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ARTIFICIAL INTELLIGENCE AND FINANCIAL DECISION MAKING: A CONCEPTUAL FRAMEWORK

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Abstract
AI is quickly transforming financial services, changing the game in areas like credit scoring, algorithmic trading, risk management, and compliance. Decision-making has never been as critical as it is today because financial markets are becoming increasingly complicated. Although the financial sector is fast adopting AI, not much information has been clear on how these technologies assist, complement, or criticize human judgment in the process of making decisions. This paper is set to address this gap by creating a conceptual framework that integrates AI tools with well-known financial decision frameworks, including Behavioral Finance, Decision Support Systems (DSS), and Technology Acceptance Model (TAM). The model demonstrates the role of AI as a decision support, which is affected by other factors such as trust, perceived usefulness, and ethical considerations to influence financial outcomes. The primary value addition in this matter is a logical structure with clarity, which connects the adoption of technology with the financial decision-making pragmatically. With this model, practitioners will be able to create more transparent and ethically accountable AI-powered financial systems. On the other hand, this can be further researched by researchers in the future using surveys, experiments, and analysis of secondary data.
Keywords: *AI, behavioral finance; DDS, ethics, Fintech, TAM*

Introduction

In the last few years, AI has really shaken things up in finance, changing how banks, investors, and risk managers make decisions (Bahoo et al., 2024). Finance has always been quick to catch on to new tech, from everything like computerized trading floors to making sense of huge sets of data (Rajae et al., 2024). AI is now taking it to a higher level, as it enables companies to analyze large volumes of organized and unstructured data, identify patterns not readily visible before, and receive insights at a high speed and with greater accuracy than before (Camilleri, 2023a; Weber et al., 2024). It is happening with objects such as robo-advisors, algorithmic trading, credit scoring, credit detection, and portfolio management—tools through which AI is rewriting the book on financial decisions (Crawford, 2021; Davies, 2024). These systems are beginning to push conventional concepts of expertise and judgment, introducing machine intelligence into decision-making processes of both individuals and institutions with high stakes (Rosenberg, 2023; Sharma & Pandey, 2023).

Getting the details right in financial choices is super important because they directly impact how well people live, how businesses plan for the future, and even the stability of global markets (Christian, 2020). When you're deciding whether to get a loan or predicting market swings, these decisions come with serious risks and real-world consequences (Najem et al., 2025; Pahsa, 2024). Meanwhile, investment analytics combine market signals with natural language processing of news articles to improve portfolio strategies (Mediaty et al., 2024; Reuters, 2024). AI-driven models also integrate behavioral factors, macroeconomic indicators, and real-time sentiment to enhance predictive accuracy (Camilleri, 2023b; Ruckenstein, 2023). Furthermore, developments in explainable AI and automated compliance are helping financial firms meet regulatory expectations while maintaining transparency (Lee et al., 2024; Manikandan, 2025). In addition, cross-border financial platforms now use AI to detect fraud and monitor suspicious activity more efficiently (Birch, 2024; Oyasiji et al., 2023). Recent studies also show that machine learning can improve asset allocation and volatility forecasting, reinforcing overall market resilience (Gao et al., 2024; Sugiarto et al., 2025).

All of these advancements suggest AI could make financial decisions more efficient and stable, helping to reduce widespread risks and strengthen economic resilience (Cerneviciene & Kabasinskas, 2024; Kudelic et al., 2025; Leocadio et al., 2024; Mokander et al., 2023; Wang, 2024). There are lingering worries: Does AI genuinely help overcome human cognitive limits, or does it bring new problems, like hidden biases in algorithms and potential widespread discrimination?

Research Justification

The proposed study will aid in closing this gap by developing a conceptual framework connecting AI applications to the decision-making theory and ethics. The framework is supposed to generate a more detailed understanding of the role of AI in financial decision-making through the synthesis of the evidence of technology adoption studies, behavioral finance, and regulatory research. There are both theoretical and practical implications of such a methodology. Academically, it offers a foundation to future empirical research, resulting in studies on the way AI changes the decision-making process. Practically, it provides financial institutions, policymakers, and regulators with a systematic perspective of responsible merging AI based on

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the consideration of the desire to pursue innovation at the expense of ensuring fairness, transparency, and accountability.

1. Context of AI in Finance

The financial sector has been one of the strongest pioneers of computational and algorithmic developments historically (Manikandan, 2025). AI is a type of computational system with the ability to learn, reason, and solve problems using approaches similar to human beings (Cerneviciene & Kabasinskas, 2024). The use of AI is particularly high in Fintech (financial technology) companies, which have revolutionized conventional investment and banking services using AI-enabled alternatives (Birch, 2024). Besides, natural language processing (NLP) technology processes news feeds, company releases, and even social media sentiment to generate real-time trade signals. The overall market for AI in finance worldwide mirrors this increasing integration. A recent study by Kudelic et al. (2025) estimated the value of AI in the financial sector to be more than USD 45 billion by 2030, with a compound annual growth rate (CAGR) of over 20%. This growth reflects the demand for efficiency and the need to control increasingly complex data-driven environments.

2. Significance of Accuracy in Financial Decision-Making

Credit scoring models in the past were based on stable parameters like income, debt-to-income ratio, and payment history (Gao et al., 2024). AI-powered credit scoring models, on the other hand, can consider thousands of factors like online shopping behavior, geolocation information, and social media, thus providing a more accurate risk profile (Camilleri, 2023a). In asset management, too, AI models can provide predictive analytics on stock market movements by combining structured financial data with unstructured text like analyst commentaries and news stories (Pahsa, 2024).

3. Research Gap: Absence of a Unified Model

The passion for AI in finance does not find a corresponding reflection of theoretical synthesis in the integration of decision-making theories and AI (Weber et al., 2024). With limited attention paid to decision-making theories, most studies tend to concentrate on technical aspects like efficiency of algorithms, data precision, or model maximization (Gao et al., 2024; Mediaty et al., 2024). Theories of decision-making, from rational choice theory and bounded rationality through prospect theory, hold important explanations for how individuals and institutions form financial choices under risk and uncertainty (Christian, 2020). However, the intersection of these theories and AI tools is not well understood (Cerneviciene & Kabasinskas, 2024). For instance, bounded rationality hypothesizes that people make choices with bounded cognitive capacity and a lack of perfect information (Camilleri, 2023a). Theoretically, AI can transcend such a limitation by increasing the set of information and computational capability for the decision-maker (Birch, 2024). But whether AI truly eliminates bounded rationality or merely redraws its boundaries (e.g., by introducing algorithmic transparency and bias) is more than needs theoretical examination (Camilleri, 2023b; Ruckenstein, 2023).

Another not-so-explored realm is the ethical and regulatory consequences of AI implementation in finance (Wang, 2024). Although the literature does recognize problems of bias, fairness, and transparency in algorithms (Sharma & Pandey, 2023), there is not much intersection of these problems with wider conceptual models of decision-making (Oyasiji et al., 2023). The scholarship, therefore, continues to be in silos: technical research continues to push algorithmic efficacy (Davies, 2024), behavioral research is concentrated on human fallibilities (Rajae et al., 2024), and regulatory research focuses on compliance (Najem et al., 2025; Reuters, 2024). What is missing is a unified conceptual model that brings these streams together, highlighting how AI simultaneously reshapes, extends, and complicates financial decision-making (Kudelic et al., 2025; Sugiarto et al., 2025).

Research Objectives

1. Adoption of AI in financial decision-making through its applications in Fintech, trading, investment management, and risk assessment.
2. Link AI applications to decision-making theories by demonstrating how AI supports and contravenes traditional representations of rationality, bounded rationality, and behavioral finance.
3. Highlight adoption drivers, such as trust, transparency, and compliance with regulations, mediating the effects of AI in finance.
4. Integrate ethical factors--fairness, accountability, and explainability into the conceptual framework.
5. Offer an integrative model that can inform future empirical studies and practical applications of AI to financial decision-making.

By achieving these goals, the paper contributes not merely to scholarly debate on AI and finance but also to applied debate between financial experts, regulators, and policymakers. Finally, the framework serves as a basis for ethical innovation--promoting the application of AI for improving decision quality and efficiency while protecting standards of ethics and systemic integrity.

Literature Review

Artificial Intelligence (AI) has become a key focus of financial research, particularly as its uses transform decision-making both at the institutional and individual levels. The scholarly discussion is still dispersed in technical, behavioral, and regulatory spaces, with few efforts to consolidate these views into a single framework. This review is structured thematically to integrate work into four related streams: (1) AI technologies for finance, (2) theoretical models of financial decision-making, (3) AI and human judgment interaction, and (4) the integrated models gap.

1. **AI Technologies in Finance:** AI involves a broad range of computational methods, such as machine learning (ML), natural language processing (NLP), predictive analytics, and autonomous advisory systems (Sharma & Pandey, 2023). All these technologies have had unique applications in finance, promoting efficiency, precision, and innovation in decision-making processes (Rajae et al., 2024).
2. **Machine Learning (ML):** Machine learning algorithms prevail over today's financial AI applications. Supervised learning models are used extensively in credit rating, fraud detection, and default estimation. For example, Bahoo (2024) highlights how ML methods surpass old logistic regression models by including nonlinear interactions and high-dimensional information. Under unsupervised learning, clustering methods have been used to classify customers for specific financial products, while reinforcement learning has been in the spotlight due to its capability to optimize trading strategies dynamically(Mokander et al., 2023).

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3. **Natural Language Processing (NLP):** Another rapidly developing AI application in finance is natural language processing. Increasingly, financial decisions are based on the interpretation of unstructured data obtained through annual reports, news content, and even social media updates (Manikandan, 2025). NLP software makes sentiment analysis easier, which is added to market predictions to measure investor mood over and above a numeric value. According to Cerneviciene and Kabasinskas (2024), NLP technologies in finance do not merely increase in trading, but also in compliance monitoring and regulatory reports, where text analysis can be used to reveal abnormalities and threats.
4. **Robo-Advisors and Automated Systems:** Robo-advisors are a disruptive FinTech company that has created an equal opportunity in investment management by offering services on an algorithm-based portfolio at a fraction of the price of a traditional advisor (Reuters, 2024). Robo-advisors are based on ML and optimization algorithms that address risk-return bias, and some are even behaviorally informed nudges that are consistent with investor psychology (Weber et al., 2024). Camilleri (2023b) has merged predictive analytics with portfolio rebalancing, demonstrating how AI can replace and, in certain aspects, outperform traditional financial advisory functions (Sugiarto et al., 2025).
5. **Predictive Analytics:** Predictive analytics is not applied to the management of a portfolio only, as it is also used in predicting risk and systemic stability. Ruckenstein (2023) asserts that artificial intelligence-inspired forecasting systems have a much higher level of efficacy in predicting foreign exchange volatility, credit risk, and stock returns as compared to econometric models (Kudelic et al., 2025). Moreover, these systems are also being integrated with real-time monitoring dashboards, which enable financial institutions to make adaptive decisions in an environment of uncertainty (Christian, 2020). Yet the literature tends to address them separately, examining each narrowly with an emphasis on technical performance without integrating them into a wider theoretical framework for decision-making (Leocadio et al., 2024).
6. **Financial Decision-Making Theories:** In order to put the role of AI in the financial sector into perspective, classical and modern theories of economic decision-making are to be considered (Davies, 2024). Rational choice theories, bounded rationality theories, and behavioral finance theories are some of the theories that give some fundamental understanding of how decisions are organized in different conditions of risk and uncertainty (Mediaty et al., 2024).
7. **Rational Choice Theory:** Based on classical economics, rational choice theory presumes decision-makers maximize utility from full information and stable preferences (Crawford, 2021). Financial theories like the Efficient Market Hypothesis (EMH) rest on this foundation (Birch, 2024). Yet decision-making is never actually close to such assumptions in reality, something recognized even in some of the earliest critiques of rational choice in finance (Camilleri, 2023a).
8. **Bounded Rationality:** AI is especially relevant because it promises to stretch the limits of rationality through improving information processing and minimizing cognitive load (Reuters, 2024). Nevertheless, Wang (2024) contends, AI does not abolish bounded rationality but relocates its constraints to new areas such as algorithmic obscurity, data quality, and systemic dependence.
9. **Behavioral Finance:** Empirical research indicates that investors routinely misprice assets and under- or overreact to news. AI has been identified as a corrector mechanism for such biases (Manikandan, 2025). On the prospect theory, behavioral finance focuses on systematic non-

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rationality, such as loss aversion, mental accounting, and herding. Indicatively, Oyasiji et al. (2023) observe that the moral identification in AI can shift risk attitudes within a decision-making process, a fact that indicates the potential of algorithms as well as their danger. These theories collectively explain how finance decision-making can be viewed as a delicate balance between being rational and being constrained and biased (Pahsa, 2024). However, the literature has not explored the intersection point between AI and these paradigms, as either an optimizer of rationality, an amplifier of limited rationality, or a behavioral bias transformer.

10. **AI and Human Judgment Interaction:** Beyond technical ability and theoretical foundation, there is much literature that analyzes the connection between human judgment and AI in finance decision-making(Najem et al. 2025). This connection presents the possibility of reducing bias and the threats of overdependence on algorithms technologies (Gao et al. 2024).

11. **Bounded Rationality:** One of the biggest promises of AI lies in reducing human cognitive biases through data-driven objectivity. Algorithm aversion studies by Lee et al. (2024) indicate that people first fight algorithmic decision-making but then accept it eventually as transparency and interpretability are enhanced. In finance, AI may reduce the widespread biases of overconfidence and anchoring, provided that its mechanisms are made transparent. Rosenberg (2023) agrees with this statement by placing a high emphasis on explainable AI (XAI) as a process required to give confidence to financial decision systems.

12. Overreliance Threats: On the other hand, literature cautions about excessive reliance on AI systems, which can create new risks. Birch (2024) assumes that when AI is trusted by financial specialists too much, it poses ethical threats as they do not scrutinize its accuracy. The Flash Crash of 2010, which predates the current AI capacities, demonstrates the system risk of the algorithmic trading systems responding in an unanticipated way to one another(Weber et al., 2024). More modern concerns include reinforcement learning designs that bring in short-term returns in trading but increase long-term volatility(Reuters, 2024).

13. Hybrid Decision-Making: Sharma and Pandey (2023) argue that AI usually serves to supplement human judgment, with the best outcomes being realized when computers process information-intensive tasks while humans manage contextual understanding. It is a hybrid model of augmentation as opposed to the automation that has been described by the bigger human-centered AI literature(Rajae et al., 2024). Thus, AI has demonstrated its capacity to reduce biases, but it is also raising some issues of reliance, lack of transparency, and system vulnerabilities (Wang, 2024).

14. Gap in Integrated Models: Despite the abundance of resources on the topic of AI technologies, theories of decision-making, and the interactions between humanity and AI, the existing literature is nonetheless fragmented, and not many attempts are made to combine these perspectives into a unified framework. Three major gaps are visible:

i. **Fragmentation across domains:** Technical research is concerned with the efficiency of algorithms; behavioral science is concerned with human biases; and regulatory literature is concerned with compliance and ethics. Not many studies seek to make a connection between these strands.

ii. **Limited theoretical basis:** Although bounded rationality and behavioral finance are sometimes mentioned, most articles do not systematically relate AI uptake to traditional decision theories. It leaves a gap in the conceptual understanding of whether AI is beneficial, transformational, or disorienting these theories.

iii. **Inadequate ethical integration:** Fairness, transparency, and accountability are not given due consideration as part of fair financial decision-making but rather managed as external limitations. AI may increase inequality and instability of the systems unless ethics is incorporated into the decision models.

The literature reviewed demonstrates impressive progress in the understanding of AI applications in finance, including ML and NLP, up to robo-advisors and predictive analytics. It also unveils the persisting relevance of decision-making theories and the intricate dynamics of human-AI interactions. However, the lack of comprehensive models makes the discussion incomplete. To fill this gap, one needs theoretical synthesis, embedding into ethics, and empirical testability. This paper bridges that gap by suggesting a conceptual framework that bridges AI technologies and decision-making theories, and human-AI dynamics to provide a platform for future practice and research.

Theoretical Foundations

The revolutionary nature of Artificial Intelligence (AI) in financial decision-making cannot be comprehensively appreciated without basing it on proven theoretical frameworks.

1. **Behavioural Finance and AI in Choice:** With the computational capability that comes with advanced technology, branches like finance, information systems, and behavioural sciences offer the theoretical framework that should be present to shed light on the mechanisms behind the adoption, usage, and impacts of the technologies under consideration. Three theoretical perspectives are particularly informative: Behavioral Finance, which challenges the psychological and cognitive processes inherent in decision-making; Decision Support Systems (DSS) theory, which puts artificial intelligence into the context of the history of decision-supporting tools; and the Technology Acceptance Model (TAM), which can provide more detailed information regarding the adoption and integration of AI technologies by stakeholders. Taken altogether, these frameworks represent a holistic approach through which the impact of artificial intelligence on the decision-making process in the financial sphere can be viewed to reveal the potential it has to offer, and also to emphasise the risks it poses. Thus, behavioral finance contributes to the theoretical foundation by explaining why AI is needed to offset human limitations and why caution is required to ensure that machine-driven decisions do not merely replace human biases with algorithmic ones.

2. **Decision Support Systems Theory and AI as an Evolutionary Leap:** Decision Support Systems (DSS) theory is a second basis for locating AI within financial decision-making. Historically, DSS describes computer systems that help managers make semi-structured or unstructured decisions by bringing data, models, and user interfaces together. Since the 1970s, DSS research has focused on how these systems improve decision quality through augmentation of human cognition, not substitution for it. In portfolio management, AI-powered DSS combine macroeconomic information, sentiment, and past price action to provide dynamic advice that is customized to investor types. It supports the notion that AI must serve as an augment, not a replacement, to human judgment, and thus aligns with financial ethical imperatives.

3. **Technology Acceptance Model (TAM) and AI Adoption in Finance:** Although behavioral finance and DSS theory perceive decision-making through the cognitive and systemic perspectives

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of decision-making, the Technology Acceptance Model (TAM) characterizes adoption behaviors. According to TAM, people adopt and use a new technology because of two significant changes: perceived usefulness (PU) and perceived ease of use (PEOU). Constructs such as trust, risk perception, and social influence have also been added to TAM later; hence, it is a very popular model for studying technology adoption in different industries.

TAM is also useful in the AI context of finance in explaining why some tools like robo-advisors, algorithmic trading platforms, or systems for fraud detection gain acceptance quickly, while others are resisted. If professionals see AI as improving decision quality, time savings, or better results (high PU), and if the systems are easy to use, easy to understand, and simple to fit into current routines (high PEOU), adoption is more likely to occur. If AI systems are complex, opaque, or threatening to professional identities, adoption could stall. More recent TAM extensions also emphasize the role of trust in AI adoption. Trust is of particular relevance in finance, where stakes are high, and decision-making is under regulatory pressure. Perceived risks, such as breaches of data privacy, algorithmic bias, or the possibility of systemic failures, can suppress AI's willingness to adopt even if the technology proves superior performance. In this context, TAM offers a systematic means to assess the mediating factors between technological capability and user acceptance.

By applying TAM to AI take-up in finance, we learn not only about organizational take-up but also about end-user take-up. For instance, whether retail investors are willing to employ robo-advisors rests not only on how well the algorithms perform but also on how well they can feel comfortable with yielding financial control to a non-human actor. TAM thus enhances behavioral finance and DSS theory by bringing into focus perceptions, attitudes, and social dynamics about AI.

Blending Theories Toward a Comprehensive Framework

When all these theories are considered separately, they help to realize another part of the AI role in financial decision-making. Behavioral finance throws light on the cognitive biases and psychology that AI is aimed at. The DSS theory places AI in the context of decision-support traditions, with the focus on the complementary role of a human and a machine. TAM describes the perceptions, reactions, and implementations of AI by the users in financial situations. Combined with the views, these opinions form the multi-dimensional basis of the interpretation of the effects of AI.

Notably, the integration of these theories also uncovers tensions and difficulties. For example, behavioral finance cautions against excessive use of algorithms, and TAM focuses on trust as an adoption determinant. DSS theory identifies potential cooperation between machines and humans, but behavioral evidence indicates that humans might give too much deference to machine recommendations. A complete framework must reconcile these insights by supporting AI systems that are technically sound, behaviorally attuned, and easy to use.

Justification for Theoretical Integration

Finance is not just technical; it is a field where cognitive biases, social pressures, and ethical limitations meet quantitative models and computational hardware. AI technologies enhance these intersections by adding new dimensions of automation, interpretability, and trust. No one theory captures this adequately. Behavioral finance keeps human limitations at the forefront of the

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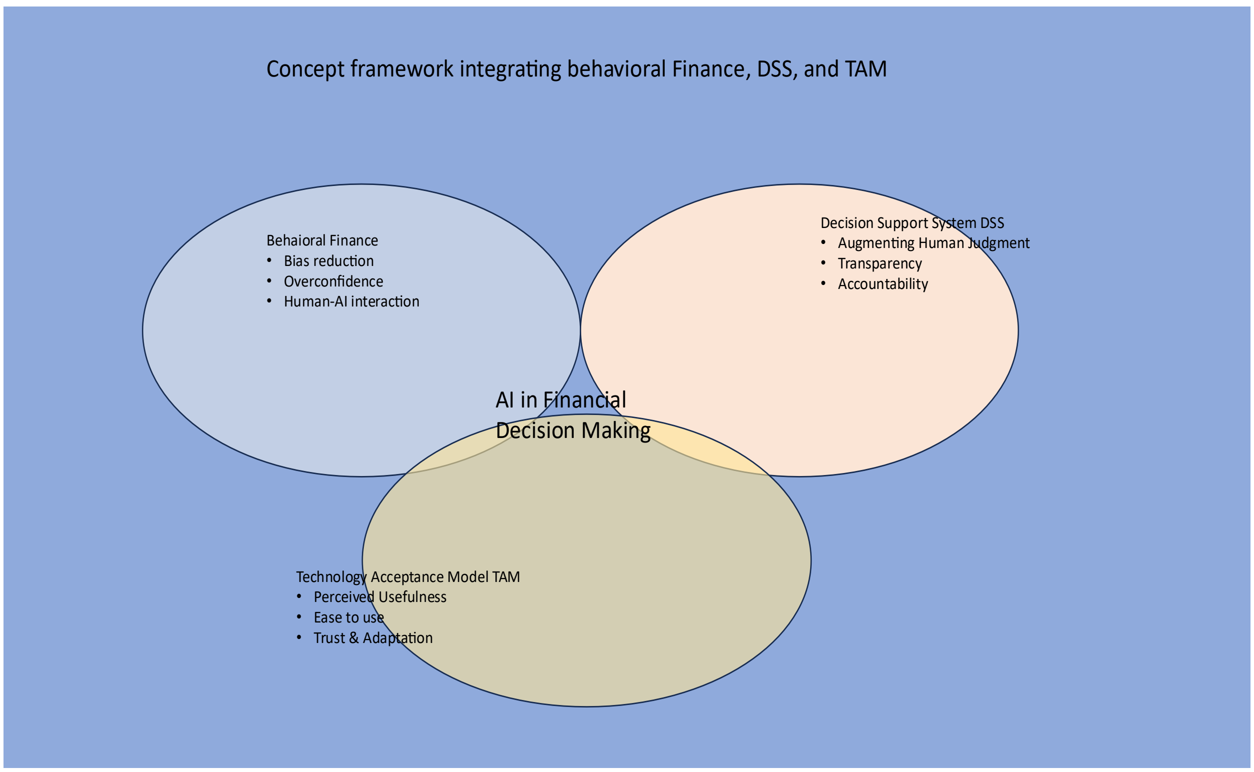
conversation, as a reminder that the goal of AI is not to replace humans but to confront biases. DSS theory focuses on system design and functionality to enhance decision-making so that AI is tested not just on accuracy but also on its ability to facilitate accountability. TAM accounts for the socio-psychological mechanisms that govern whether these technologies actually get taken up, thereby closing the theoretical promise-practical implementation gap.

Combining these theories enables the construction of a conceptual model that links technological potential to behavioral facts and adoption forces. Such a model is required in order to understand not only how AI transforms financial decision-making in the present moment but also how it could change in the future. This theoretical basis puts AI in finance at the intersection of three key approaches: the cognitive findings of behavioral finance, the system design principles of decision support systems, and the adoption processes summarized by the technology acceptance model.



Proposed Conceptual Model

Artificial Intelligence (AI) is transforming financial decision-making beyond mere incremental gains in efficiency, marking a paradigm shift towards how information is processed, interpreted, and acted upon. In the process of capturing this change, this research paper assumes a conceptual model, which integrates Behavioral Finance, Decision Support Systems (DSS) theory, and the Technology Acceptance Model (TAM). The model is created to offer a comprehensive insight into the scope of AI in the management of finances, and it ties the cognitive, technological, and adoption-related aspects to one model. Through this, it resolves the existing sparseness of the literature and provides a basis on which both research and practice may be conducted.

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Structure of Proposed Model

The model may be presented as below in the form of a three-layered system with feedback loops, where each of the theoretical bases is represented:

1. Behavioral Layer (Human Cognition & Biases): Underlying the model is human decision-making, which is informed by bounded rationality, cognitive biases, and emotions. This level summarizes the insights of behavioral finance, which recognize that despite having access to gigantic data sets, human managers and investors occasionally misinterpret signals, get into herds, or get overconfident. It is in this regard that AI technologies are presented to rectify biases and enhance rationality.

2. Technological Support Layer (AI as Decision Support): The second layer puts AI in the DSS tradition. In the given instance, the artificial intelligence systems may be viewed as advanced decision-support systems, which analyze structured and unstructured data, provide real-time analysis, and present interpretive analysis. The unique feature of AI systems as opposed to traditional DSS is that they are adaptable, learn through new information, and can take independent actions. This layer is the place where human judgment is supplemented (and sometimes contradicted) by machine intelligence.

3. Adoption Layer (Perceptions and Trust): The third layer summarizes adoption dynamics as described by TAM. Even the most sophisticated AI technologies cannot shape decision-making unless stakeholders--financial professionals, institutions, and regulators--view them as useful, trustworthy, and simple to operate. Organizational confidence, openness, and elucidability are conclusive determinants of AI technology adoption or opposition. The main part of the model is Financial Decision-Making that is AI-enhanced through the intersection of these three layers. The model represents the financial decision-making process in a cyclical manner, in which AI reduces human biases, improves decision-making with superior analytics, and gains legitimacy through its acceptance by the stakeholders.

4. Integration of Theories: The advantage of this model is that it combines the information that has traditionally been regarded separately. Based on Behavioral Finance, the paradigm is aware of the cognitive bias of humans, and, therefore, the need for AI. It, however, also warns about new threats, including overreliance on algorithms, which requires checks and balances. Based on the DSS theory, the model views AI as a part of a large family of decision aids. It stresses augmentation rather than substitution, acknowledging the need for transparency, accountability, and human monitoring in financial situations. From TAM, the model emphasizes the socio-psychological aspect of adoption, revealing that technological superiority is insufficient for integration. Perceptions of usefulness, ease of use, and trust are essential for widespread adoption.

By interlacing these strands together, the model displays a rounded perspective: AI is not merely a technical innovation but also a behavioral fix and a socially negotiated instrument whose success is contingent on perceptions and trust.

Textual Outline of the Model

1. **Input:** A human decision situation (biases, bounds of rationality) + data world (structured/unstructured).

2. **AI Intervention:** Machine learning, natural language processing, predictive analytics, and robo-advisory software process inputs, identify patterns, and produce outputs.
3. **Decision-Support Role:** AI outputs are input to DSS, where humans engage with outcomes, read signals, and exercise professional judgment.
4. **Adoption Filter:** The degree to which humans adopt, trust, and depend upon AI hinges on TAM drivers (usefulness, ease of use, transparency, trust).
5. **Output:** Financial decisions augmented by AI (e.g., investments, credit scores, detection of fraud).
6. **Feedback Loop:** Decisions and results create new data that feed back into both AI development and human opinion, affecting future adoption and trust.

Implications of the Proposed Model

1. Theoretical Implications

i. It brings together gaps among technology and finance theory, providing an integrated framework that integrates cognitive, technological, and adoption visions.
ii. It expands on behavioral finance by illustrating how AI not only acts against biases but potentially introduces new kinds of dependency, which requires a revision of • It limits of rationality in an AI world.
iii. It enriches TAM and DSS by placing them within the high-stakes, regulated environment of finance, thus adding domain-specific depth to otherwise generic models.

2. Practical Implications

i. Banks can apply it to develop credit and risk systems that blend human supervision with AI output, providing fairness and accountability.
ii. Investors can apply the framework to reconcile dependence on robo-advisors with human critical judgment, preventing automaticity.
iii. Regulators can apply it to determine where transparency and explainability are most crucial to maintain public trust.

In both instances, the model emphasizes the need for systems to be crafted with AI acting as an assistant rather than a substitute, thereby enhancing decision-making results without sacrificing accountability.

3. Policy Implications

i. Ethical standards are necessary to avoid discriminatory decisions, especially when it comes to lending and credit scoring.
ii. Transparency provisions need to be mandated to ensure that financial systems based on AI provide explanations that are understandable to professionals and consumers alike.
iii. Data governance frameworks need to ensure that AI systems are trained on representative and unbiased datasets to reduce systemic risk.

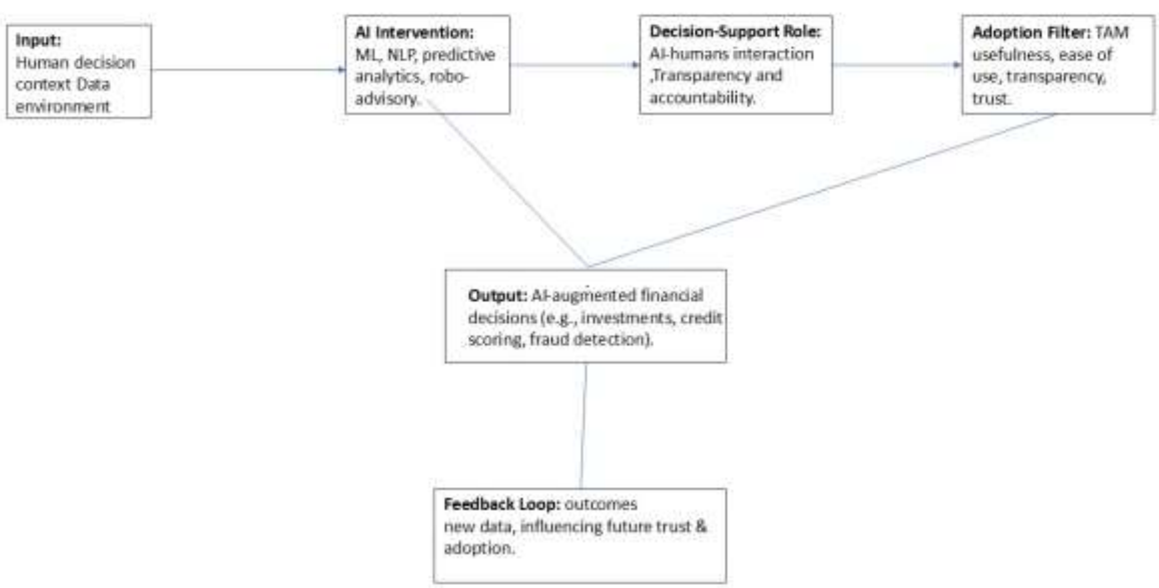
Future Research Directions

The model proposed, though conceptual, throws open several research directions for empirical work:

1. **Human–AI Interaction:** Studies can examine how experts resolve the tension between human intuition and AI suggestions, exploring under what conditions collaboration produces better results.

2. Trust Processes: Longitudinal experiments can measure how trust in AI changes as stakeholders gain experience with it, especially during times of economic crisis.
3. Empirical Tests of Behavioral Corrections: Future studies will be able to empirically investigate the way AI can correct specific biases, including overconfidence or herding, in different financial environments.
4. Cross-Cultural Differences: As different cultures have different perceptions about technology, cross-cultural comparative studies can be carried out to establish the pattern of technology adoption in other financial systems.
5. Regulation Impacts: The researchers may examine how the alteration of regulatory environments influences the design, adoption, and performance of AI-based financial decision-making systems.

The theoretical framework presented here is an effort to integrate different streams of the literature into a single structure for explaining AI as an instrument for making financial decisions. The model integrates behavioral finance, DSS theory, and TAM, which gives priority to the interaction between human cognition, technological ability, and adoption dynamics. Its applications are broad, providing theory contributions, practitioners' guidance, and policy recommendations. Above all, the model highlights the need for addressing AI as much more than a computational technology but as a socio-technical system that influences, and is influenced by, human conduct, organizational form, and regulatory contexts.



Proposed conceptual model of AI in Financial Decision Making

Conclusion

This research has outlined a holistic conceptual model that bridges Artificial Intelligence (AI) and financial decision-making under theoretical frameworks of Behavioral Finance, Decision

Support Systems (DSS), and the Technology Acceptance Model (TAM). The model highlights how AI acts as both revolutionary input and facilitating support that passes through factors of adoption to support more informed financial outputs. Notably, the model has a feedback loop that acknowledges the dynamic quality of financial ecosystems where human learning and AI optimization are in an end-state of constant interaction, which forms the foundation of interdisciplinary research. It offers useful information to banks, investors, and regulators to develop AI-based systems that balance efficiency, transparency, and accountability.

From a policy perspective, the model underscores the need for ethical standards, fairness auditing, and regulatory intervention to protect against over-reliance on obscure algorithms and unforeseen effects. Albeit its merits, the paper acknowledges that this work is still conceptual. Empirical verification is the next decisive step. Future studies must validate the model based on various methods, including surveys among financial practitioners, behavioral experiments mimicking AI-facilitated trading environments, and secondary data analysis (e.g., financial performance metrics of AI-embracing companies). Validation will not only make the model better but also confirm whether the model applies universally, ranging from nascent markets to mature finance centers.

Even though AI could change the financial sector, its achievement will depend on human approval, moral integration, and theoretical basis. The study provides the foundation for future scholarly studies and guides practice in a responsible, evidence-based application of AI in making financial decisions.

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