Multi-Agent LLMs in Finance: A Survey

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Abstract

This survey paper provides a comprehensive exploration of the interdisciplinary integration of multi-agent large language models (LLMs) in the financial sector, emphasizing human-AI collaboration, task allocation, AI governance, ethics, and regulatory compliance. The paper outlines a conceptual framework that simulates complex decision-making processes, akin to financial committees, to elucidate the operational dynamics of multi-agent LLMs. It underscores the significance of frameworks that categorize LLM-based agents, facilitating their effective deployment in financial applications. Key themes include the evolution of AI as a collaborative partner in financial decision-making, the optimization of task allocation between AI systems and human agents, and the necessity of AI governance frameworks for responsible deployment. The survey also addresses AI ethics, focusing on algorithmic fairness, transparency, and accountability, and highlights regulatory compliance challenges and opportunities within the financial sector. Through case studies and applications, the paper illustrates the transformative potential of human-AI collaboration and autonomous financial agents in enhancing operational efficiency and market stability. The survey concludes with future directions, emphasizing the need for regulatory alignment and ethical considerations to ensure responsible AI integration in finance. Overall, the paper provides a robust foundation for understanding the complexities and opportunities presented by AI technologies in financial contexts, advocating for interdisciplinary collaboration to navigate these challenges.

1 Introduction

1.1 Conceptual Framework of Multi-Agent LLMs in Finance

The conceptual framework of multi-agent large language models (LLMs) in finance integrates theoretical and practical methodologies that facilitate their application in financial systems. A pivotal component is the simulation of complex decision-making processes, similar to those of financial committees such as the Federal Open Market Committee, exemplified by the MiniFed approach [1]. This simulation elucidates the operational dynamics of multi-agent LLMs, underscoring the importance of replicating real-world financial decision-making environments.

Categorizing LLM-based agents into single-agent and multi-agent systems is essential for comprehending their distinct operational methodologies [2]. Such frameworks enhance the deployment of LLMs in financial applications by clarifying roles and interactions within multi-agent settings.

The autonomous generation of smart contracts through multi-agent systems utilizing LLM capabilities marks a significant advancement in human-machine interaction [3]. This integration streamlines financial processes, enhancing transaction reliability and efficiency, and illustrates the transformative potential of LLMs in finance.

Incorporating human-AI collaboration is crucial, as demonstrated by the Human-AI Collaboration (HAIC) guided deferral system, which merges human expertise with AI capabilities to foster trust

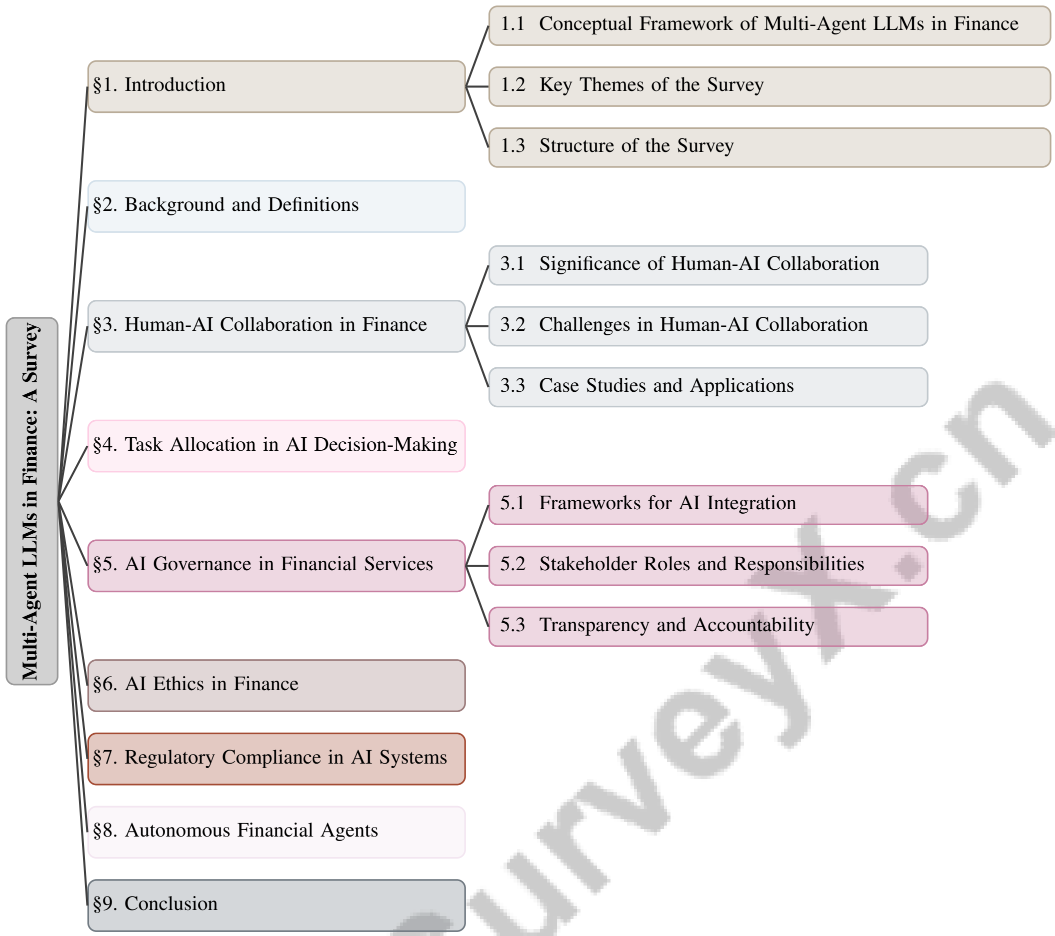


Figure 1: chapter structure

and improve decision-making [4]. This system exemplifies the synergistic potential of human-AI collaboration in refining financial operations.

The adaptability and personalization of multi-agent systems are bolstered by developing distinct LLM personalities, enhancing applications in social simulations and human-machine interactions [5]. Such personalization is vital for tailoring financial services to diverse client needs.

The theoretical foundations of human-AI collaboration in auditing LLMs highlight the integration of human insights with LLM capabilities, crucial for maintaining transparency and accountability in financial audits [6]. This integration ensures the accuracy and reliability of financial operations.

The AGENTVERSE framework illustrates the adaptability and effectiveness of autonomous agents in managing complex financial tasks by enabling dynamic adjustments in agent composition based on problem-solving progress [7]. This adaptability is essential for responding to the dynamic nature of financial markets.

Function allocation logic categorizes the human-AI relationship into various roles and responsibilities, emphasizing the necessity for a dynamic allocation agent to optimize task distribution and enhance collaborative efficiency in financial systems [8].

The interdisciplinary synergy among AI, finance, and economics is pivotal, as highlighted in recent surveys summarizing significant developments and potentials of AI in finance [9]. This synergy underscores the importance of integrating diverse disciplinary insights to fully leverage the capabilities of multi-agent LLMs in financial contexts.

The Co-Creative Framework for Interaction design (COFI) categorizes interaction components and models based on collaboration dynamics and creative processes, providing a structured approach to designing effective human-AI interactions in finance [10]. This framework is essential for fostering innovation and creativity in financial services.

The conceptual framework of multi-agent LLMs in finance is characterized by its modular, collaborative, and user-centered design, effectively addressing the intricate challenges of financial decision-making. It incorporates specialized LLM-powered agents, each fulfilling distinct roles such as fundamental analysts, sentiment analysts, and risk managers, thereby simulating the collaborative dynamics of real-world trading firms. This approach enhances anomaly detection and automates due diligence processes in structured finance, improving trading performance—evidenced by significant gains in cumulative returns and reductions in human error—while establishing a robust foundation for developing sophisticated financial systems that can adapt to market complexities [11, 12, 13].

1.2 Key Themes of the Survey

The exploration of multi-agent LLMs in finance is anchored on several key themes pivotal for understanding the integration and impact of AI technologies within this sector. A central theme is human-AI collaboration, emphasizing AI's evolution from a computational tool to a collaborative partner in financial decision-making [14]. This transition necessitates advanced methodologies to enhance collaboration between AI systems and human decision-makers, particularly in financial environments [4]. Intelligent agents' ability to simulate complex human interactions and support organizational processes through guided conversations is crucial for effective collaboration [3]. Furthermore, optimizing AI systems for teamwork rather than individual accuracy is vital for enhancing decision-making processes across various domains [15].

Task allocation within multi-agent systems is another significant theme, focusing on optimizing task distribution between AI systems and human agents to ensure efficient financial decision-making. Effective task allocation involves reasoning through debates and managing contextual information, essential for improving LLM adaptability, emotional intelligence, and cultural sensitivity [2]. Integrating human domain expertise with machine learning methods is particularly crucial in areas of high complexity and importance, such as financial decision-making [16].

AI governance and ethics are integral to the survey, addressing frameworks necessary for responsible AI deployment in financial services. The transition into a phronetic paradigm to define actionable recommendations and normative solutions highlights ethical dilemmas in AI conception and application [17]. The survey also covers topics related to AI user interface design, human-AI conversations and collaboration, explainability, accountability, fairness, and bias, all critical for ethical AI practices [8]. The challenges of capturing organizational value from AI investments underscore the need for productive human-AI interactions [4].

Regulatory compliance emerges as a crucial theme, analyzing the legal and ethical standards that AI systems must adhere to within the financial sector. Structured workflows and addressing issues like cascading hallucinations and logic inconsistencies are essential for achieving regulatory alignment [14]. Discussions on types of AI models, human-AI collaboration, and evaluation metrics are crucial for understanding the regulatory landscape [18].

These themes collectively provide a comprehensive overview of the multifaceted challenges and opportunities presented by integrating multi-agent LLMs in finance. They underscore the need for interdisciplinary collaboration and innovative frameworks to navigate the complexities of AI technologies in this field [19].

1.3 Structure of the Survey

This survey is systematically organized to provide a comprehensive exploration of multi-agent large language models (LLMs) in finance. It begins with an introduction to multi-agent LLMs, emphasizing the significance of human-AI collaboration, task allocation, AI governance, ethics, and regulatory compliance in the financial sector. Following the introduction, a comprehensive conceptual framework delineates the theoretical principles and practical methodologies essential for effectively integrating multi-agent LLMs into financial systems, highlighting their roles in enhancing anomaly detection, automating data validation, and improving decision-making processes within complex financial environments [12, 13, 20, 11, 21].

The survey then delves into the background and definitions, thoroughly explaining core concepts such as multi-agent systems, large language models, human-AI collaboration, task allocation, AI governance, AI ethics, autonomous financial agents, and regulatory compliance. This section sets the stage for understanding the relevance of these concepts in financial services.

Subsequent sections explore the dynamics of human-AI collaboration in finance, examining strategies for task allocation between AI systems and human agents, and discussing governance frameworks necessary for integrating AI technologies in financial services. Each section provides insights into the operational and ethical considerations of deploying AI in the financial sector.

The survey addresses ethical considerations surrounding AI in finance, emphasizing concerns such as algorithmic bias, fairness, and transparency within AI systems. It explores the ethical ramifications of deploying autonomous financial agents, particularly regarding their decision-making processes and the potential societal impacts of these technologies. Furthermore, it reviews existing ethical frameworks and tools aimed at mitigating these issues, assessing their effectiveness in promoting accountability and responsible AI deployment in financial contexts [9, 22]. This is followed by an analysis of the regulatory landscape for AI systems in the financial sector, highlighting the challenges and opportunities in achieving regulatory compliance.

The survey examines the evolution and implementation of autonomous financial agents, specifically those powered by LLMs like FinVerse and FinRobot. It discusses the potential advantages of these agents, such as enhanced data processing capabilities and improved decision-making in trading, while addressing inherent risks, including model governance challenges and complexities in ensuring compliance in financial services. Furthermore, it evaluates the broader implications of these agents on financial markets and services, including their ability to outperform traditional traders and the necessity for effective monitoring and management strategies to mitigate associated risks [20, 23, 14, 21]. The paper concludes with a summary of key findings, reflections on the current state and future directions of multi-agent LLMs in finance, and an emphasis on the importance of interdisciplinary collaboration to address the challenges and opportunities presented by AI technologies in the financial sector.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Core Concepts of Multi-Agent LLMs

The integration of multi-agent large language models (LLMs) in finance involves leveraging multi-agent systems (MAS) to enhance decision-making through collaborative interactions. MAS, composed of multiple agents working together, facilitate labor division and specialization, which are vital for adaptability and efficiency in financial applications [24, 7]. LLMs significantly contribute by processing and prioritizing extensive trading information, refining decision-making in trading environments [9]. However, challenges persist in simulating individual investor behaviors due to LLMs' limitations in handling irrational decision-making and numerical comprehension [5]. This necessitates developing LLMs capable of modeling complex market dynamics and behaviors more effectively.

LLMs in MAS enhance problem-solving tasks by fostering human interaction and decision-making processes [15]. By categorizing LLM capabilities into individual skills (cognition, perception) and collective skills (social abilities), a framework emerges for understanding their potential in human-centric applications [8]. However, the lack of distinct personalities in current LLMs limits their effectiveness in real-world applications, where human-like interactions are crucial [5].

Human-AI collaboration within multi-agent LLMs emphasizes autonomy and meaningfulness in work tasks, highlighting AI systems' role in supporting human decision-making [10]. The theoretical foundation of multi-agent LLMs draws from complex systems and statistical physics, utilizing models to explore phase transitions and collective behaviors within the Human-AI ecosystem [6]. Adaptability is critical for these systems in financial contexts, enhancing effectiveness in simulating and responding to complex market conditions [25]. Evaluating LLMs' decision-making abilities in multi-agent games underscores their significance in dynamic environments [26]. Collaboration between human and AI in fraud detection, especially with limited human prediction data, illustrates the necessity for effective collaboration to achieve optimal outcomes [27].

AI-generated, for reference only.

These core concepts establish a foundation for deploying multi-agent LLMs in finance, facilitating efficient, ethical, and human-aligned operations. They emphasize interdisciplinary collaboration and innovative frameworks to address AI technologies' challenges, particularly in enhancing trust, explainability, and transparency within human-AI systems. This approach is vital for navigating complexities in high-stakes environments such as healthcare and manufacturing, where improved task performance and decision-making are paramount [28, 29, 30, 31].

2.2 Theoretical Foundations and Frameworks

The theoretical foundations of multi-agent large language models (LLMs) in finance emphasize collaborative and autonomous problem-solving capabilities. These models address the need for sophisticated solutions leveraging collaborative intelligence, particularly in complex corporate environments [24]. Categorizing LLM capabilities into cognitive, perceptual, analytical, executive, and social skills aids in understanding their multifaceted roles in financial decision-making. The taxonomy of hybrid intelligence systems supports LLM integration by categorizing systems based on task characteristics, learning paradigms, and human-AI interactions [32].

Frameworks like Self-Determination Theory and the SMART model highlight autonomy, competence, and relatedness in designing LLM-based systems for human-centric financial environments. Integrating AI with traditional asset review processes enhances agency and collaboration between human and AI agents, improving efficiency and accuracy in structured finance due diligence [20, 12, 33, 34].

Facilitating effective collaboration and autonomous problem-solving among agents requires understanding Human-AI dynamics and adaptive behaviors for complex task interactions. This is crucial for advancing intelligent systems capable of achieving or exceeding human-level intelligence [35, 36]. Extending models to include higher-order interactions and diverse agent types enhances comprehension of collaborative processes in financial decision-making.

Trust in Human-AI Interaction (HAI) teams is informed by a tripartite structure of trust antecedents from psychological and computer science literature. This positions multi-agent LLMs as reliable collaborators by leveraging specialized AI agents to enhance anomaly detection, streamline financial analysis, and improve decision-making processes [37, 11, 13].

Integrating Blockchain Technology (BCT) within MAS is explored, highlighting its potential to foster accountability and trusted interactions in various domains, including finance, where transparency and security are paramount [20, 38, 39]. A socio-technical perspective enriches the framework by emphasizing the interplay between tasks and contexts in understanding complex problem-solving, essential for developing adaptive systems in dynamic financial markets [40, 20, 19, 18, 41].

Personality engineering in AI interactions emphasizes integrating psychological principles into AI design, with research showing that highly agreeable AI agents can enhance human-AI collaboration by achieving confusion rates exceeding 60

The discussed theoretical foundations and frameworks underscore interdisciplinary collaboration and innovative methodologies' importance in implementing multi-agent LLMs in finance. These studies illustrate how collaborative networks of specialized AI agents can enhance tasks such as anomaly detection, financial analysis, and decision-making, improving efficiency and accuracy while reducing human intervention [37, 13, 20, 36, 11]. They provide a comprehensive understanding of these systems' operational dynamics and potential, paving the way for more sophisticated financial operations.

3 Human-AI Collaboration in Finance

The integration of artificial intelligence (AI) into financial decision-making processes is increasingly essential as organizations strive to enhance operational efficiency and decision accuracy. Understanding the dynamics of human-AI collaboration is crucial, as it combines human intuition with AI's computational prowess to achieve superior outcomes. This synergy necessitates a thorough examination of its implications for financial practices, particularly in enhancing data security, addressing ethical considerations, and navigating regulatory compliance [40, 42, 34].

3.1 Significance of Human-AI Collaboration

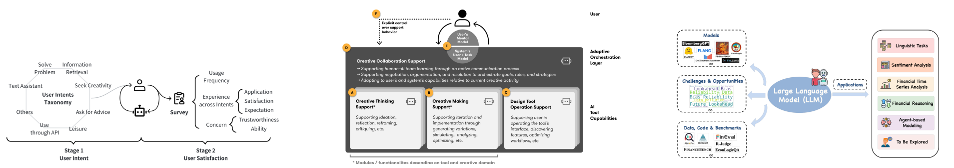
Human-AI collaboration is recognized as a transformative force in financial decision-making, leveraging human cognitive strengths and AI's computational capabilities to create valuable synergies in complex environments [32]. Integrating Theory of Mind (ToM) capabilities in AI agents enhances collaboration and communication in shared tasks, improving interaction efficacy [43]. The application of large language models (LLMs) in processing multi-modal data and performing complex reasoning is pivotal in financial trading, where nuanced decision-making is critical [44]. Frameworks developed for collaborative dialogue dynamics further support complex interactions essential for effective collaboration [45]. Moving beyond explainability to foster active participation and agency in AI systems is vital for ensuring AI systems act as partners in decision-making [46]. Multi-agent large language models (MA-LLMs) demonstrate higher accuracy in financial applications compared to single-agent models, underscoring the benefits of collaborative approaches [24]. Achieving complementary team performance (CTP), where combined human-AI efforts surpass individual capabilities, is crucial for navigating complex financial scenarios. Factors such as information asymmetry, domain expertise, and trust in AI recommendations are key to fostering an effective collaborative environment [42, 34].

3.2 Challenges in Human-AI Collaboration

Effective human-AI collaboration in finance faces technical and ethical challenges. A significant issue is the lack of empirical evidence on the impact of incorrect AI explanations on human understanding in high-stakes domains [47]. Robust evaluation metrics capturing qualitative and quantitative aspects of collaboration are needed, as traditional metrics focus on task performance [48]. AI system complexity can obscure transparency and limit user agency, restricting active engagement necessary for effective collaboration [46]. Communication barriers between humans and AI agents further impede collaboration, necessitating improved interaction designs [49]. Trust is critical, yet ensuring consistent, transparent AI behavior remains challenging, potentially leading to distrust [50]. Human decision-makers' selective compliance with algorithms can exacerbate discrimination and unfair outcomes, highlighting the need for equitable collaboration frameworks [51]. Understanding communication effects, particularly when AI possesses ToM capabilities, is crucial for enhancing interactions [43]. Limited communication channels between humans and AI systems further hinder collaboration, underscoring the need for improved interaction designs [10]. Auditing LLMs and addressing confirmation bias among auditors are additional challenges in maintaining transparency and accountability [6]. Leveraging information and capability asymmetries effectively is another significant obstacle [34]. Addressing these challenges requires developing adaptive, trustworthy AI systems that foster mutual understanding and trust, essential for leveraging Multi-Agent Large Language Models (MA-LLMs) in corporate environments [30, 52, 24].

3.3 Case Studies and Applications

Human-AI collaboration in finance is illustrated through various case studies and applications, showcasing AI's transformative potential in decision-making processes. A foundational framework for analyzing human-AI decision-making emphasizes understanding reliance and implications, crucial for designing systems that leverage AI capabilities while maintaining human oversight [53]. In financial trading, the Co-Learning framework enhances human-AI collaboration by integrating data-driven insights into decision-making, improving efficiency and accuracy [54]. Theory of Mind (ToM) models in AI systems represent significant advancements, predicting AI actions and assisting human understanding during collaborative tasks [43]. Simulators allowing human intervention and feedback in security scenarios highlight potential applications in finance, enhancing AI adaptability and alignment with human objectives [55]. Exploring communication styles and performance differences between human-agent and human-human teams provides insights into optimizing collaboration in dynamic environments [56]. Providing second opinions alongside AI recommendations enhances decision-making performance by encouraging critical evaluation of AI suggestions [57]. Experiments with PersLLM demonstrate that simulating human-like interactions improves user experiences in social applications, applicable to financial contexts where personalized interactions are crucial [5]. Information and capability asymmetries can enhance collaboration, leading to improved decision-making outcomes [34]. These case studies illustrate the diverse ways human-AI collaboration is harnessed to drive innovation and efficiency in finance, enhancing decision-making sophistication and responsiveness. This synergy addresses critical challenges in financial data security, predictive analytics, and automated threat detection, shaping a more resilient financial ecosystem [29, 40, 42, 34, 49].



(a) User Intent and Satisfaction Survey[58]

(b) Collaborative Creative Support for Human-AI Teams[59]

(c) Large Language Model (LLM) in Finance: Challenges, Opportunities, and Applications[19]

Figure 2: Examples of Case Studies and Applications

As shown in Figure 2, the integration of human and AI systems in finance paves the way for innovative solutions and enhanced decision-making. The "Human-AI Collaboration in Finance; Case Studies and Applications" example provides a comprehensive overview of this collaboration. The "User Intent and Satisfaction Survey" case study highlights a systematic approach to understanding user satisfaction by capturing intents such as problem-solving and information retrieval, emphasizing alignment of AI capabilities with user needs. "Collaborative Creative Support for Human-AI Teams" presents a framework to bolster creativity within teams by providing structured support across creative thinking and tool operation, maintaining explicit control over AI support behaviors to enhance user experience. The "Large Language Model (LLM) in Finance" case study explores the dynamic interaction between LLMs and financial applications, addressing challenges and opportunities such as reliability and bias, while showcasing potential applications in linguistic processing. These examples illustrate the multifaceted approach to leveraging AI in finance, highlighting both the potential benefits and complexities involved in human-AI collaboration [58, 59, 19].

4 Task Allocation in AI Decision-Making

Category	Feature	Method
Complementary Capabilities and Task Allocation	Human-AI Collaboration	HAIC[52], CRF[51]
Task Allocation and Efficiency	Adaptive Task Distribution	DyLAN[60], US[61], MARF[37], LLM-AMF[62], CA-HBM[63], AV[7]

Table 1: Table summarizing various methods and frameworks employed in the strategic allocation of tasks between AI systems and human agents in financial decision-making. The table categorizes these methods into complementary capabilities and task allocation, as well as task allocation and efficiency, highlighting their roles in optimizing collaboration and performance.

In AI decision-making, optimizing task allocation is crucial for maximizing efficiency and accuracy. Table 1 provides a comprehensive overview of the methods and frameworks used to enhance task allocation and efficiency in human-AI collaboration within financial contexts. Table 2 presents a detailed comparison of various methods and frameworks employed to optimize task allocation and efficiency in human-AI collaboration, particularly within financial settings. This section analyzes frameworks and methodologies that strategically divide responsibilities between AI systems and human agents, leveraging their complementary strengths. Understanding these interactions is vital for improving performance in complex financial settings. The following subsection delves into the complementary capabilities that facilitate effective task allocation and their implications for collaborative decision-making in financial contexts.

4.1 Complementary Capabilities and Task Allocation

Strategic task allocation between AI systems and human agents is essential for maximizing efficiency in financial decision-making. Interaction pattern taxonomies, such as AI-first assistance and delegation, are key to structuring effective collaborations [8]. These frameworks delineate roles and responsibilities, optimizing task allocation and enhancing operational efficiency.

The Collaborative AI with Human Belief Model (CA-HBM) incorporates human beliefs into AI decision-making, aligning AI actions with human expectations in complex financial contexts [63]. The Compliance-Robust Fairness method optimizes algorithmic recommendations to ensure fairness across diverse human compliance patterns [51].

Role specialization enhances workflow by allowing agents to operate within their expertise, critical in precision-driven financial operations. The Human-AI Collaboration for Training Novices (HAIC) method exemplifies the complementary capabilities of AI systems and human subject matter experts during training, highlighting the importance of role specialization [52].

Integrating large language models (LLMs) as co-labeling agents enhances the annotation process through explanations and interactive discussions, supporting informed decision-making [25]. This integration is vital for utilizing AI's analytical strengths alongside human insights. Moreover, establishing a systematic framework for LLM-based multi-agent systems (MAS) addresses challenges in inter-agent communication and adaptability [35].

The -Bench framework evaluates LLMs in complex scenarios with multiple players and actions, showcasing AI's potential to complement human decision-making through stable insights [26]. This evaluation is crucial for reflecting real-world decision-making processes.

This survey categorizes human-AI systems based on performance outcomes, highlighting scenarios where human-AI synergy yields better results than either entity alone, a concept vital for optimizing task allocation [49]. However, challenges like the need for extensive training data and risks of unintended consequences from uncontrolled learning processes remain significant obstacles [32].

Recognizing and utilizing the complementary capabilities of AI and humans is essential for optimizing task allocation in financial decision-making. By integrating human insights with AI capabilities, these strategies enhance the efficiency and effectiveness of financial operations, ensuring tasks are assigned to the most suitable agents for optimal performance. The strengths of these benchmarks lie in their capacity to provide insights into the collaborative intelligence of MA-LLMs, leading to improved problem-solving in complex scenarios [24].

4.2 Task Allocation and Efficiency

Effective task allocation is crucial for enhancing the efficiency and accuracy of financial operations, particularly when integrating multi-agent systems (MAS) and human-AI collaboration. Strategically distributing tasks between AI systems and human agents ensures optimal performance across diverse financial contexts [60]. DyLAN, for instance, employs an unsupervised metric called Agent Importance Score to select the most contributory agents, optimizing task allocation [60].

The integration of multi-agent frameworks, such as AGENTVERSE, demonstrates significant improvements in collaboration, outperforming single agents in various tasks [7]. This underscores the benefits of collaborative intelligence in financial operations, where task complexity necessitates a nuanced understanding of both quantitative data and qualitative insights. Experiments with GAMA()-Bench further illustrate the advantages of dynamic scoring systems and flexible game settings, facilitating effective task allocation and evaluation of AI systems in environments reflective of real-world financial decision-making processes [26].

Moreover, frameworks like MARF enhance financial question answering by leveraging collaborative approaches among agents to improve numerical reasoning and answer accuracy, showcasing the impact of effective task allocation on decision-making efficiency [37]. The ability to dynamically select and weight alpha factors, as proposed by Kou et al., allows adaptation to changing market conditions, emphasizing the importance of dynamic task allocation in financial contexts [62].

The integration of explainable AI (XAI) techniques, such as presenting AI predictions alongside visual heatmaps, enhances decision-making efficiency by providing transparent insights into the factors influencing AI recommendations [61]. Nevertheless, challenges persist regarding the complexities of imperfect XAI and its effects on users with varying expertise levels, indicating a need for more comprehensive approaches to explainability in financial contexts [61].

Additionally, providing both data and AI performance information significantly impacts effective delegation in human-AI collaboration, enhancing decision-making efficiency and accuracy [63]. This allows for more precise and context-aware task allocation, critical in the fast-paced financial sector.

However, challenges such as potential risks in code security and difficulties in debugging complex problems necessitate ongoing human expertise in nuanced scenarios [49].

Optimizing financial operations relies on strategically allocating tasks between AI systems and human agents, leveraging the complementary strengths of both parties. Research indicates that human discretion in utilizing AI advice, coupled with a robust understanding of AI capabilities, is essential for achieving superior joint performance. Systematic reviews reveal that while human-AI combinations can enhance performance in creative tasks, they may underperform in decision-making scenarios. Thus, a nuanced approach to task allocation is critical for improving both efficiency and accuracy in financial operations [53, 49]. By harnessing the strengths of AI and human expertise, financial institutions can enhance operational capabilities, ensuring tasks are allocated to the most capable entities for optimal performance.

In recent years, the integration of artificial intelligence (AI) within financial services has necessitated the establishment of robust governance frameworks. These frameworks are essential for ensuring that AI applications are not only effective but also ethical and compliant with regulatory standards. As depicted in Figure 3, the hierarchical structure of AI governance in financial services is illustrated, detailing the frameworks for AI integration, stakeholder roles and responsibilities, and the importance of transparency and accountability. This figure highlights key components, challenges, and collaborative approaches necessary for responsible AI deployment, emphasizing the significance of aligning governance frameworks with corporate objectives and regulatory requirements. By examining this structure, we can better understand the multifaceted nature of AI governance and its implications for the future of financial services.

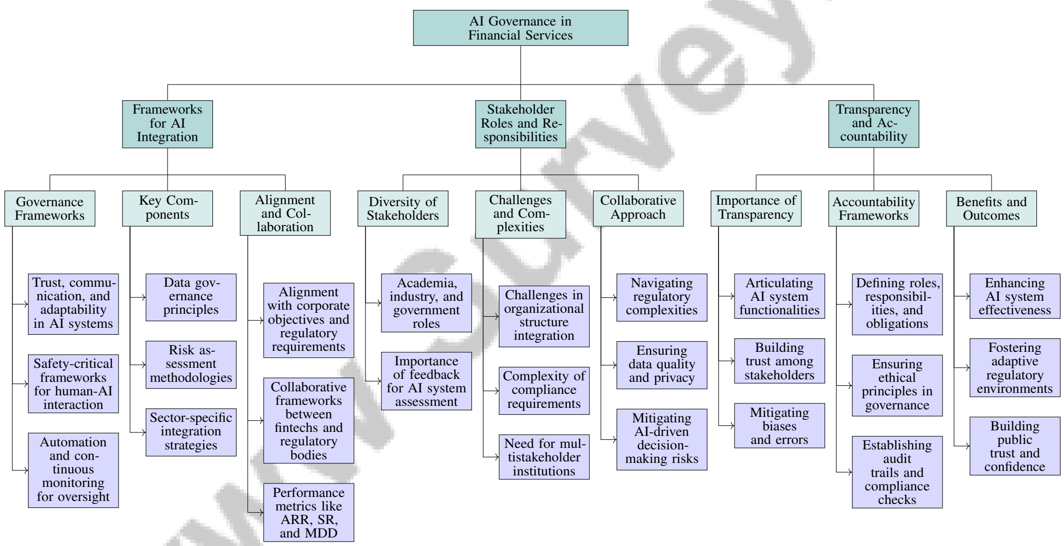


Figure 3: This figure illustrates the hierarchical structure of AI governance in financial services, detailing the frameworks for AI integration, stakeholder roles and responsibilities, and the importance of transparency and accountability. The figure highlights key components, challenges, and collaborative approaches necessary for responsible AI deployment, emphasizing the significance of aligning governance frameworks with corporate objectives and regulatory requirements.

Feature	Collaborative AI with Human Belief Model (CA-HBM)	Compliance-Robust Fairness	Human-AI Collaboration for Training Novices (HAIC)
Task Allocation Strategy	Human-aligned Actions	Fairness Optimization	Role Specialization
Efficiency Enhancement	Fairness Optimization	Diverse Compliance Patterns	Training Enhancement
Collaboration Framework	Human Beliefs Integration	Algorithmic Recommendations	Human-AI Synergy

Table 2: This table provides a comparative analysis of three distinct methodologies for task allocation and efficiency enhancement in human-AI collaboration within financial contexts. It highlights the unique features of Collaborative AI with Human Belief Model (CA-HBM), Compliance-Robust Fairness, and Human-AI Collaboration for Training Novices (HAIC), focusing on their task allocation strategies, efficiency enhancement techniques, and collaboration frameworks. The comparison underscores the diverse approaches to optimizing human-AI interactions for improved decision-making and operational performance in complex financial environments.

5 AI Governance in Financial Services

5.1 Frameworks for AI Integration

Integrating AI technologies into financial services necessitates robust governance frameworks to ensure responsible and effective deployment. Emphasizing trust, communication, and adaptability, recent studies underscore the importance of structured communication protocols among specialized agents to enhance collaboration and operational cohesion of AI systems [50, 33]. Safety-critical frameworks formalize human-AI interactions to ensure reliability and ethical functioning [64]. Automation and continuous monitoring are crucial for maintaining oversight in dynamic environments, as advocated by system-level frameworks promoting self-regulation [17].

Key components of AI governance include data governance principles, risk assessment methodologies, and sector-specific integration strategies that manage extensive data processed by AI systems, reduce human error, and enhance decision-making accuracy [65]. The FinVerse framework exemplifies the integration of large language models (LLMs) with specialized APIs and embedded code interpreters, facilitating real-time data retrieval and analysis critical for informed decision-making [1].

Defining AI governance within the broader governance landscape ensures alignment with corporate objectives and regulatory requirements, maintaining transparency and accountability throughout the AI system lifecycle—from research to operation [14, 66]. Categorizing research into stages of technology integration, such as command regulation and self-regulatory models, offers a structured understanding of governance evolution in financial services [67]. Collaborative frameworks between fintechs and regulatory bodies are necessary to enhance risk management practices while fostering innovation [68].

The governance of frameworks like TradingGPT highlights the significance of transparency and accountability in AI deployment for financial trading. By prioritizing these principles, financial institutions can build trust with stakeholders and ensure responsible AI use [6]. Performance metrics such as Annual Rate of Return (ARR), Sharpe Ratio (SR), and Maximum Drawdown (MDD) underscore the need for robust governance to optimize financial outcomes [44].

Developing and implementing governance frameworks for AI integration in financial services is essential for responsible, secure, and effective deployment. Addressing both technical and social dimensions, these frameworks facilitate seamless AI system integration, enhancing operational efficiency while ensuring compliance with regulatory standards [69].

5.2 Stakeholder Roles and Responsibilities

The deployment of AI technologies in financial services involves a complex interplay of stakeholders, each with distinct roles and responsibilities vital for effective implementation. The diversity of stakeholders—spanning academia, industry, and government—underscores the importance of feedback in assessing and governing AI systems [70]. This feedback is crucial for aligning AI strategies with broader societal and organizational objectives.

Understanding AI's position within existing organizational structures presents challenges that complicate effective system implementation [71]. Clear delineation of roles and responsibilities among stakeholders is necessary for seamless integration. The complexity of compliance requirements and ambiguities within the Artificial Intelligence Act (AIA) further complicate stakeholder roles, particularly concerning conformity assessments [72].

Corporate governance structures often struggle to align diverse stakeholder interests with corporate goals, highlighting the need for dedicated multistakeholder institutions that mediate interests and ensure ethical AI deployment [73]. The multifaceted nature of accountability and the sociotechnical structure of AI systems require stakeholders to establish clear accountability frameworks addressing both technical and social dimensions [64].

Navigating regulatory complexities, ensuring data quality, protecting customer privacy, and mitigating AI-driven decision-making risks are critical responsibilities for stakeholders involved in AI deployment [74]. A collaborative approach, where stakeholders work together, is essential for addressing challenges and leveraging AI technologies to enhance financial services.

The multifaceted roles and responsibilities of stakeholders necessitate coordinated efforts to ensure responsible, ethical, and effective AI system implementation. By promoting collaboration among academia, industry, and government, stakeholders can effectively tackle the intricate challenges of AI governance, developing frameworks that integrate ethical standards—such as fairness and accountability—into AI systems. These frameworks enhance model governance and risk management, enabling organizations to navigate AI complexities while reinforcing compliance and security against emerging digital threats [40, 23, 71, 73, 69].

5.3 Transparency and Accountability

Transparency and accountability are crucial in governing AI systems, particularly in the financial sector, where AI-driven decisions can significantly impact economic and social outcomes. The unique characteristics of AI models, including uncertainty in assumptions and lack of explicit programming, present substantial challenges to governance practices [23]. Governance frameworks must prioritize transparency to enable stakeholders to understand and evaluate AI decision-making processes effectively.

Transparency entails clearly articulating AI system functionalities, decision-making criteria, and the algorithms driving these processes. This clarity is essential for building trust among stakeholders—regulators, financial institutions, and end-users—allowing informed assessments of AI systems' reliability and fairness. Moreover, transparency is vital in identifying and mitigating biases and errors in financial operations, upholding the integrity of financial systems. Leveraging advanced technologies, organizations can enhance their ability to detect discrepancies and ensure compliance with regulatory standards, fostering trust and operational efficiency in financial markets. This proactive approach addresses systemic risks while promoting ethical governance, safeguarding consumer interests and market integrity [18, 12, 40].

Accountability in AI deployment necessitates comprehensive frameworks defining the roles, responsibilities, and obligations of stakeholders, ensuring ethical principles translate into actionable governance processes that promote compliance, oversight, and enforcement while addressing the sociotechnical complexities inherent in AI systems [74, 66, 71, 64, 22]. These frameworks should encompass both technical and ethical dimensions, ensuring AI systems operate within established legal and regulatory boundaries while adhering to ethical standards. Establishing accountability mechanisms, such as audit trails and compliance checks, is vital for monitoring AI systems' performance and aligning them with organizational and societal values.

Incorporating transparency and accountability within AI governance frameworks enhances the effectiveness of AI systems and fosters adaptive regulatory environments. These environments are essential for navigating the complexities of AI technologies, ensuring compliance with ethical standards, and building public trust. By promoting clear accountability measures—such as defined roles, oversight processes, and compliance standards—policymakers can better address the challenges posed by AI's rapid evolution and its societal implications [74, 71, 64, 22, 69]. By fostering an environment of openness and responsibility, financial institutions can leverage AI to drive innovation and efficiency while maintaining public confidence and safeguarding against potential risks.

6 AI Ethics in Finance

6.1 Ethical Considerations in AI Deployment

Integrating AI systems into finance requires careful ethical scrutiny to ensure responsible use. Transparency and accountability are critical, yet often inadequately addressed by existing corporate governance frameworks, leading to potential biases and reduced trust among stakeholders [69]. Challenges in externalizing tacit knowledge and enhancing communication through AI trainers further complicate trust and decision-making processes [52]. The ethical deployment of large language models (LLMs) in finance, especially in subjective risk data annotation, demands contextual awareness to achieve ethical outcomes [25]. Incorporating Theory of Mind (ToM) capabilities in AI agents, although not significantly affecting team performance, improves human understanding, emphasizing the need for ethical oversight in AI-human interactions [43].

Algorithmic fairness is essential in human-AI collaboration, where compliance-robust fairness accommodates human decision-making variability, preventing unfair outcomes and aligning AI systems with human expectations [75]. Current research often lacks systematic frameworks, complicating effective communication among agents [35]. Misleading AI explanations can impair knowledge retention and reasoning, paralleling ethical concerns of deception in human interactions, necessitating ethical frameworks prioritizing honesty and transparency [47, 50]. Advancements in user experience, transparency, and user feedback integration are crucial for trust and acceptance [46].

Ethical AI deployment in finance requires transparency, accountability, and ethical practice integration. By addressing these considerations and implementing robust data governance frameworks, financial institutions can responsibly leverage AI technologies to enhance data security, ensure regulatory compliance, and build stakeholder trust, mitigating risks associated with algorithmic decision-making [40, 74, 18, 68, 17].

6.2 Bias and Fairness in AI Systems

Bias and fairness in AI systems are critical in financial services, where decision-making stakes are high. Achieving fairness in AI-driven applications is complicated by the intricacies of modeling human interactions and risks of misleading users through uncalibrated confidence levels [76]. Public datasets' reliance underscores the need for transparency and ethical standards adherence [77]. Training AI on diverse datasets is crucial for reducing bias and fostering fairness. However, fairness assessment tools often lack stakeholder participation, raising concerns about 'ethics washing' [22]. Broader stakeholder involvement is necessary to ensure alignment with ethical and societal values.

In fraud detection, trade-offs between false positive and negative rates are crucial, reflecting financial operations' cost-sensitive nature [27]. Selecting appropriate metrics is essential to maintain fairness and minimize biased AI decisions' adverse impacts. Non-verbal cues reliance in human-agent interactions highlights the necessity for AI systems to effectively communicate intentions and decision-making processes [43], fostering trust and understanding.

Addressing bias and fairness requires robust evaluation metrics, stakeholder engagement, and transparent communication strategies. Prioritizing ethical AI deployment ensures equitable operations, mitigating inherent biases in algorithmic decision-making and promoting a fairer financial landscape. Adhering to regulatory frameworks and ethical guidelines enhances consumer trust, fosters financial inclusion, and safeguards against systemic risks [78, 17, 18, 40].

6.3 Ethical Implications of Autonomous Financial Agents

Autonomous financial agents present significant ethical implications requiring careful consideration. TradingAgents, for instance, enhance decision-making through improved collaboration and explainability, positively contributing to financial operations [13]. However, ethical deployment is challenged by ambiguities in personalized investment advice and potential conflicts of interest [79]. This raises concerns about aligning autonomous agents with fiduciary responsibilities, necessitating robust ethical frameworks.

Research identifies limitations in addressing AI system biases, insufficient staff training on data governance, and lack of standardization in auditing practices [74]. These gaps can lead to biased decision-making, undermining fairness and reliability. Compliance-robustly fair policies improve fairness in human-AI collaboration, suggesting similar approaches could benefit autonomous agents [51].

Future research should focus on regulatory frameworks enforcing ethical practices, enhancing stakeholder participation, and clarifying assessment distinctions [22]. Such frameworks ensure autonomous agents operate within ethical boundaries and contribute positively to financial services. Ethical considerations from AI deployment in sectors like healthcare underscore the need for oversight and accountability, equally relevant in finance, where autonomous agents' impact can have far-reaching consequences [4].

7 Regulatory Compliance in AI Systems

7.1 Regulatory Challenges and Opportunities

The regulatory environment for AI in finance presents both challenges and opportunities, necessitating careful navigation to ensure compliance and protect stakeholders. A key challenge is the complexity and opacity of AI systems, which can lead to unpredictable behaviors that infringe on user rights [80]. This situation is complicated by the absence of a standardized AI definition, hindering the establishment of uniform regulatory standards across jurisdictions [81]. Current legal frameworks often struggle with the unique characteristics of AI, especially when autonomous agents act independently, challenging existing definitions of collusion [82]. This highlights the need for updated legal definitions that address AI behavior nuances and compliance implications.

Ambiguities in compliance criteria and auditing processes under the Artificial Intelligence Act (AIA) further contribute to regulatory uncertainty [72]. Regulatory competition risks insufficient protections for individuals and society [81]. Despite these hurdles, significant opportunities exist to enhance compliance. Comprehensive data governance frameworks are essential for ethical data use and stakeholder trust in AI adoption in banking [74]. These frameworks provide the necessary structure for responsible data management and adherence to ethical standards.

The reliance on large language models (LLMs) poses regulatory challenges, especially if generated contracts contain inaccuracies, underscoring the need for compliance to maintain financial operation integrity [3]. Addressing cultural and ethical considerations in diverse teams is vital for achieving compliance, promoting an inclusive approach to AI deployment [30]. The speculative nature of AI advancements and the lack of regulatory frameworks to tackle ethical and legal challenges present both limitations and opportunities for regulatory innovation [69]. By proactively developing regulatory regimes that mitigate potential harms and address existing issues, stakeholders can foster a more robust and adaptive regulatory environment [83].

7.2 AI Act and Regulatory Proposals

The AI Act, adopted in June 2024, marks a pivotal development in AI regulation, particularly in finance [80]. This legislation introduces phased provisions to address AI technology challenges, enhancing transparency, accountability, and ethical standards. The AI Act ensures AI systems operate within a robust legal framework, protecting stakeholders and fostering trust.

Current regulatory proposals are divided into four regimes: disclosure, registration, licensing, and auditing [83]. Disclosure emphasizes transparency in AI functionalities and decision-making. Registration maintains a comprehensive AI system database for oversight. Licensing establishes deployment criteria, ensuring only compliant systems are authorized. Auditing provides a systematic approach to evaluating AI performance and regulatory adherence.

These proposals profoundly impact finance, emphasizing disclosure and transparency for financial institutions to provide clear AI-driven decision information. This practice builds trust, aligns with regulatory and ethical standards, and ensures compliance with frameworks like GDPR and CCPA. Effective data governance and accountability mitigate AI application risks, fostering a more equitable digital society and enhancing financial service integrity [17, 40, 74]. Registration and licensing ensure AI systems meet standards before deployment, reducing unethical practice risks. Auditing is crucial for ongoing evaluation, allowing regulators to identify and address potential issues proactively.

By implementing these regimes, the AI Act aims to balance innovation encouragement with AI technology risk safeguards. Financial institutions must adapt to evolving requirements, integrating compliance measures into AI strategies to align with legal and ethical standards. This proactive approach mitigates risks like cyber threats and strategically positions institutions to responsibly harness AI advancements. By integrating AI for enhanced data security, predictive analytics, and compliance, institutions strengthen resilience against threats while ensuring ethical governance and maintaining trust within financial ecosystems [66, 40].

7.3 Stakeholder Collaboration and International Standards

Achieving AI regulatory compliance in finance requires stakeholder collaboration and adherence to international standards. The complexity of AI technologies necessitates a coordinated approach among regulators, financial institutions, technology developers, and end-users for responsible AI deployment. Diverse perspectives highlight the need for clarity in definitions and balancing regulation with innovation [80]. This collaboration is crucial for creating a regulatory environment that fosters innovation while safeguarding societal values and ensuring ethical AI deployment.

International standards are vital in harmonizing regulatory practices across jurisdictions, providing a consistent AI governance framework that transcends national boundaries. These standards facilitate best practice exchange and enhance mutual understanding among stakeholders, improving regulatory compliance efficacy. Future research should focus on developing feasible frameworks balancing societal values with regulatory objectives and exploring emerging AI governance trends [83]. By aligning regulatory approaches with international standards, stakeholders ensure AI systems operate within a globally recognized legal and ethical framework, promoting trust and accountability in AI-driven financial services.

Fostering stakeholder collaboration and adhering to international standards are essential for AI regulatory compliance, promoting accountability, fairness, and effective governance in AI technology deployment [72, 64]. By adopting a cooperative and standardized AI governance approach, stakeholders can navigate AI technology complexities and contribute to developing a robust regulatory landscape that supports innovation while protecting societal interests.

8 Autonomous Financial Agents

8.1 Development and Deployment of Autonomous Financial Agents

The advancement of autonomous financial agents represents a significant leap in the financial sector, driven by sophisticated AI technologies that enable high levels of autonomy. These agents leverage real-time data to continuously learn and adapt, essential for navigating the complexities of financial markets [84]. Such adaptability enhances their decision-making processes and operational effectiveness.

Empirical studies using data from the Chinese A-shares market, particularly the SSE 50 Index, demonstrate that these frameworks significantly improve financial decision-making and operational efficiency [62]. By employing advanced AI models, these agents can analyze extensive financial data, discern patterns, and execute trades with precision, optimizing investment strategies and maximizing returns.

The deployment of autonomous agents offers numerous benefits, including increased operational efficiency, reduced human error, and uninterrupted operation. These agents utilize Large Language Models (LLMs) to manage complex financial tasks like portfolio optimization, risk assessment, and market analysis, traditionally susceptible to human biases, thereby enhancing decision-making speed and accuracy in quantitative strategies [37, 85, 62]. Automation enhances accuracy and consistency, ultimately improving financial performance.

LLM-powered agents provide a competitive edge in fast-paced trading environments by rapidly analyzing and responding to market fluctuations. Simulating collaborative dynamics akin to real-world trading firms, these agents synthesize insights from diverse data sources, including fundamental, sentiment, and technical analyses, thus enhancing trading performance and risk management [13, 20, 85, 62, 21]. Their real-time responsiveness enables financial institutions to capitalize on emerging opportunities and mitigate potential risks effectively.

8.2 Impact on Financial Markets and Services

Autonomous financial agents profoundly impact financial markets and services by enhancing efficiency, accuracy, and adaptability. These agents utilize advanced AI capabilities to process vast data volumes, enabling precise and rapid trade execution, portfolio management, and risk assessment. This technological advancement significantly reduces transaction costs and improves market liquidity by facilitating quicker, more informed trading decisions [84].

Moreover, autonomous agents contribute to market stability through continuous monitoring and rapid responses to fluctuations, mitigating volatility impacts. Their ability to swiftly analyze real-time data allows financial institutions to seize market opportunities and minimize losses, particularly advantageous in high-frequency trading environments where milliseconds can determine trade success [62].

Integrating autonomous agents into financial services enhances product personalization. By utilizing LLMs and multi-agent frameworks to analyze individual client data, these agents craft customized investment strategies and recommendations tailored to each client's unique needs. This personalized approach improves investment decision accuracy, boosts customer satisfaction, and fosters loyalty, as clients receive insights from comprehensive market analyses and real-time evaluations [37, 20, 11, 41, 62]. This differentiation is crucial in a competitive market.

However, the widespread adoption of autonomous agents raises challenges, including systemic risks associated with concentrated decision-making power in AI systems. The reliance on AI algorithms introduces concerns regarding transparency and accountability, particularly due to the opaque nature of many algorithmic processes, often termed "black boxes." This complexity necessitates robust governance frameworks that translate ethical principles—such as fairness and accountability—into practical applications, ensuring ethical deployment and safeguarding against biases and discrimination. As AI governance evolves, harmonizing ethical guidelines and fostering a collaborative approach to Corporate Digital Responsibility (CDR) is crucial for creating an equitable digital society [17, 71, 64, 22]. Additionally, workforce challenges may arise from the displacement of human roles, necessitating investment in reskilling and upskilling initiatives.

8.3 Human-AI Collaboration in Autonomous Financial Agents

Integrating human-AI collaboration within autonomous financial agents is crucial for optimizing task performance and enhancing users' perception of autonomy. Research by Nakahashi et al. indicates that implicit guidance significantly improves task performance while enhancing perceived autonomy compared to explicit guidance [86]. This underscores the importance of designing collaborative frameworks that balance human oversight with AI autonomy, facilitating more effective interactions in financial contexts.

Such collaboration fosters a synergistic environment that leverages the unique strengths of both humans and AI, enhancing decision-making through complementary team performance (CTP). Productive dialogues that build trust and mutual knowledge gains are vital for maximizing the value derived from AI investments. Understanding human-AI interaction dynamics can lead to improved outcomes, particularly in tasks requiring creativity and complex decision-making, enabling organizations to achieve performance levels unattainable by humans or AI alone [29, 53, 33, 34, 49]. The cognitive and analytical capabilities of AI complement human intuition and oversight, resulting in more robust decision-making processes, particularly in complex financial tasks like portfolio management and risk assessment.

Moreover, human-AI collaboration enhances the adaptability and responsiveness of autonomous agents. By incorporating feedback mechanisms and interactive interfaces, financial agents can continuously learn from human inputs, refining their strategies and performance over time. This iterative learning, particularly effective with advanced LLMs and multi-agent architectures, allows agents to evaluate market conditions dynamically and perform complex numerical reasoning. Such systems improve decision-making capabilities and adapt to varying market dynamics, leading to more robust financial outcomes [37, 62]. This dynamic interaction ensures that autonomous financial agents align with human objectives and ethical standards, fostering trust and acceptance among users.

Investigating human-AI collaboration within frameworks like FinVerse and FinRobot reveals substantial opportunities for enhancing financial operations. These systems utilize LLMs and integrate extensive financial APIs, facilitating precise data analysis and decision-making. By addressing challenges like information asymmetry and fostering productive human-AI interactions, this collaboration can enhance analytical capabilities, streamline workflows, and democratize access to sophisticated financial tools, ultimately leading to informed financial decisions and increased operational efficiency [40, 20, 33, 34, 14]. Balancing AI autonomy with human oversight allows financial institutions to achieve greater efficiency, accuracy, and ethical compliance in their operations.

AI-generated, for reference only.

9 Conclusion

9.1 Future Directions and Opportunities

The trajectory of multi-agent large language models (LLMs) in finance is poised for significant innovation, driven by the need for greater adaptability and collaboration within complex financial landscapes. Future research will likely emphasize the integration of reinforcement learning to enhance the adaptability and performance of AI systems amid dynamic market conditions, thereby ensuring resilient and responsive financial operations. Expanding empirical studies across various domains and developing prescriptive knowledge for hybrid intelligence system design will be crucial in advancing human-AI collaboration. Enhancements in LLM-driven AI agents, particularly through multi-level Theory of Mind (ToM) processes and improved non-verbal communication, are expected to enable more intuitive human-AI interactions. Prioritizing the optimization of MA-LLMs for efficiency and exploring their applications across corporate scenarios will harness their potential to drive innovation in financial services. Future research should also focus on innovative human-AI collaboration processes, especially in creative tasks, and develop robust evaluation metrics to assess performance outcomes. The exploration of interactive AI systems that allow active user modifications and multi-modal interactions will aim to balance system autonomy with user control, thereby enhancing engagement and trust. In terms of legal and regulatory frameworks, future investigations should explore new structures to address the complexities of AI in financial advising, including potential liability frameworks and the notion of AI personhood. Additionally, refining frameworks for sequential decision-making scenarios and improving model calibration and flagging mechanisms will enhance the accuracy and accountability of AI systems in finance. By pursuing these future directions, the financial sector can fully leverage the potential of multi-agent LLMs, fostering innovation and improving efficiency while ensuring responsible and ethical AI integration, thus contributing to the sustainable development of the financial industry.

9.2 Regulatory Alignment and Ethical Considerations

The advancement of AI in finance requires a focused effort on regulatory alignment and ethical considerations to ensure responsible and effective integration. The Artificial Intelligence Act (AIA) represents a critical step in AI regulation; however, its successful implementation necessitates clearer guidelines and definitions to address the unique challenges posed by AI systems. As AI technologies continue to evolve, regulatory frameworks must remain adaptable to maintain their relevance and effectiveness in safeguarding public interests. Interdisciplinary collaboration is essential for deepening the understanding of large language models (LLMs) and their interaction with human behavior, particularly in addressing ethical considerations during deployment. Such collaboration can lead to the development of comprehensive ethical frameworks governing human-AI interactions, balancing effective collaboration with moral responsibilities. Additionally, refining accountability frameworks and exploring practical implementations are crucial for addressing the evolving nature of AI technologies and their societal impacts. Establishing specific guidelines and standards for independent audits tailored to various industries can enhance the transparency and accountability of AI systems. These measures are vital for building trust among stakeholders and ensuring that AI systems operate within ethical and legal boundaries. Furthermore, integrating regulatory technology (RegTech) into financial services should prioritize public interests and address systemic risks, thereby contributing to a more resilient and equitable financial ecosystem.

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