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Chapter 10: The human-artificial intelligence partnership: Enhancing financial professionals' capabilities through artificial intelligence collaboration

10.1. Introduction

Recent advancements in artificial intelligence (AI) are dramatically transforming the way humans approach and solve problems. On the one hand, AI has the potential to be an advisor that augments human capabilities. On the other, AI also has the potential to enter an ever-increasing number of domains and compete with human expertise. Lawyers, doctors, writers, journalists, and even salesmen or artists have begun to feel the effect of AI competition like never before. AI is a technology that simulates human intelligence-based machines to perceive and interpret the environment so that they can learn, reason, and self-correct. It is aggressively reshaping every facet of society's functioning and humanity as a whole. It is having an increasingly pervasive effect on human life and the fate of individuals while at the same time being omnipresent in the chronicles of life. This might be one of the strongest doubts facing humanity now (Shaffer et al., 2020; Bandi et al., 2023; Boni, 2021). It is further claimed that AI can comprehend, think, learn, create, and understand language as well as humans. Accordingly, humans are no longer/are fast becoming the best-performing information-intelligent beings on the planet. Their rapid evolution and integration into every quotidian aspect of human life harbor perils to civilization that warrant serious concern. While AI systems are improved and further empowered to take-on more mature human roles, including manual and discernment tasks, the number of clarion calls for the need for regulation, precautions, and limits to AI has surged. From academics and practitioners, business and technology, as well as government and civil rights movements, voices have been raised and formal steps are being taken to better understand, regulate, and constrain the ethical approaches of current and future AI. The introduction of the "AI Bill of Rights" in the US, and calls for a 6-month AI development slowdown, echo growing scrutiny, reservations, and demands for formulating remedial measures (Gupta et al., 2024; Banerjee et al., 2025; Deloitte et al., 2024).

A partner's operation should resemble a helicopter view, overpassing details, and concentrating on performance enhancement. Outputs should include results of products, milestones of assistance, and behavioral changes. Like a power advisory, the operation of a partner should be based on the principle of human autonomy. Verifying a partner's capabilities is a central and long-term rigorous task for financial executives and institutions against limits of use cases and capabilities.

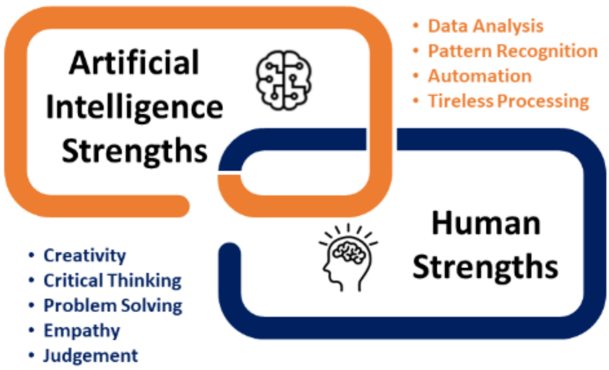

Fig 10.1: Human Intuition and Artificial Intelligence Collaboration

10.1.1. Background and significance

Artificial Intelligence (AI) development or machine learning (ML) in conjunction with technologies is evolving the business models of financial firms, financial institutions, and organizations. Data analysis is increasingly automated through AI or machine learning. Investment decisions, transaction codes, and transactions in settlement, clearing, and uploading are all expected to be automated. Furthermore, natural language processing technology will clarify statements and documents as well as facilitate communications. Generative AI would serve as an insightful power, consulting expert, advisor, and mentor. Finance professionals are expected to have AI partners with a number of core capabilities.

Financial professionals need to check input data and model returns and risks and understand the relationship between estimates and performances. A partner should comprehend the data, distances across fields, ranges, and aggregations, the intricacies of models, and the interaction across dimensions. Besides, a partner should check correctness and estimates of input data and models, and performance functions. It should recognize the measurements as well as be flexible with a diverse sample of error observations. A partner should then scrutinize inputs and estimates according to arithmetics and units, and find outliers, use inappropriate models, mis-specified return, and model misspecification. Furthermore, a partner should be able to produce explanations in layman's speech, displaying risks in financial languages, and interpretation grounded in product/law/compliance designs. In addition, a partnership current/report should provide insights across data/soundness/inputs/models/output. A partner should suggest performance improvements, revisions of models and their parameters, and an upward design process for correcting data errors or finding new data.

10.2. Understanding AI in Finance

"Artificial intelligence holds great promise for improving how the financial profession does its work–augmenting capabilities such that more can be accomplished". The idea here is that the unique human attribute of cognitive ability can be married with great processing capability of many forms such that partnership can happen in a way beneficial to all. Time and attention log jams can potentially be reduced, resources reallocated, and creativity augmented.

More generally, bringing AI into the finance sector has great implications for improving how the sector functions and enhancing people's quality of life. Financial stability is critical for the economic health and well-being of society. AI refers to the capability of a machine to imitate and exhibit human-like intelligence in possible functions including perception, cognition, natural language understanding, and learning. Such machines can perceive their surroundings and the situation they are in, understand them, and learn from the same experience. They can recommend actions to pursue, and/or if enacted, then observe and learn whether their recommendations worked as suggested. This allows for automatic improvement, without people in the loop, beyond the capabilities of what's human alone. Such systems can offer a myriad of benefits to the finance sector and are being aggressively deployed.

10.2.1. Overview of AI Technologies

AI, which stands for Machine Intelligent, is a strategic branch of FinTech which focuses on the autonomous intelligence of machines. It is the outstanding technology for augmented intelligence research and development, generally referred to as human-AI partnership. Backed by AI technology, augmented intelligence or human-AI partnership is the result and combination of AI technology(s) and finance, usually referred to as

FinTech. The assimilation of augmented intelligence and AI technologies is co-founded with finance. The co-evolution allows the financial sector to make a rebound in development and regain trust and confidence from the public. AI in the financial sector has gained more significant momentum in recent years. People's appetite for AI technology is also growing as a result of the pandemic. AI technology is at the forefront of capital investment initiatives, from risk assessment to tax investigation. AI technology combined with big data can integrate long-tail markets, enlarge personal finance applications, and improve fund allocation efficiency and financial risk management. Feature extractions, identity recognition, sentiment analysis, and natural language processing technology can allow machines to supplement customers with interactive and intelligent services. By combining financial intelligence with AI, a "fin-brain" can be constructed, containing a knowledge engine offering inclusive financial service. Fun-brain will lead to finance more straightforward and more transparent while generating more products. Accounting trade and transparency, time sequence analysis, supplementary quantitative approach, multilateral big data handling, and sentiment analysis through text mining and natural language processing can detect market scamming behavior and reduce false trading risks. Question- and willing-answer technology and chat robots can effectively study and enhance resolution competence. Statistical learning and regression analysis technology can avoid anomalous trades and kick-outs in trading. The combined AI and FinTech with credit assessment technology can significantly reduce the threshold of traditional professional financial services, which usually has high entrance requirements on information or wealth. As a result, ordinary people are typically ignored by corporate financial groups. The advent of big data significantly promotes risk control application in retail financing. Credit assessment technology can realize security identification and let the umbrella of finance cover individual users, effectively constructing a rational coping mechanism to mitigate the risks of high-leverage financial product oversight cases. However, credit assessment is still defective in treating flow patterns.

10.2.2. Current Applications in Financial Services

Several existing applications of AI in finance, particularly where AI augments financial professionals' capabilities through collaboration, are explored. Financial professionals currently use AI primarily in the following three areas: 1. Automated and semi-automated trading; 2. AI as a data analyst by extracting data, creating and maintaining financial databases, and data insight generation; and 3. AI as a decision advisor by improving risk scoring and asset allocation.

Automated trading systems leverage AI to determine trading decisions, entry/exit points, and position sizes. Such systems can be fully automated or semi-automated, where they operate under the supervision of human portfolio managers. Numerous financial institutions use these systems to replace algorithmic trading nowadays. Other examples of AI substitution applications are real-time financial news interpretation for potential investment opportunities, social media monitoring of traders' sentiment and behavior on certain assets for trading cues, and ETF liquidity prediction using neural networks to uncover the price-range pattern immediately after trades. Semi-automated trading systems typically assist an existing trader by analyzing stock signals gleaned from vast amounts of data, including market data, company filings, news, and Twitter feeds processed by a sentiment analysis engine.

To provide advice, AI typically processes raw data to generate insights. Raw data could include tabular data from financial filings, consistent but unstructured text from annual reports, non-textual data such as financial news, simulation model information, and time-stamped trading data. These insights augur well for portfolio construction, risk judgment, corporation assessment, and market anomaly detection. Natural language processing technology can assist in reading financial statements and extracting data points traditionally required by human analysts. Deep learning models and clustering algorithms can classify firms or estimate price movements. Financial professionals employ numerous AI applications to automate the data extraction and cleaning processes, including scraping forms for fundamental tabular data, converting PDF annual reports into CSV files, filtering out the junk from the crawl, and translating non-English filings.

10.3. The Role of Financial Professionals

As digitization accelerates, demand for financial services rises dramatically across all demographics globally. Despite the financial professional industry being both resource and data rich, financial service providers find it challenging to cater to the emerging demands of fast, affordable, customized, and user-friendly financial services. New technology-driven players disrupt the industry by addressing these main demand gaps which are intangible in nature and cannot be measured via conventional financial key performance indicators (KPIs). The shortage of talent in the financial professional space hinders incumbents and can be addressed by AI-led automation particularly in the operational risk reduction segment. Given proper augmentation with explainable, customizable, and trustable AI models it would allow more scalable work divisions. To gain competitive advantage in AI adoption financial professionals should be utilizing process proficiency and data advantage, while focusing on addressing the psychological distrust of AI collaboration.

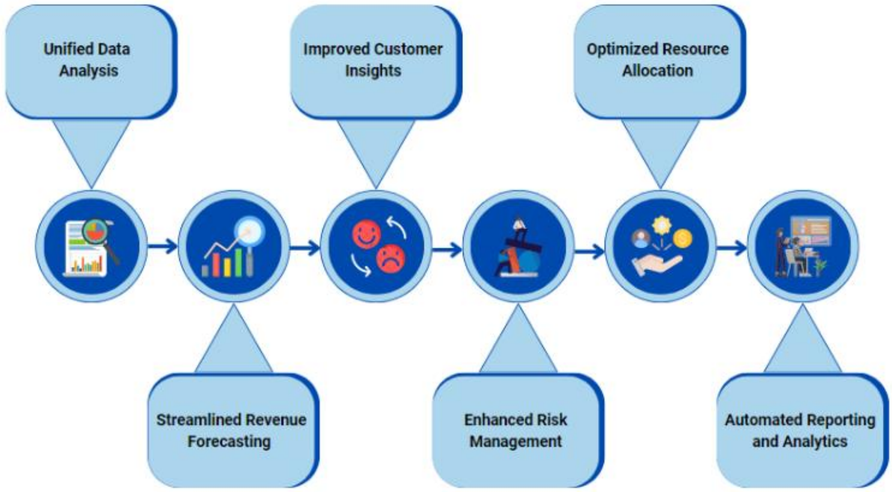

Fig 10.2: AI Revolutionizing Finance and Sales

Financial professionals seem to be better off but still vulnerable with further digitization. As incumbents seek to make AI collaboration commercially viable and dominant, it has to be positioned as a value chain and a defined space in the business model. To leapfrog create genuine AI in its design and work style, a financial coming of age is needed. Capturing intangibles and generative AI would be the main enablers. Capturing intangibles is about adopting cognitive and compute processes that can deal with uncovered data dimensions. Generative AI is making AI indistinguishable from humans in its output and behavioral style by continuously generating unique responses and inputs with training data and interactively modifying them. It is less concerned with data quality fitness, maturity, and regulation. More pressure and factors promoting the biomimetic AI prospect should be studied and incorporated in the mapping and innovation of financial professionals' AI collaboration.

The comprehensive impacts and reasons of the new forms of generative AI. Examine its user interface designs, rendering drawing, MP3 demo generation, financial idiosyncratic stories production, finance wide user trials and exchanges. Understanding the cognitive structure and processes of a simple Math tutoring AI assistant. To a degree adjust and accuse in the non-transparent hidden techniques as well as the grammar, quality clarity of delivery, emoji enrichment, side chats, and logical sense of the general thinking. Investigate the puzzled impossibility of these AI products mimicking humans in behavioral thoughts without AI awareness (or data) on financial concepts and their interconnections. It seems necessary to elaborate on how humans can benefit from these products in bidding off the explanatory component of finance so robustly.

10.3.1. Traditional Responsibilities

The practice of finance has implications for individual financial decisions: At the personal level, consumers face a myriad of potentially consequential decisions involving savings, loans, investments, and insurance. At the macro level, market participants engage in speculation, hedging, and pricing, defining global economic entrée points. While decisions are taken regarding how clients frame and structure advice, so, too must decisions be taken by the firms themselves regarding AI implementation characteristics. AI is naturally seen as an evaluation tool that would monitor the advice provided by financial health coaches and alert them in case of plausibly insufficient advice. However, it could also suggest potentially better advice, thus, collecting and aggregating data on individual financial health from multiple sources would need to be physically and legally possible. Using AI to identify existing potential and likely clients early would require adopting the pervasive evaluation and surveillance techniques commonly employed in marketing research. At the present stage, most AI-supported interactions seem to presume advice being first mandated and then bought in a human-AI setup. Individuals are queried by either an AI or an AI-augmented coach, and answers are assessed based on pre-set metrics of risk and goal adequacy. Where AI support is concerned, there are, at present, two lines of development in the finance and financial advice business. First, programmed AI are now being employed in wealth management. Here, input built on the aforementioned assessment protocols leads to preset stocks and ETFs being recommended, plus continuous monitoring for price movements. In the classic sense, coaching and compliance to pre-set goals and advice are reviewed periodically.

10.3.2. Evolving Skill Sets

As business informatics becomes increasingly important in high-level executive decisions, CEOs are expected to broaden their horizons and embrace digitalization. The demand for higher education programs to teach AI/ML concepts is also increasing. Boeing provides AI training for its decision-makers and workforce. The desire for this type of training calls for the establishment of collaborations between academia and large organizations, which often are more familiar with machine learning terminology and concepts. In this paper, a two-component influence model for competitiveness is proposed to better explain the influence HEIs can have on various stakeholders' in resisting threats. As business informatics become indispensable for senior executives' high-level decision making, development in this area is also expected from university-side decision-makers. A curriculum on AI/machine learning (ML) concepts and their business implications is necessary to broaden higher education qualifications for executives, especially in terms of digitalization. Such demand is supported by recent developments and annual reports from large organizations. Like many other multinational companies, Boeing has its own AI training track for decision-makers and wider workforce. There has been a general demand for this type of training. Stakeholders' reactions on learning AI ML concepts are based on business literature widely available.

10.4. The Human-AI Collaboration Framework

It is essential to see how human-AI collaboration can be designed to encourage financial professionals to embrace its full potential, while complementing, rather than disrupting, their work. To that end, we review the existing literature on human-AI collaboration to identify established factors and concepts that influence the acceptance, productivity, and quality of human-AI collaboration. We analyze key insights from humans' and AI agents' perspectives, which is the starting point to identify drivers and obstacles for successful human-AI collaboration. Finally, we combine these insights into a comprehensive theoretical framework, the Human-AI Collaboration Framework (HACF).

The HACF attempts to shed light on the needs and requirements for effective human-AI collaboration, especially for financial professionals. This framework is based on insights mainly drawn from the more general human-AI collaboration literature. However, it specifically focuses on socio-technical design requirements, challenges, and drivers for financial professionals in their daily human-AI collaboration. Increasingly capable AI technologies offer new affordances to automate, augment, or democratize situated sensemaking. While these technologies promise a lot of opportunities, they also amplify existing challenges or spawn new ones, such as individuals' difficulty in navigating the collaborative task and responsibility, or institutions' risk in regulatory compliance or brand reputation. To capitalize on AI's potential and mitigate its dangers, human-AI collaboration needs to be designed in a way that respects humans' understanding and agency while solidifying and clarifying which work is done by whom and with what consequences. Given the wide variety of tasks, users, types of AI, and socio-technical contexts, there is no universal silver bullet. However, the HACF provides a starting point for developing AI designs that consider and integrate socio-technical requirements for effective human-AI collaboration.

10.4.1. Defining Collaboration

Different terms are used to describe the collaboration between humans and AI, with the most common being human-AI team, human-AI collaboration, and human-AI decision-making. These concepts are interrelated and emphasize combining the capabilities of humans and AI. The notion of a human-AI team refers to an organizational setup in which AI agents or systems are increasingly considered team members rather than just support tools for humans. In contrast, human-AI decision-making specifically refers to the collaboration of humans and AI in decision-making tasks. For example, the AI could offer data-driven decision recommendations, while humans leverage their domain expertise, emotional intelligence, and ethical considerations to combine AI recommendations with their judgment to reach a final team decision. In this context, human-AI decision-making is focused on as a key application area of human-AI collaboration.

The increasing capabilities of AI, fueled by advancements in machine learning and computational power, have contributed to its use in a growing number of applications domains, such as medicine, finance, and customer services. Consequently, AI-based technologies are increasingly employed in processes and systems with varying degrees of human involvement, ranging from fully autonomous decision-making to auxiliary support for the humans who make the final decision. However, in traditionally human-centered processes, AI acts as a recommendation provider, supporting human decision-makers by finding new patterns in large datasets, predicting future developments, or assessing the impact of potential decisions. Humans are decision-makers relying on AI recommendations alongside their domain expertise, knowledge of procedural rules, and ethical considerations. This delegation of tasks means humans and AI engage in complementary teamwork and elicits several critical questions (e.g., how to design the collaboration in a way that it is complementary).

With the concept of complementarity and the exciting potential of human-AI collaboration, AI can offer unique insights beyond human decision-makers' capability. Overall, AI's superiority in systematic computational processing over huge datasets for more reliable predictions than humans is expected to support, rather than threaten, human decision-making. However, conventional implementations of AI decision support systems differ from the general concept of human-AI collaboration. Today's static, single-task recommendation systems based on machine learning technologies typically lack the capability of discussable collaboration. They have a limited understanding of the environment, inputs, decisions, feedback, and learning mechanisms, which humans utilize in their models to inform the decisions.

10.4.2. Models of Human-AI Interaction

Models of human-AI collaboration as orchestrated in tasks alongside people include (1) organizational models that consider the distributed nature of tasks or the longitudinal perspective of team formation; (2) task and interaction models focusing more on interaction, collaboration, and decision-making; and (3) cognitive models that attempt to model human and AI cognition in a collaborative setting. propose a conceptual framework titled "Anatomy of Human-AI Collaboration" to argue for the side-by-side kind of joint cooperation between human and AI. This approach highlights how task and interaction data are partitioned among agents. However, in many high-stakes applications across domains, full automation is not desirable as much as possible. Therefore, an alternative approach is that agents in the human-AI system perform parallel collaboration but share less information at a point of time. The interaction is directed and driven from either the human or AI side in a push-pull manner instead of bidirectionally biannually. introduced the notion of "Co-learning" to elaborate on the multi-round and adaptive nature of human-AI collaboration. This conceptual framework emphasizes mutual understanding, mutual benefits, and mutual growth, thus recognizing the dynamic nature of both human and AI agents in their self-learning processes and contributions in the collaboration. Nevertheless, the concepts of "benefit" and "growth" are abstract, yielding a gap to translate them into a more concrete interaction. As such, it is essential to bridge this gap through the development of a practical model for human-AI co-learning interaction.

To explore human-AI co-learning as a specific kind of co-creative collaboration, discussed the major differences of the former between the notion of co-creation and other models of collaboration such as enumeration and advice interaction. It is crucial to specify additional requirements for human-AI co-learning to be valid and effective beyond creativity. For instance, the input of a learning task could vary with different training data; otherwise, fine-tuning a pre-trained large AI model may become meaningless if AI agents in the collaboration are either updated with the same old data or with the new records that were extracted precisely and repeatedly by the previous one. Moreover, the input of a human-AI co-learning task could be distinct from the human agent as well, such as when performing a continual learning task when the operational input never required by a human coder needs to be processed after being accumulated during the AI-driven part.

10.5. Benefits of AI Collaboration for Financial Professionals

In light of the aforementioned performance gaps in the human-AI partnership in finance, there is a need to better understand the potential benefits that the AI collaboration will offer to financial professionals. As this understanding is not clear for all AI types, different stakeholders in the financial industry can benefit from these insights. Regulatory agencies benefit through gaining insights on how to promote the development of useful AI. Financial companies gain valuable insights on how to exploit AI technologies more effectively. Lastly, external vendors gain a deeper understanding of the utility and potential future operation of their products.

The first benefit of the AI collaboration consists of stating the implications of financial professionals working with AI in the output role on two potential upcoming developments of AI technologies. The benefit of human-AI teaming approaches considers the numerous human benefits that emerge in the form of task performance improvements and a more enjoyable working experience when working with AI collaborative agents. Available AI-based technologies that could enable the collaborative approach work on two sets of assumptions based on applicants' willingness to change and modify their working procedures. For the AI collaboration, financial professionals can benefit from individual AI actuators.

The responsibility benefit points to the most contentious issue surrounding the rise of AI: the issue of liability and accountability. Currently, financial professionals are obliged to sign contracts that state the ultimate human responsibility and accountability for every AI output. A redefinition benefit is stated concerning the first research sub-question regarding the potential transformations of the financial professional's responsibilities and work tasks. Such was the significantly increasing replacement of rudimentary work tasks performed by financial professionals by AI technologies. In addition, the list of newly generated outputs that would become viable and useful would drastically evolve in the wake of an advantage stipulated by taking an AI-augmented perspective on fundamental financial processes.

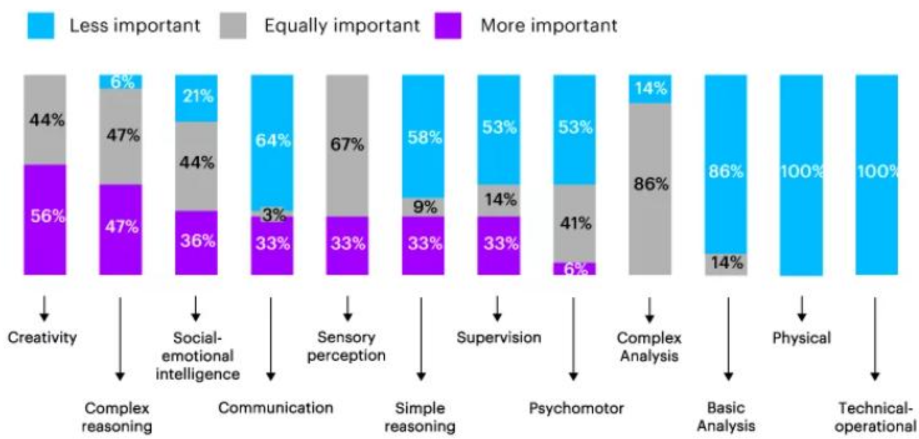

Fig : Missing middle skills for Human-AI collaboration

10.5.1. Enhanced Decision-Making

We argue how AI can enhance decision-making significantly by improving the robustness of predictions and recommendations of financial professionals. Decision-making in financial contexts, such as portfolio management, mission critical for banks, insurers and asset managers, is often characterized by input uncertainty. There is a need to assess how sensitive a decision's consequences will (not) hold up against variations in input arguments, e.g., uncertainties in forecasts concerning future inflation rates. In view of decision-makers' limited understanding of AI/ML architecture and the often limited intrinsic interpretability of the latter, financial professionals must be able to assess whether model predictions are just "performing magic" with respect to their inputs or whether "robustness checks" of such inputs are performed. Seeking to explain within the realms of AI plausible endeavors to generate such model precision checks, possible collaborative efforts of financial professionals and AI might be elaborated. Additionally, examples might be given of decision-making types which are fruitful for the collaboration between financial professionals and AI, and how the financial professionals' decision-making would be enhanced.

With regards to recommendations, AI should not discriminate against recommended actions that, while being essentially the same, differ in input arguments. The approach might be comprehended as an "explanatory" version of an explanation via Ceteris Paribus: Insist on the recommended action, while keeping all but one input argument constant. Moreover, with regards to intuitive action means AI might visually generate action realizations from the emissions of an exemplary implementation of the algorithm. Desired action characteristics, e.g., trading strategies robustness against forecast uncertainty might be underscored. Interventions must remain "light touch" so that financial professionals still participate in recommending tasks of investing. Additionally, it might be discussed how the recommendation types enhance the capabilities of financial professionals.

10.5.2. Increased Efficiency

AI developing systems capable of performing tasks that would otherwise typically be done by human intelligence including visual perception, decision making, speech recognition, translation between languages, as well as a variety of other tasks. More fundamentally, while AI threatens the loss of traditionally knowledge-based jobs, at the same time, AI powers the previously unthinkable evaluation of massive amounts of data, the development of fully autonomous vehicles, the basis for purchase suggestions of many e-commerce providers, and much more. The understanding of such automated or semi automated aids to complement human efforts is ultimately determined by both characteristics of the aid itself (e.g., trustworthiness/reliability, complexity, etc.), and by aspects of the task (e.g., type of task, goals, etc.). Understanding such influences will be paramount unlocking the full potential of collaboration with human-AI. Trust, in particular, in human-machine interactions is very complex and multifaceted as there are multiplicities of influences affecting trust in automation. Performance, in particular, has been identified as an integral element in understanding trust in human-automation interactions. Performance has typically been described as some kind of a percent reliability or through the overall quality of the interaction. While intuitive enough, there are numerous illustrated problems in the understanding of trust in smart automation and in the design of a system understanding such trust influences on human automation interaction. Hence, the understanding of this key element is crucial both for theoretical and practical reasons.

10.6. Challenges and Ethical Considerations

The rapid rise of generative AI technologies has ushered in an age of unprecedented change, not only in terms of technological evolution, but also in relation to their societal, business and economic implications. The rapid advances in generative AI cannot be overstated. Generative AI refers to algorithms capable of extracting patterns from previous texts to create new texts that resemble the originals. In a knowledge-based environment, generative AI models have tremendous promise for producing coherent and meaningful documents in response to user queries. However, the rise of generative AI may also have far-reaching negative impacts. Such models can be trained to easily deceive individuals by producing elaborate and coherent misinformation and disinformation that misrepresents facts. Such risks bring about a major ethical dilemma for human-AI partnerships in the field of ethical financial management through financial professionals' AI collaboration with generative AI. On the one hand, it requires adopting sophisticated AI generative techniques that could potentially pose negative financial or ethical impacts to either customers or financial institutions if misapplied or misused. On the other hand, it necessitates understanding manipulation risks and investing more in informed decisions despite the inherent AI complexity and obscure underlying algorithms.

In the business sector, the rapid rise of generative AI technologies may offer new business models, generate new value propositions or ecosystems, and create game-changing opportunities for the banks of the future. However, generative AI tools are relatively new, and their implications for business strategy have not been fully explored. As financial institutions consider implementing generative AI, they need to assess potential benefits and unintended consequences. It is critical to understand how generative AI can be integrated into traditional roles and processes, and whether the financial sector is ready for such partnership with generative AI systems. Financial institutions need to rethink value creation and assess generative AI's impact on customer experience, business models and employee roles. Examining how generative AI could enhance or undermine banks' existing value propositions is also critical. Much insight can be gained from examining how AI chatbots have influenced the banking sector.

Some unexplored areas include: whether generative AI can help nurture relationships and loyalty; how banks should adapt existing non-human customer touchpoints, products, metrics and KPIs; and what additional data generative AI requires to build a comprehensive view on relationships. In addition, banks should assess whether generative AI can help manage emerging complexities in regulation, compliance and security. Generative AI's unreliability poses risks for reputation, regulatory compliance and customer trust, engendering potential chaos.

Regulators must develop new rules to ensure safe deployment, and institutions need to reassess internal controls and guardrails to account for generative AI's evolving nature. With generative AI conceivably undermining trust in financial institutions, banks must create robust internal controls and reputation restoration strategies. It would be valuable to analyze how AI chatbots and more rigid AI tools have created a trust dilemma for the financial sector, and to what degree those insights transfer to generative AI. Assessing whether the risks associated with generative AI tools are well-known enables banks to ensure that training and guardrails are in place, or whether this is a wide area of ignorance. Finally, there is a growing concern about AI being biased against particular groups, resulting in financial exclusion. Financial institutions must assess whether generative AI poses additional risks in diagnosing complex relationships and intent relative to current systems, and to what degree those risks may be alleviated by simpler systems.

10.6.1. Data Privacy Issues

Data privacy issues are critical in understanding the implications of NLP systems in the workplace and ensuring individuals' rights to privacy and autonomy. Existing research has shown that individuals are nervous about sharing personal information with AI and concerns about the mishandling of sensitive data. Privacy concerns might arise due to information leakage, unintended behaviours caused by implicit personal biases, or misinformation leading to distrust in technologies. While these concerns are mostly technical, it is essential to consider the power dynamics at play in these scenarios, framing data privacy as one dimensional and controllable instead of acknowledging the inherent complexities revolving around individuals' relationships to data. The approach of 'design for data empowerment' tackles this issue by exploring the questions of who has the right to work with personal data, under what conditions, and with what degree of emancipatory potential. It is a fundamental right of 'data subjects' to know how and by whom personal data will be used, acknowledge the biases and limitations involved in the collection and handling, and make decisions on whether, how, and by whom data-related processes should take place. Privacy was framed as the capacity to control understandings of personal exposure to technologies, handled by technical solutions and communications. Recognising data privacy concerns through power relations were left outside the scope of inquiry. Although issues of privacy abuse through power dynamics were acknowledged, this critique was not brought to the specific context at hand – the understanding and future development of AI-driven NLP in professional workplaces.

10.6.2. Bias in AI Algorithms

AI algorithms are not free of bias. Underlying societal biases can lead to biased algorithms, defined as those that unfairly penalize individuals or groups based on certain attributes, or that favor a particular group over others. For example, regarding the provision of loans, it was discovered that black applicants received significantly fewer loans than white applicants. However, there was no direct indication of a racist bias in the algorithm: only the attributes available to the algorithm were the same. The discrimination arose from access to socioeconomic background data, which were taken into account by the algorithm in the indicative variable “creditworthiness.” Conversely, this data was not viewed as a discriminatory attribute in loan decisions, even though it anticipated the applicants’ ethnic backgrounds, given that these group memberships statistically implied average disparities in creditworthiness. In other cases, it has been shown that companies like Google and Amazon have granted extremely few analytics jobs to people of color, with no direct indication of racial bias in the algorithms, but rather a lack of training data from these candidates . In line with these findings, barricades to inclusion can inadvertently be erected through algorithmic recruitment and selection, as it has been shown that weighted scoring systems used by AI recruitment software can be biased against English as second language applicants.

Additional biases can arise from human feedback that introduce biases against certain ethnicities, such as a higher frequency of punishment in Intel’s AI chip as it was tuned on evidence including human-produced hate speech from Twitter. AIMC seeks to address this issue through a partnership with Microsoft as they work to provide a fairer tool for human resource providers. Some approaches to countering algorithmic bias or discrimination include biased group averaging, meta-learning approaches, and augmentation and adversarial data augmentation. Febrile and category-specific skews may arise amid the duality of luck and strategy, in a recursive sense until exhaustion. Actor/policy iterations recursively remove problems on one level while introducing problems on another. Some feedback mediates incentives based on reward and punishment structures, and seeking a feedback medium that accounts for fairness across all demographics is critical. Thus far, fairness has mostly been neglected in machine learning, and two directions need further exploration: fairness in fair representations, and expensive fairness.

10.7. Conclusion

AI has fundamentally changed the way financial analysts, traders, and other investment professions conduct their daily chores. Some have even claimed that AI will replace half of the current financial workforce. The co-operability between financial professionals and AI agents can be significantly deepened; in other words, financial professionals can get smarter and achieve greater productivity if they can better collaborate with AI. To address this unstudied yet significant research opportunity, this study sheds light on two foundational conditions of successful AI to financial professionals collaboration, that is, AI transparency and trust. This study argues that AI transparency can foster financial professionals' trust in AI and investigates how trust relates to human-agent cooperation effectiveness. Furthermore, this study investigates how ambiguities of the AI transparency affects the dynamics of these predictive relationships. This study contributes to the nascent literature by providing a richly elaborated understanding of how financial professionals learn to leverage their AI co-pilot's capabilities, as well as its primary antecedents and outcomes.

In the age of AI, humans are often found working alongside artificial intelligence systems. Such collaboration between human and AI systems has been recognized as an emergent human-AI team. The human-AI team paradigm is different from, for instance, human-machine teams in the sense that AI systems are intended as agents that can take initiative and act autonomously. Within this paradigm, AI systems empower human teammates by augmenting team awareness and formulating and executing recommendations, requests, or actions that the human teammate may not have thought of. However, teams formed through homogenous entities can also collaborate on problem solving. In fact, AI systems learn and evolve continuously through data generated by their human teammates and through their own behavioral trajectories. Such dynamics and interdependence present additional challenges when understanding how to cultivate and sustain insightful collaboration in human-AI teams.

There is an emergent need for an understanding of the co-learning process between humans and AI systems. Since the two learning entities have distinct mental models and complementary capabilities, they can augment each other's capabilities to achieve superior results.

10.7.1. Emerging Trends

As Artificial Intelligence becomes a topic of increasing relevance in the profession, solutions that supplement rather than replace financial professionals are likely. Financial services professionals trained to understand how AI can improve engagement strategies, identify clients most likely to take action, and provide relevant solutions are needed.

These professionals can help clients make sense of a confusing market, enabling them to reach financial wellness. Financial professionals equipped with AI solutions can focus on delivering better outcomes for clients through transparency of guidance creation processes. Besides upskilling financial advice professionals with knowledge of how AI creates recommendations, training may be extended to client-facing support staff and sales engagement teams in wealth management.

The use of AI at an organizational level to improve internal processes is on the rise. However, without well-structured processes delivering accurate data across departments, machine learning adoption is challenging. Start-ups building data-bridging tools can rapidly gain uptake. With AI no longer solely the prerogative of large tech giants, wealth managers might look towards smaller companies to build these structures. AI-powered automated reporting can provide subscribers with a full understanding of their portfolio. The opportunity to leverage AI to produce a client-centric news service is clear. Such an endeavor must consider customized client buying profiles with the potential for insights driven by predictive analytics. Industry-based AI technology initially offers the greatest immediate prospects, enabling highly trained and lower-cost resources to monitor, triage, and respond to client inquiries, producing substantial operational cost savings. Automated post-trade processing reduces the risk of errors and trade failures resulting from replicated manual processes across multiple systems.

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