024), “Construction of a Japanese Financial Benchmark for Large Language Models”, *arXiv*, available at: http://arxiv.org/abs/2403.15062 (accessed 9 May 2024).

Huang, A. H., Wang, H. and Yang, Y. (2023), “FinBERT: A Large Language Model for Extracting Information from Financial Text”, *Contemporary Accounting Research*, Vol. 40, No. 2, pp. 806–841, doi: 10.1111/1911-3846.12832.

Huynh, J. *et al.* (2023), “Understanding the effectiveness of very large language models on dialog evaluation”, *arXiv* [Preprint], https://doi.org/10.48550/arXiv.2301.12004.

Karimi Mahabadi, R., Belinkov, Y. and Henderson, J. (2020), “End-to-End Bias Mitigation by Modelling Biases in Corpora”, in *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, Association for Computational Linguistics, pp. 8706–8716, doi: 10.18653/v1/2020.acl-main.769.

Commented [BB6]: Please provide the doi or URL.

Commented [BB7]: Please provide the doi or URL.

Commented [BB8]: (re-alphabetised)

Kirtac, K., Germano, G. (2024), “Sentiment trading with large language models”, *Finance Research Letters*, Vol. 62, Art. 105227, doi: 10.1016/j.frl.2024.105227.

Krause, D. (2023), “Large Language Models and Generative AI in Finance: An Analysis of ChatGPT, Bard, and Bing AI” [Preprint], available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4511540 (accessed 9 May 2024).

Kukafka, R. *et al.* (2003), “Grounding a new information technology implementation framework in behavioral science: a systematic analysis of the literature on IT use”, *Journal of Biomedical Informatics*, Vol. 36, No. 3, pp. 218–227, doi: 10.1016/j.jbi.2003.09.002.

Lemke, C. *et al.* (2023), “Exploring the Student Perspective: Assessing Technology Readiness and Acceptance for Adopting Large Language Models in Higher Education”, in *22nd European Conference on e-Learning: ECEL 2023*, Academic Conferences and Publishing Limited.

Li, Y. *et al.* (2023), “Large Language Models in Finance: A Survey”, in *ICAIF ’23: 4th ACM International Conference on AI in Finance*, ACM, Brooklyn, NY, pp. 374–382, doi: 10.1145/3604237.3626869.

Ling, C. *et al.* (2023), “Domain specialization as the key to make large language models disruptive: A comprehensive survey”, *arXiv* [Preprint], https://doi.org/10.48550/arXiv.2305.18703.

Liu, Z. *et al.* (2021), “Finbert: A pre-trained financial language representation model for financial text mining”, in *Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence*, pp. 4513–4519, available at: https://www.ijcai.org/proceedings/2020/0622.pdf (accessed 9 May 2024).

Lo, A. W., Ross, J. (2024), “Can ChatGPT Plan Your Retirement?: Generative AI and Financial Advice”, *Harvard Data Science Review* [Preprint], doi: 10.1162/99608f92.ec74a002.

Luchini, C. *et al.* (2021), “Assessing the quality of studies in meta-research: Review/guidelines on the most important quality assessment tools”, *Pharmaceutical Statistics*, Vol. 20, No. 1, pp. 185–195, doi: 10.1002/pst.2068.

Luk, M. (2023), “Generative AI: Overview, economic impact, and applications in asset management” [Preprint], available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4574814 (accessed 11 May 2024).

Merton, R. C., Bodie, Z. (1995), “A conceptual framework for analyzing the financial system”, in *The Global Financial System: A Functional Perspective*, Harvard Business School Press, , pp. 3-31, available at : https://un.uobasrah.edu.iq/lectures/1782.pdf.

Moreira, J. *et al.* (2019), “A systematic review of women’s entrepreneurship and internationalization literature”, *Thunderbird International Business Review*, Vol. 61, No. 4, pp. 635–648, doi: 10.1002/tie.22045.

Neuendorf, K. A. (2018), “Content analysis and thematic analysis”, in *Advanced Research Methods for Applied Psychology*, Routledge, pp. 211–223, available at: https://www.taylorfrancis.com/chapters/edit/10.4324/9781315517971-21/content-analysis-thematic-analysis-kimberly-neuendorf (accessed 12 May 2024).

Oshodin, O. *et al.* (2017), “Is FinTech a Disruption or a New Eco-system? An Exploratory Investigation of Banks’ Response to Fintech in Australia”. *ACIS 2017 Proceedings.* 95. https://aisel.aisnet.org/acis2017/95

Pelster, M., Val, J. (2024), “Can ChatGPT assist in picking stocks?”, *Finance Research Letters*, Vol. 59, Art. 104786, doi: 10.1016/j.frl.2023.104786.

Commented [BB9]: Please provide the doi or URL.

Commented [BB10]: editors? publisher info?

Commented [BB11]: editors?

Commented [BB12]: Please complete this reference (journal info, etc.).

Poh Soon, J. N. *et al.* (2024), "The Impact and Acceptance of Large Language Models in Healthcare: A Perspective from China", *Journal of Advanced Research in Applied Sciences and Engineering Technology*, Vol. 58, No. 4, doi: 10.37934/araset.58.4.119167.

Polak, M. P., Morgan, D. (2024), "Extracting accurate materials data from research papers with conversational language models and prompt engineering", *Nature Communications*, Vol. 15, No. 1, Art. 1569, doi: 10.1038/s41467-024-45914-8.

Russo, D. (2024), "Navigating the complexity of generative AI adoption in software engineering", *ACM Transactions on Software Engineering and Methodology* [Preprint]. https://doi.org/10.1145/3652154

Sanderson, S., Tatt, I. D. and Higgins, J. P. (2007), "Tools for assessing quality and susceptibility to bias in observational studies in epidemiology: a systematic review and annotated bibliography", *International Journal of Epidemiology*, Vol. 36, No. 3, pp. 666–676, doi: 10.1093/ije/dym018.

Shin, M., Kim, J. and Shin, J. (2024), "The Adoption and Efficacy of Large Language Models: Evidence from Consumer Complaints in the Financial Industry", [Preprint], (accessed 12 Jan 2025). Available at SSRN: https://ssrn.com/abstract=5004194 or http://dx.doi.org/10.2139/ssrn.5004194

Son, G. *et al.* (2023), "Beyond Classification: Financial Reasoning in State-of-the-Art Language Models", *arXiv*, doi: 10.48550/arXiv.2305.01505.

Stowell, D. P. (2010), "An Introduction to Investment Banks, Hedge Funds, and Private Equity", *Academic Press*, pp. 115–124, ISBN : 0080922899, 9780080922898.

Telenti, A. *et al.* (2024), "Large language models for science and medicine", *European Journal of Clinical Investigation*, Vol. 54, No. 6, Art. e14183, doi: 10.1111/eci.14183.

Toumeh, A. A. (2024), "Assessing the potential integration of large language models in accounting practices: evidence from an emerging economy", *Future Business Journal*, Vol. 10, No. 1, Art. 82.

Walter, I. (1999), "The global asset management industry: Competitive structure and performance", *Financial Markets, Institutions & Instruments*, Vol. 8, No. 1, pp. 1–78.

Walter, I., Sisli, E. (2007), "The asset management industry in Asia: Dynamics of growth, structure, and performance", *Financial Markets, Institutions & Instruments*, Vol. 16, No. 1, pp. 1–77.

Wan, X. *et al.* (2024), "Enhancing the Efficiency and Accuracy of Underlying Asset Reviews in Structured Finance: The Application of Multi-agent Framework", *arXiv*, available at: http://arxiv.org/abs/2405.04294 (accessed 11 May 2024).

Wang, Z. *et al.* (2024), "Bias Amplification: Language Models as Increasingly Biased Media", *arXiv* [Preprint]. available at: https://doi.org/10.48550/arXiv.2410.15234

Xie, Q. *et al.* (2023), "PIXIU: A Large Language Model, Instruction Data and Evaluation Benchmark for Finance", *arXiv*, doi: 10.48550/arXiv.2306.05443.

Xu, W. *et al.* (2024), "Pride and prejudice: LLM amplifies self-bias in self-refinement", in *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 15474–15492.

Yang, H., Liu, X.-Y. and Wang, C. D. (2023), "FinGPT: Open-Source Financial Large Language Models", *arXiv*, doi: 10.48550/arXiv.2306.06031.

Zeng, J. *et al.* (2024), "Large Language Models for Social Networks: Applications, Challenges, and Solutions", *arXiv*, available at: http://arxiv.org/abs/2401.02575 (accessed 25 February 2024).

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Commented [BB15]: Please provide the doi or URL.

Zhang, B. *et al*. (2023), "Enhancing Financial Sentiment Analysis via Retrieval Augmented Large Language Models", in *ICAIF '23: 4th ACM International Conference on AI in Finance*, ACM, Brooklyn, NY, pp. 349–356, doi: 10.1145/3604237.3626866.

Zhang, H. *et al*. (2024), "Unveiling the Potential of Sentiment: Can Large Language Models Predict Chinese Stock Price Movements?", *arXiv*, doi: 10.48550/arXiv.2306.14222.

Zhou, H. *et al.* (2024), "Mitigating the Bias of Large Language Model Evaluation", *arXiv*, doi: 10.48550/ARXIV.2409.16788.