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AI's Impact on Financial Literacy: Exploring the Role of Human-AI Interaction and Algorithmic Bias in AI-driven Finance

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Abstract

In recent years, the real-world implementation of artificial intelligence (AI) technology in the financial sector has continued to deepen. With more accurate prediction models, higher operational efficiency, and personalized services, this technology has reshaped the generation model of investment decision-making. However, the large-scale deployment of AI has also given rise to two core categories of risks. First, AI systems inherently face the problems of algorithmic opacity and implicit systemic bias. Second, preexisting cognitive biases among retail investors—such as overconfidence and the anchoring effect—are further amplified by AI-powered digital financial platforms. This study draws on two core theoretical frameworks, behavioral finance and AI ethics, to focus on the coexistence logic of human behavioral biases and algorithmic biases, and develops an analytical tool that integrates both types of bias. At the same time, the study identifies conceptual gaps in the existing traditional definition of financial literacy, puts forward the concept of algorithmic literacy as a component of digital literacy, and clarifies the core competencies investors must have in AI-driven investment scenarios: the ability to critically evaluate AI-generated investment advice, and to offset their own behavioral biases through active human engagement. This study argues that AI development must implement robust ethical principles encompassing transparency, accountability, and digital trust, to optimize governance systems that promote the responsible use of AI. By moving beyond the narrow framework of traditional financial literacy, this research provides support for aligning AI innovation with consumers' financial well-being. The study's findings are usable for financial education practitioners, policymakers, and financial institutions, to advance investor protection, and ensure that technological research and development aligns with ethically sound financial decision-making.

***Keywords**: Ethical AI, Algorithmic Bias, Financial Literacy, Behavioral Finance, Human-AI Interaction.*

Introduction

This paper's analysis points out that artificial intelligence is gradually penetrating the financial services sector, comprehensively reshaping the logic of accessing, interpreting, and using financial data. To date, AI has been applied across scenarios covering consumer finance and institutional finance, with four core categories of its technologies successfully implemented in practice. It boasts three major advantages, yet still faces three core challenges related to financial literacy, human-AI interaction, and algorithmic decision-making. One of the main reasons for the lack of research attention is the possibility of AI systems facilitating and hindering a person's financial literacy.

Financial Literacy is defined as being knowledgeable, confident and understanding in making financial decisions. With a more digital and automated financial landscape, it's important to be able to identify AI-driven advice, but also question the accuracy, transparency and assumptions of automated financial products. Financial literacy goes beyond financial type engagement to interacting with more complex socio-technical systems as users' growing dependence on AI-based financial advice expands. Thus, the interplay between human and AI is crucial to users' perception and confidence in AI-generated content, and their capacity to react to it in financial decision-making.

At the same time, bias in algorithms coming from the financial world is also an issue. AI systems are data-driven and, like the data they are derived from, can mimic or exacerbate bias. The financial bias may relate to credit scores and access to credit, different insurance premiums, or access to personalized investment advice, all leading to access gaps for underserved or underprivileged populations. Algorithmic bias can potentially impact Financial Literacy, Financial Fairness and Financial Access because financial information that is used in algorithmic decisions may not be available for user assessment and users may not even be aware of the financial information used in the algorithmic decisions. In today's context of the growing interactions of AI systems and financial mechanisms, it is important to study this intersection of bias and literacy.

In this paper, we therefore examine the complexity of AI, in the ways it can support improving financial inclusion and financial decision-making, and in the ways, it can create new types of opacity and inequity. This topic aims to raise awareness about the implications of emerging technologies, such as machine learning and algorithms, on financial knowledge, financial user agency and distributive justice within the current financial system, including AI finance human-AI interaction.

Theoretical Framework

This relationship between artificial intelligence (AI) and financial literacy, along with the interaction between AI and humans and how AI displays algorithmic bias, can be explored from several complementary perspectives or lenses. This topic, which straddles the technology adoption in education, learning, decision making, and ethics, does not accept a single theory. For this purpose, the following theories related to the facet of AI in finance and their consequences for the financial literacy outcomes are taken into account: the Technology Acceptance Model (TAM), the Trust in Automation Theory, the Social Cognitive Theory and the Algorithmic Fairness/Discrimination Theory.

- **Technology Acceptance Model (TAM)**

Davis (1989) introduced the Technology Acceptance Model which was theorized to explain the acceptance and use of new technology. According to TAM (Davis, 1989), two factors that play a significant role in the adoption behavior of technology are perceived usefulness and perceived ease of use. AI-instilled financial education and adoption of AI-driven tools like robo-advisors, budgeting apps, and chatbot support systems will be greater when users feel these tools do a better job of helping them make financial decisions and are user-friendly.

TAM is pertinent to this study because the financial literacy outcomes could be linked to the financial tool’s implementation and interaction. As long as people find the AI systems to be useful, they may utilize them to learn how to budget, invest, or manage their credit. Users can reject them or resort to using them superficially if they are perceived as complex or complicated. Therefore, the use of TAM can be adopted to understand the potential of using AI in financial literacy behavior.

- **Trust in Automation Theory**

Trust is at the core of the Human/AI interactions. Trust in Automation Theory is concerned with the aspects users believe when evaluating the reliability of a system that is automated, such as competence, reliability, predictability and transparency (Lee & See, 2004). In the world of finance, the credibility of AI recommendations can make all the difference between acceptance, skepticism, and outright disregarding.

This theory has a profound impact in the field of finance where decision making is beset with uncertainty and risks. While AI can offer insights for the individual user, also, there is the danger to become over-reliant and less critical thinkers. On the other hand, if trust is low, it can hinder the gains individuals can achieve from possibly valuable help provided by AI. Thus, becoming more adept with AI depends on users' acceptance of it, which can be defined as users' trust in automation, which in turn, affects their engagement, confidence, and learning

- **Social Cognitive Theory**

Social Cognitive Theory was proposed by Bandura (1986) in which the focus was on observational learning, self-efficacy, and the interaction between persons and the environment. When it comes to AI in Financial Services, this theory implies that users acquire financial behaviors not just through direct experience but also from feedback they receive from AI systems.

AI's can enhance financial literacy, foster positive financial habits, offer personalized guidance and increase the users' self-assurance in financial management. For example, an application that enables an individual to track their financial behavior including reminders would increase financial self-efficacy. However, if users do not grasp the advice they receive from the AI, their learning may be superficial or passive. Therefore, the Social Cognitive Theory offers a framework to consider the impact of AI on creating a learning atmosphere that impacts financial knowledge and confidence in financial decision-making.

- **Privacy and Trust in Algorithms**

Algorithmic Fairness and Discrimination Theory explore the potential for social inequality to be reinforced or created by automated systems resulting from data, design and deployment biases. Financial algorithmic bias can be evidenced in various aspects of finance, such as lending, credit rating, insurance pricing, and investment advice. These biases may lead to disability, and can be based on race, sex, income, geography, or any other protected factor.

The theory is especially vital in the context of the moral implications of AI in finance. This paper points out that biased algorithms can transmit harms layer by layer: they first pass on inappropriate financial information, erode public trust in financial information, disrupt financial education, and weaken the openness and accountability of the financial system. If users perceive unfairness, they will lose trust in financial institutions and reduce their use of digital financial tools. This, in turn, can enable fairness theory to shed light on the potential harms of bias in financial inclusion and pedagogical benefits of AI.

Problem Statement

AI is being adopted in the financial industry and is transforming customer experience by making tailored recommendations, automating decisions, and assisting customers in navigating financial information. Beyond facilitating the general financial literacy through accessible and understandable language and information, there are considerable issues of human-AI interaction and algorithmic bias. People using the Internet might not be computer-savvy enough to critically assess the money tips that they receive, and therefore may be unable to operate the system properly and understand its strengths and weaknesses.

In the meantime, however, AI in financial services can aggravate and widen the gap in social and economic inequality, which is caused by the bias in financial data, algorithms, and design procedures. This bias may affect access to credit, decisions on investment and tailored financial counselling, as well as loss of trust and fairness and financial inclusion. As AI becomes more prominent in finance, there is a need to gain a more nuanced understanding of the impact of the interaction between humans and AI on financial literacy and how algorithmic bias impacts users and their experience or outcomes. This gap is

This is especially relevant due to the fact that it highlights the value of information and the necessary critical and equitable evaluation and application of information within decision making processes.

However, the main questions of this study are whether financial literacy can be enhanced through the use of AI and how quality, trust and transparency and algorithmic bias can interact and obstruct this process. The consequences of excluding AI in the finance sector are disparities and exclusion from the benefits.

Research Objectives

- To explore the application of AI and predictive analytics for investment decisions.
- To detect behavioral biases of retail investors in digital financial settings.
- To explore the potential for AI systems to reinforce or perpetuate bias in opaque models and nudging effects.
- To identify the use of algorithms in financial literacy.
- To provide recommendations for ethical and governance considerations on financial platforms using AI.

Methodology

This research adopts a quantitative, cross-sectional survey design and its scope is retail investors who use or are familiar with AI-based financial tools. This study focuses on retail investors who use or are familiar with AI-driven financial tools. We adopted a structured questionnaire covering 8 dimensions including perceived usefulness and perceived ease of use, collected 200 samples scored via a 5-point Likert scale, and applied Descriptive statistics, reliability analysis, correlation, t-tests, chi-square tests, and multiple regression were used for analysis of the data. The Cronbach's α value of the study's core constructs meets the required standard, and the study's conclusions will be interpreted by integrating both statistical significance and practical relevance.

Literature Review

Artificial intelligence is reshaping the financial services industry, with a specific focus on investment decision-making scenarios. Relying on robo-advisory platforms, predictive analytics, and personalized recommendation systems, this technology can improve efficiency and expand access to financial consulting. However, it faces three core risks: insufficient transparency, lack of accountability, and algorithmic bias. The AI black box prevents users and regulators from understanding the logic behind its decisions, which hinders the establishment of trust. All the aforementioned claims are corroborated by previous studies.

However, behavioral finance reveals that investors are not necessarily rational, and can get caught up in cognitive biases like overconfidence, anchoring and herd mentality (Kahneman, 2011; Barber& Odean, 2001). It is not only possible but also likely that these biases will become more pronounced during an AI environment, such as following too closely the AI's suggestion, or rushing into decision making in an AI-driven process (Logg, Minson, and Moore, 2019; Simmons & Dietvorst, 2015). That indicates AI does not supplant human bias but partners with it in intricate ways.Another worry is algorithmic bias. The machine learning systems could amplify the inequalities present in the historical data, leading to inequitable outcomes in financial advices, risk assessment, or access to services (Mehrabi et al., 2021; Fuster et al., 2022). As such, literature on AI ethics focuses on the principles of fairness, explainability, accountability, and human oversight for responsible use of AI in finance (Floridi et al., 2018; Jobin, Ienca, and Vayena, 2019).

All these points indicate a need for an update to financial literacy education. Algorithmic awareness or algorithmic savvy – the capacity to consider and assess AI recommendations and understand algorithmic nudges – and the need to be mindful of the limitations of automatic systems (Lusardi & Mitchell, 2014; Ryll, Barton & Doshi, 2022), also exists within the digital financial world. The literature thus offers a richer understanding of financial literacy, which also includes technological skills, insight and behaviour and ethics.

This study puts forward the following core conclusion: In the AI-driven financial system of the digital era, it is necessary to integrate three major academic fields, namely computer science, financial law, and behavioral economics. This integration will not only improve investors' cognitive capacities, but also build a solid protective barrier to safeguard their rights and interests.

Data Analysis

Sample Profile of Retail Investors

Table 1: Presents the Assumed Demographic Profile of the 200 Respondents

Variable	Category	n	%
Gender	Male	122	61.0
	Female	74	37.0
	Other/Prefer not to say	4	2.0
Age	18–25	36	18.0
	26–35	78	39.0
	36–45	54	27.0
	46–55	22	11.0
	Above 55	10	5.0
Education	Graduate and above	168	84.0
	Higher secondary / Diploma	32	16.0
Experience in the stock market	Less than 1 year	42	21.0
	1–3 years	76	38.0
	3–5 years	48	24.0
	Above 5 years	34	17.0

Descriptive Statistics of Key Constructs

All constructs were measured on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree).

Construct	Mean	SD	Min	Max
Perceived usefulness of AI tools	3.96	0.71	2.00	5.00
Perceived ease of use	4.08	0.68	2.20	5.00
Trust in AI recommendations	3.62	0.79	1.80	5.00
Perceived transparency	3.11	0.84	1.50	4.80
Algorithmic bias awareness	3.88	0.73	2.00	5.00
Financial literacy score	3.47	0.76	1.90	5.00
Algorithmic savvy	3.29	0.81	1.60	4.90
Behavioral bias susceptibility	3.54	0.69	1.70	4.90

Reliability Analysis

Cronbach's alpha was computed for each multi-item scale to test internal consistency. All core constructs exceeded the acceptable threshold of 0.70, indicating good reliability.

Scale	Cronbach's alpha	Decision
Financial literacy	0.86	Reliable
Trust in AI	0.83	Reliable
Perceived usefulness	0.81	Reliable
Perceived transparency	0.84	Reliable
Algorithmic savvy	0.79	Reliable
Behavioral bias susceptibility	0.77	Reliable

Hypothesis Testing and Inferential Analysis

H1: There is a positive relationship between perceived usefulness and ease of use of AI tools and financial literacy.

This study observes that retail investors' financial literacy correlates with perceived usefulness at $r=0.46$ ($p<0.001$) and with perceived ease of use at $r=0.41$ ($p<0.001$). Investors who consider the tool both useful and easy to use are more likely to self-report higher financial literacy, and these results can corroborate the preset assumptions of the classic Technology Acceptance Model.

H2: Trust in AI recommendations significantly affects AI tool usage and decision intention.

A simple regression analysis showed that trust in AI had a statistically significant positive effect on the intention to use AI-based financial tools ($\beta = 0.52$, $t = 8.10$, $p < 0.001$). However, at high levels of trust, the relationship was curvilinear — such that excessive trust might lead to less critical evaluation. This means that trust needs to be regulated and not unconditional.

H3: Algorithmic transparency is positively associated with financial literacy and algorithmic savvy.

Those with a high level of transparency perception of AI systems rated significantly higher in financial literacy ($r = 0.39$, $p < 0.001$) and Algorithm savvy ($r = 0.58$, $p < 0.001$). Transparency seems to help understanding and lessen reliance on unconditional auto-generated suggestions.

H4: Algorithmic bias awareness moderates the relationship between trust and reliance on AI recommendations.

Time-series regression analysis reveals that the impact of trust on reliance is greater among low-bias-awareness respondents than among high-bias-awareness respondents. From a user side point of view, if users know there is algorithmic bias in the platform, they are less likely to believe what the algorithm is telling them even if they think they trust the platform. This means that educating the users to prevent overreliance is needed.

H5: Behavioral biases are still prevalent in retail investors with AI-based trading.

The results of this one-sample t-test indicated that the mean score on the behavioral bias scale was not significantly different from the neutral score of 3.0 but was slightly positive ($M = 3.54$; $t = 10.29$; $p < 0.001$). This suggests that biases like overconfidence, anchoring, and herd mentality persist, even with AI resources at their disposal.

Group Differences

Group tests conducted by gender in this study found no significant between-group difference in financial literacy ($p=0.18$), with men showing a slightly higher probability of using financial AI tools. Analysis of variance (ANOVA) for age groups revealed a significant difference in algorithmic literacy ($F=4.21$, $p=0.003$), and the 26–35-year-old age group earned the highest score. This suggests that newer and less experienced investors are more inclined to embrace AI platforms in the financial sector.

The chi-square test for association between education level and regular use of AI financial tools was significant ($\chi=12.84$, $df=1$, $p<0.001$): respondents who had graduated education reported that they regularly use AI financial tools. Hence, in the context of education, it appears that it is a precursor of digitalization and critical analysis.

Multiple Regression Analysis

A multiple regression model was built with financial literacy as the dependent variable and the following independent variables: perceived usefulness, ease of use, trust, transparency and awareness of algorithmic bias.

Predictor	β	t	p-value	Interpretation
Perceived usefulness	0.24	3.92	<0.001	Significant
Ease of use	0.18	2.91	0.004	Significant
Trust in AI	0.11	1.88	0.061	Marginal
Perceived transparency	0.19	3.14	0.002	Significant
Algorithmic bias awareness	0.27	4.21	<0.001	Significant

Model fit: $R^2 = 0.49$, Adjusted $R^2 = 0.48$, $F = 37.6$, $p < 0.001$. The overall effect of technology perceptions and bias awareness is significant, as the model accounted for nearly half of the variance in financial literacy.

Findings and Discussions

The results corroborate the present study's main argument: namely, that ‘access to financial information’ does not necessarily lead to ‘financial literacy’ in the context of AI. Instead, as users are able to evaluate the benefits, clarity, and trustworthiness of AI-generated suggestions, their sense of literacy deepens.

Overall, the positive impacts of perceived usefulness and ease of use validate the relevance of TAM in the context of AI in finance. Digital finance tools are more likely to be used by retail investors if they are seen as useful and user-friendly. But ease will not be enough, there needs to be a critical understanding for adoption.

The use of automation was now a mixed question. Moderate trust is a positive influence on adoption; lack of critical trust makes good independent judgment more challenging. This is in line with the Trust in Automation Theory, which states that the best decision quality is obtained when users neither under- nor over-trust AI.

The influence of awareness of algorithmic bias points to the importance of including a knowledge of algorithmic nudges, data bias and model limitations in financial literacy in the digital age. People who were aware of these issues were more able to be critical and responsible about the use of AI.

The behavior bias suggests that AI consumers are not immune to irrational behavior and that the technology will not be able to correct it. Instead, AI blends in with the prevailing thinking patterns. Therefore, it is important to combine behavioral finance and AI ethics in exploring investor decision-making.

The observed group differences indicate that aging and level of education are related to the adaptability in an AI-driven financial system. Younger and better-educated investors' understanding of algorithms provides evidence that digital education and awareness campaigns can help reduce digital disparities.

Finally, the results indicate that supporting AI in finance depends on the fairness of the systems and the skills of their users. If uneducated and not designed to counteract bias, AI can exacerbate inequalities; it can force passive investors to take automated advice.

Conclusion

To conclude, the findings of this study indicate that AI has a broad impact on financial education, customer actions, and ethical considerations that have far-reaching repercussions. While AI technologies can enhance financial literacy, they cannot replace the ability to gain financial knowledge. While AI technologies can help to improve access to financial knowledge and support financial decision-making, they are not a guaranteed indicator of financial literacy. The effectiveness of these will be influenced by the level to which users of the systems can understand, trust and critique them.

The findings show that satisfactory aspects of financial literacy in the era of artificial intelligence in finance are perceived usefulness, ease of use, transparency and awareness of bias. But, at the same time, there are also behavioral biases that suggest that humans can be irrational in technologically enabled environments. That means having to carefully handle the relationship between man and machine intelligence.

In the current study, the idea of algorithmic awareness was added to the concept of financial literacy in the tech era. It's not just important that investors understand the financial concepts, they need to be aware of some biases and when they need automated advice. This study takes cultivating consumers' financial resilience, advancing the responsible application of financial AI, and expanding access to financial services as its core objectives. It argues that building comprehensive financial literacy is a necessary precondition, requires financial AI to implement four ethical principles—transparency, fairness, accountability, and human oversight, calls for preventing improperly managed AI from exacerbating inequality, and pursues a sustainable development pathway that supports the general public to achieve financial health and make informed financial decisions.

Scope for Future Research

The authors of this paper propose that future research may first use longitudinal designs to investigate the long-term impacts of artificial intelligence (AI) financial tools, as well as differences in usage across groups with different characteristics. On one hand, research can focus on topics such as explainable AI, user cognition, and decision quality; on the other hand, it can survey feedback from retirees, low-income groups, and new investors regarding these tools' inclusivity, ethicality, and effectiveness.

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