Ethical Challenges in Adoption of AI in Financial Services: A Conceptual Framework

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ABSTRACT

The rapid integration of artificial intelligence (AI) into financial services has transformed how institutions operate, assess risk, and engage with customers. While AI enhances efficiency, reduces costs, and supports financial inclusion, it also raises significant ethical concerns. This study develops a conceptual understanding of these challenges, focusing on key issues such as algorithmic bias, lack of transparency, data privacy, accountability, and their implications for trust and financial stability. Adopting a conceptual research design, the study synthesises recent literature to examine how ethical risks emerge across different stages of the AI lifecycle, from data collection to deployment and monitoring. Through thematic analysis, a multi-dimensional framework is proposed, integrating ethical risk dimensions, lifecycle stages, and governance mechanisms. The study also advances a set of propositions linking ethical factors with outcomes such as user trust, perceived risk, and AI adoption. The findings reveal that ethical challenges are highly interconnected, with fairness and transparency playing a central role in shaping trust and acceptance. The study highlights the importance of governance mechanisms, including explainable AI and ethical oversight, in mitigating risks. Overall, the research provides a foundation for responsible and sustainable AI adoption in financial services.

Keywords: Artificial Intelligence in Financial Services, AI Ethics, Algorithmic Bias, Explainable AI (XAI), Data Privacy and Governance

INTRODUCTION

The integration of artificial intelligence (AI) into financial services has accelerated rapidly in recent years, fundamentally transforming the way financial institutions operate, assess risk, and engage with customers. AI plays very important role in the success of every business in this modern world (Shrinivas et al.,2025). Technologies such as machine learning, natural language processing, and predictive analytics are now widely embedded in applications ranging from credit scoring and fraud detection to algorithmic trading and robo-advisory platforms. These developments have enhanced efficiency, reduced operational costs, and enabled more personalised financial services (Boukherouaa et al., 2021). At the same time, AI has contributed to broader financial inclusion by enabling access to credit and financial products for previously underserved populations (Fuster et al., 2022; Yang, 2024). Despite these benefits, the adoption of AI in financial services presents a range of ethical challenges that are increasingly attracting the attention of scholars, practitioners, and regulators. One of the most critical ethical concerns is algorithmic bias and fairness. AI systems are inherently dependent on historical data, which may reflect existing social and economic inequalities. As a result, AI-driven decision-making systems can inadvertently perpetuate or even exacerbate discrimination, particularly in areas such as lending, insurance underwriting, and credit scoring (Barocas et al., 2019; Mehrabi et al., 2021). Even in the area of entrepreneurship where creativity has very important role in attracting customers and investors, AI can lead to unethical creativity raising concern on morality and accountability (Kambalapadavu et al.,2026). Empirical research has demonstrated that biased algorithms can lead to unequal access to financial services, disproportionately affecting marginalised groups (Fuster et al., 2022; Hurley & Adebayo, 2017). In the context of financial services, such outcomes raise significant ethical concerns regarding justice, equity, and inclusivity. Addressing algorithmic bias requires not only technical solutions, such as fairness-aware machine learning, but also organisational commitment to ethical principles and inclusive data practices (Mehrabi et al., 2021; Radanliev, 2025).

Closely related to fairness is the issue of transparency and explainability. Many AI models, particularly deep learning systems, function as "black boxes," making it difficult for stakeholders to understand how decisions are generated. This lack of transparency poses serious challenges in financial services, where accountability and regulatory compliance are paramount (Boukherouaa et al., 2021; Guidotti et al., 2019). For example, when a loan application is rejected by an AI system, customers and regulators may demand an explanation for the decision. The inability to provide clear and interpretable explanations can undermine trust and limit the acceptability of AI systems (Doshi-Velez & Kim, 2017; Guidotti et al., 2019). Consequently, the development of explainable AI (XAI) has become a key research priority, aiming to enhance the interpretability of AI systems without compromising their performance (Adadi & Berrada, 2018; Rai, 2020). Data privacy and security represent another major ethical challenge in the adoption of AI in financial services. AI systems rely on vast volumes of personal and financial data, raising concerns about how this data is collected, stored, and used. The increasing use of alternative data sources, such as social media activity and behavioural data, further complicates the ethical landscape by blurring the boundaries between legitimate data usage and intrusive surveillance (Boukherouaa et al., 2021). Data breaches and misuse of sensitive information can have severe consequences for individuals, including financial loss and identity theft (Radanliev, 2025). Moreover, the lack of transparency in data processing practices can erode consumer trust and lead to regulatory challenges, particularly in jurisdictions with strict data protection laws such as the General Data Protection Regulation (GDPR) (Voigt & Von dem Bussche, 2017). Ensuring robust data governance frameworks, informed consent, and ethical data practices is therefore essential. Another important ethical dimension is accountability and responsibility. The autonomous nature of AI systems creates ambiguity regarding who is accountable for decisions and outcomes. In traditional financial systems, responsibility is typically assigned to human decision-makers; however, in AI-driven environments, responsibility may be distributed across developers, data scientists, and financial institutions (Coeckelbergh, 2020; Floridi et al., 2018). This diffusion of responsibility complicates the assignment of liability in cases of harm or error, raising significant ethical and legal concerns. Establishing clear accountability frameworks is therefore crucial to ensure that AI systems are deployed responsibly and that affected stakeholders have access to mechanisms for redress (Floridi et al., 2018; Radanliev, 2025).

Trust and consumer perception also play a vital role in the ethical adoption of AI in financial services. Financial decision-making often involves high levels of uncertainty and risk, making trust a fundamental component of customer relationships. The use of AI can either enhance or undermine trust, depending on how it is implemented and perceived (Gomber et al., 2018; Rai, 2020). Studies indicate that consumers are more likely to trust AI systems that are transparent, fair, and aligned with their expectations (Boukherouaa et al., 2021; Chang, 2026). Conversely, concerns about bias, privacy, and lack of human oversight can lead to scepticism and resistance. Building trust therefore requires not only technical reliability but also ethical design, effective communication, and user education. In addition to individual-level concerns, the adoption of AI in financial services raises broader systemic and societal risks. The increasing reliance on AI-driven systems in financial markets can lead to interconnected risks, where failures in one system may cascade across the financial ecosystem (Danielsson et al., 2022). For instance, algorithmic trading systems operating at high speeds may amplify market volatility and contribute to financial instability. Such systemic risks highlight the need for a holistic approach to AI governance that considers not only micro-level ethical issues but also macro-level implications for financial stability and economic resilience (Boukherouaa et al., 2021; Danielsson et al., 2022).Regulation and governance are therefore central to addressing the ethical challenges associated with AI adoption in financial services. While existing regulatory frameworks provide some guidance, they often struggle to keep pace with the rapid evolution of AI technologies (Arner et al., 2017; Zetzsche et al., 2020). Recent efforts by international organisations and policymakers emphasise the need for adaptive, risk-based regulatory approaches that balance innovation with ethical responsibility (OECD, 2019; European Commission, 2021). These approaches include the development of ethical guidelines, industry standards, and auditing mechanisms to ensure that AI systems operate in a fair, transparent, and accountable manner. Furthermore, interdisciplinary collaboration among technologists, ethicists, and regulators is essential to address the complex and evolving nature of AI ethics in financial services.

In conclusion, while AI offers significant opportunities for innovation and efficiency in financial services, its adoption is accompanied by a range of ethical challenges that must be carefully managed. Issues related to bias, transparency, privacy, accountability, trust, and systemic risk underscore the need for a comprehensive and ethically grounded approach to AI implementation. Addressing these challenges requires a combination of technical solutions, organisational practices, and regulatory frameworks that prioritise ethical considerations alongside economic objectives. As the financial sector continues to evolve in the age of AI, ensuring that these technologies are developed and deployed responsibly will be critical to maintaining public trust and achieving sustainable growth.

Theoretical Framework

The growing body of literature on the adoption of artificial intelligence (AI) in financial services reflects both the transformative potential of these technologies and the complex ethical challenges they introduce. Since 2018, scholarly attention has increasingly focused on examining how AI reshapes financial decision-making processes while simultaneously raising concerns related to fairness, transparency, accountability, and data governance. This section critically reviews recent literature from reputable academic databases, synthesising key themes and identifying gaps that continue to shape the discourse on ethical AI in finance.

A dominant theme across the literature is the pervasive issue of algorithmic bias and fairness. Several studies emphasise that AI systems in finance are heavily reliant on historical datasets, which often embed existing socio-economic inequalities (Mehrabi et al., 2021; Fuster et al., 2022). As a result, AI-driven credit scoring and lending decisions may inadvertently discriminate against certain demographic groups, thereby reinforcing financial exclusion (Bahlool et al., 2026). A systematic review by Bahlool et al. (2026) highlights that despite the high predictive performance of AI-based credit scoring models, concerns regarding fairness and ethical compliance significantly constrain their adoption in high-stakes financial decisions. Furthermore, Yang (2024) demonstrates that perceived algorithmic fairness directly influences user satisfaction and trust in AI-enabled financial inclusion services. These findings collectively suggest that fairness is not merely a technical attribute but a central ethical requirement that determines both the legitimacy and acceptance of AI systems in finance.

Another extensively discussed ethical concern is the lack of transparency and explainability in AI models. The literature consistently identifies the "black-box" nature of many machine learning algorithms as a critical barrier to trust and accountability (Guidotti et al., 2019; Rai, 2020). A comprehensive systematic review by Černevičienė and Kabašinskas (2024) reveals that explainability is essential for improving risk assessment, enhancing trust, and ensuring regulatory compliance in financial applications. Similarly, recent bibliometric analyses indicate a growing emphasis on explainable AI (XAI) as a means to bridge the gap between model complexity and interpretability in finance (Yeo et al., 2023). The literature further suggests that explainability is particularly crucial in applications such as credit approval and fraud detection, where decisions must be justified to both customers and regulators (Oyasiji et al., 2023; Chopra, 2024). Despite advancements in XAI techniques, scholars argue that a consensus on standardised explainability metrics and frameworks remains lacking, indicating an important area for future research. Data privacy and security emerge as another critical ethical dimension in the literature. The increasing reliance on large-scale personal and behavioural data in AI systems has raised concerns about data misuse, surveillance, and breaches (Boukherouaa et al., 2021). Studies highlight that financial institutions are increasingly utilising alternative data sources, including social media and digital footprints, to enhance predictive accuracy, thereby intensifying ethical concerns surrounding consent and privacy (Malali, 2025). Wang (2024) further notes that existing regulatory frameworks, such as GDPR, provide a foundation for data protection; however, gaps in implementation and enforcement continue to pose risks to consumer rights. This strand of literature underscores the need for robust data governance frameworks that balance innovation with ethical responsibility, particularly in contexts where sensitive financial data is involved.

Accountability and responsibility represent another significant area of scholarly debate. The literature highlights that the autonomous nature of AI systems complicates the attribution of responsibility for decisions and outcomes (Floridi et al., 2018; Coeckelbergh, 2020). Chopra (2024) argues that the diffusion of responsibility across developers, financial institutions, and regulators creates ambiguity in cases of algorithmic failure or harm. Similarly, Malali (2025) emphasises the need for clearly defined accountability frameworks to ensure that ethical standards are upheld throughout the AI lifecycle. Recent research also points to the importance of integrating governance mechanisms, such as audit trails and ethical oversight committees, to enhance accountability in AI-driven financial systems (Fundira & Mbohwa, 2025). These studies collectively highlight that accountability is not only a legal necessity but also a cornerstone of ethical AI adoption. Trust and user perception are increasingly recognised as critical factors influencing the adoption of AI in financial services. The literature suggests that trust is shaped by multiple ethical dimensions, including fairness, transparency, and reliability (Gomber et al., 2018; Rai, 2020). Empirical evidence indicates that users are more likely to accept AI-driven financial services when they perceive the underlying algorithms as fair and transparent (Yang, 2024). Conversely, concerns about opaque decision-making and data misuse can undermine trust and hinder adoption (Černevičienė & Kabašinskas, 2024). This highlights the importance of adopting a user-centric approach to AI design, where ethical considerations are integrated into both technical development and customer engagement strategies.

In addition to micro-level ethical concerns, the literature also addresses broader systemic risks associated with AI adoption in financial markets. Scholars argue that the increasing reliance on AI-driven systems may lead to interconnected risks, where failures or biases in one system can propagate across the financial ecosystem (Danielsson et al., 2022). The literature further suggests that algorithmic trading and automated decision-making systems may amplify market volatility and contribute to financial instability if not properly regulated (Boukherouaa et al., 2021). These findings indicate that ethical considerations in AI extend beyond individual institutions to encompass the stability and resilience of the entire financial system. Regulation and governance frameworks are therefore central to addressing the ethical challenges identified in the literature. Several studies highlight that existing regulatory approaches are often reactive and fragmented, struggling to keep pace with the rapid evolution of AI technologies (Zetzsche et al., 2020). A recent systematic review by Fundira and Mbohwa (2025) emphasises that while regulatory efforts have increased, significant gaps remain in ensuring comprehensive oversight of AI applications in banking. Similarly, Oyasiji et al. (2023) argue that effective regulation must balance innovation with ethical considerations, promoting transparency, fairness, and accountability. The literature also points to the growing importance of international guidelines, such as those proposed by the OECD and the European Commission, in shaping ethical AI governance.

Despite the substantial progress in understanding ethical challenges, the literature reveals several gaps that warrant further investigation. First, there is a lack of standardised frameworks for evaluating ethical AI in financial services, particularly in relation to fairness and explainability. Second, empirical studies examining the real-world impact of ethical AI practices on organisational performance and customer outcomes remain limited. Third, interdisciplinary research integrating perspectives from finance, computer science, law, and ethics is still emerging, highlighting the need for more holistic approaches to studying AI ethics.

In conclusion, the literature on ethical challenges in the adoption of AI in financial services underscores the multifaceted nature of the issue. While AI offers significant benefits in terms of efficiency, accuracy, and innovation, it also introduces complex ethical concerns related to bias, transparency, privacy, accountability, trust, and systemic risk. Addressing these challenges requires a comprehensive approach that combines technological innovation with robust governance frameworks and ethical awareness. As the financial sector continues to evolve, future research must focus on developing practical solutions that ensure the responsible and sustainable use of AI, thereby aligning technological advancement with societal values.

METHODOLOGY

Research Design

This study adopts a conceptual research design aimed at developing a theoretically grounded understanding of the ethical challenges associated with the adoption of artificial intelligence (AI) in financial services. Conceptual research is particularly suitable for emerging and interdisciplinary domains, where knowledge remains fragmented and requires integration into coherent frameworks (Jaakkola, 2020; Gilson & Goldberg, 2015). Rather than relying on primary data collection, this study synthesises existing scholarly insights to identify key constructs, relationships, and underlying mechanisms shaping ethical AI adoption. Such an approach enables the development of a multi-dimensional conceptual framework, offering both theoretical clarity and practical relevance (Saxena, 2022; Saheb et al., 2022). The research design follows a theory-building approach, focusing on the integration and interpretation of prior literature to generate new conceptual insights (Jaakkola, 2020). This approach is particularly appropriate in the context of AI in financial services, where rapid technological advancements often outpace empirical validation and regulatory development.

Literature Identification and Selection

To support the conceptual development, this study employs a structured and critical review of contemporary literature. While not a formal systematic literature review, the process follows a transparent and rigorous approach to ensure the inclusion of relevant and high-quality sources. Relevant literature was identified through searches in leading academic databases, including Scopus, Web of Science, Science Direct, Springer Link, IEEE Xplore, and Emerald Insight. These databases were selected due to their strong coverage of interdisciplinary research spanning finance, technology, and ethics (Amoako et al., 2021).

The search strategy utilised a combination of keywords such as:

- "artificial intelligence in financial services"
- "AI ethics in finance"
- "algorithmic bias in banking"
- "explainable AI financial services"
- "AI governance and accountability"

Boolean operators (e.g., AND, OR) were applied to refine the search and ensure comprehensive coverage of relevant studies.

The initial search yielded a broad pool of literature (approximately 400+ studies). Through iterative screening based on relevance, quality, and conceptual contribution, a refined set of key studies was selected to inform the analysis. Priority was given to peer-reviewed journal articles and high-quality conference papers published from 2018 onwards, ensuring alignment with recent developments in AI technologies.

Inclusion and Exclusion Criteria

To enhance the rigour and relevance of the study, explicit inclusion and exclusion criteria were applied.

Inclusion Criteria

- Peer-reviewed publications indexed in reputable databases
- Studies published from 2018 onwards
- Research addressing AI adoption in financial services or closely related domains
- Studies discussing ethical dimensions such as fairness, transparency, privacy, accountability, or governance

Exclusion Criteria

- Studies focusing solely on technical or algorithmic performance without ethical considerations
- Research unrelated to financial services or socio-economic implications
- Non-scholarly sources, including editorials, opinion pieces, and non-peer-reviewed materials

- Studies lacking theoretical or conceptual relevance to AI ethics

This structured filtering ensured that the selected literature provided a robust foundation for conceptual synthesis, consistent with best practices in conceptual research (Jaakkola, 2020; Amoako et al., 2021).

Analytical Approach: Thematic and Conceptual Synthesis

The study employs a thematic analysis approach to systematically identify and synthesise key ethical challenges associated with AI adoption. Thematic analysis is widely recognised as an effective method for organising and interpreting qualitative data in conceptual research (Braun & Clarke, 2006; Saheb et al., 2022).

The analysis was conducted in three stages:

Open Coding

In the initial stage, selected studies were examined to identify recurring ethical themes. Key themes emerging from the literature included:

- Algorithmic bias and fairness
- Transparency and explainability
- Data privacy and security
- Accountability and governance
- Trust and user perception
- Systemic and regulatory risks

Axial Coding

In the second stage, these themes were grouped into broader conceptual categories, establishing relationships between ethical challenges and AI adoption processes. For example, issues of transparency were closely linked to explainability and trust, while bias was associated with data quality and model design.

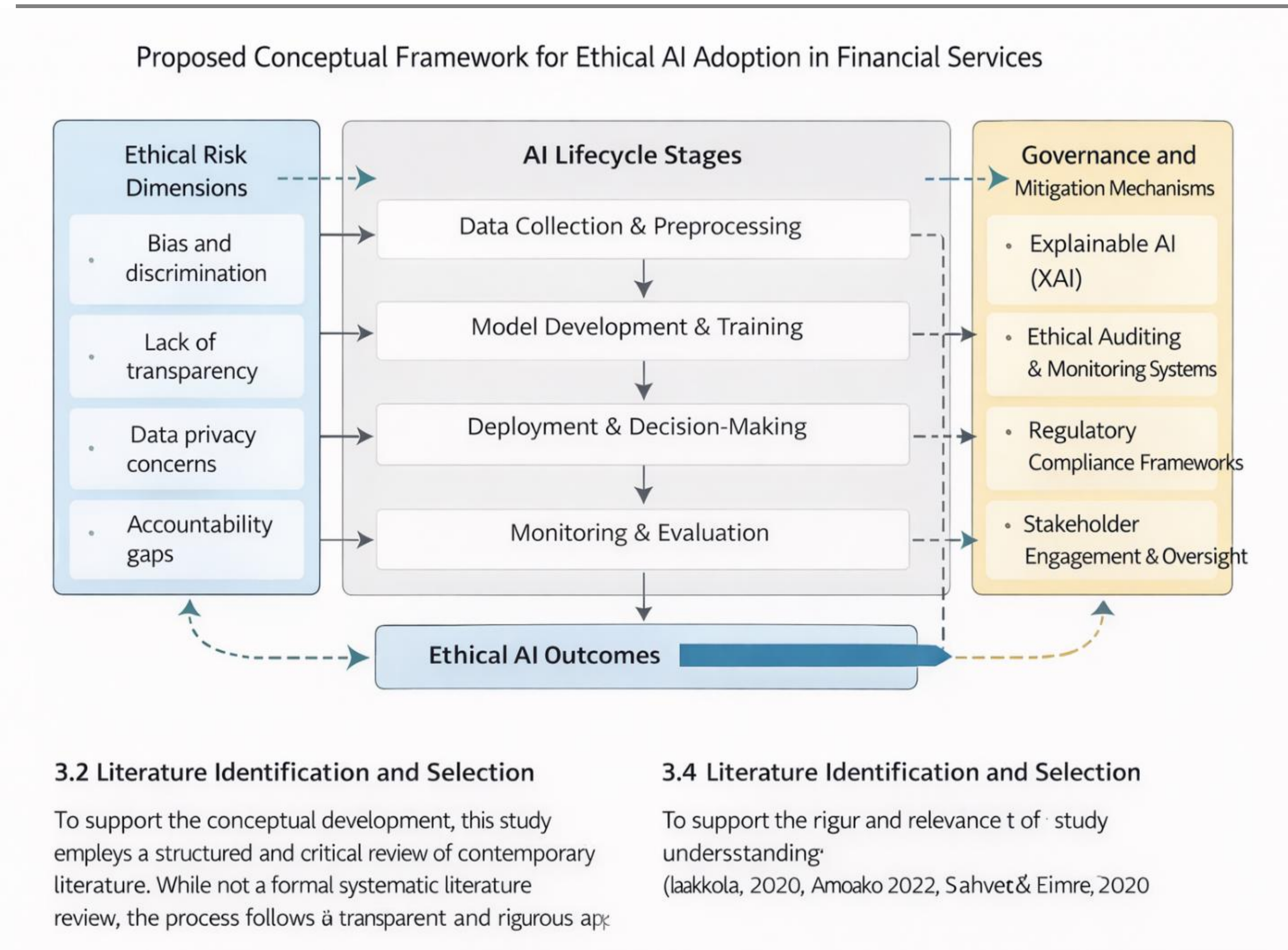
Selective Coding

In the final stage, the identified categories were synthesised into a coherent conceptual structure, highlighting how ethical challenges interact across different stages of AI implementation. This integrative approach enables a deeper understanding of the dynamic and interconnected nature of ethical issues in AI-driven financial systems.

Development of the Conceptual Framework

Figure 1- Conceptual Framework.

Figure 1 presents the proposed conceptual framework for ethical AI adoption in financial services. The framework illustrates the relationships between key ethical risk dimensions, including algorithmic bias, transparency, data privacy, and accountability, and their influence on critical outcomes such as trust, perceived risk, and user acceptance. These outcomes subsequently affect AI adoption, system reliability, and sustainable implementation. The framework further highlights the moderating role of governance and mitigation mechanisms, such as explainable AI, ethical auditing, and regulatory compliance, in reducing ethical risks. Additionally, the framework adopts a lifecycle perspective by embedding these ethical considerations across the stages of data collection, model development, deployment, and monitoring.



Building on the thematic synthesis, this study develops a multi-dimensional conceptual framework for ethical AI adoption in financial services. Conceptual frameworks are essential tools for structuring complex phenomena and guiding both academic research and practical implementation (Saxena, 2022; Zimmermann et al., 2020).

The proposed framework is organised around three interrelated dimensions:

Ethical Risk Dimensions

This dimension captures the primary ethical challenges identified in the literature, including:

- Bias and discrimination
- Lack of transparency
- Data privacy concerns
- Accountability gaps

AI Lifecycle Stages

Ethical challenges are mapped across key stages of AI implementation:

- Data collection and preprocessing
- Model development and training
- Deployment and decision-making

- Monitoring and evaluation

Governance and Mitigation Mechanisms

This dimension outlines strategies to address ethical challenges, including:

- Explainable AI techniques
- Ethical auditing and monitoring systems
- Regulatory compliance frameworks
- Stakeholder engagement and oversight

This integrative structure ensures that ethical considerations are embedded throughout the AI lifecycle, rather than treated as isolated concerns.

Philosophical and Theoretical Underpinning

The study is grounded in a normative ethical perspective, drawing on principles such as fairness, accountability, transparency, and responsibility (Floridi et al., 2018). These principles provide a foundation for evaluating the ethical implications of AI adoption in financial services. Additionally, the study adopts a socio-technical systems perspective, recognising that AI implementation is shaped by interactions between technological systems, organisational practices, and human decision-makers. This perspective enables a more holistic understanding of ethical challenges in real-world contexts (Chia, 2025).

Validity and Rigour

To ensure academic rigour and credibility, several measures were adopted:

- **Triangulation of sources**: Literature from multiple databases and disciplines was analysed.
- **Structured selection process**: Clear inclusion and exclusion criteria ensured consistency
- **Iterative analysis**: Themes were refined through multiple stages of coding
- **Conceptual coherence**: Strong alignment between literature, analysis, and framework

These practices enhance the trustworthiness and theoretical robustness of the study (Jaakkola, 2020; Saheb et al., 2022).

Contribution of the Methodology

This methodology contributes to the literature in three key ways. First, it provides a structured synthesis of fragmented research on ethical AI in financial services. Second, it develops a comprehensive conceptual framework integrating ethical, technological, and governance dimensions. Third, it establishes a foundation for future empirical research, enabling scholars to test and refine the proposed framework in real-world contexts.

Propositions Development

Based on the conceptual synthesis of the literature, this study proposes the following propositions to explain the relationships between ethical challenges, governance mechanisms, and AI adoption outcomes in financial services.

P1: Algorithmic Bias and Trust

Algorithmic bias negatively influences user trust in AI-driven financial services.

Bias embedded in training data can lead to discriminatory outcomes, particularly in credit scoring and lending decisions, thereby undermining perceived fairness and trust (Mehrabi et al., 2021; Fuster et al., 2022). Reduced trust may ultimately hinder the adoption of AI-based financial solutions.

P2: Transparency and User Acceptance

Transparency and explainability of AI systems positively influence user acceptance of AI-driven financial services.

Transparent AI systems enhance interpretability, enabling users to understand decision-making processes, which fosters confidence and acceptance (Rai, 2020; Guidotti et al., 2019).

P3: Data Privacy and Perceived Risk

Data privacy concerns positively influence perceived risk associated with AI adoption in financial services.

The extensive use of personal and behavioural data in AI systems raises concerns about misuse and surveillance, increasing users' perception of risk (Boukherouaa et al., 2021).

P4: Accountability and Institutional Trust

Clear accountability mechanisms positively influence institutional trust in AI-enabled financial systems.

The presence of defined responsibility structures and governance frameworks enhances confidence among stakeholders by ensuring ethical compliance and recourse mechanisms (Floridi et al., 2018; Coeckelbergh, 2020).

P5: Governance Mechanisms and Ethical Risk Mitigation

Effective governance mechanisms (e.g., explainable AI, ethical auditing) significantly reduce ethical risks in AI adoption.

Governance tools such as explainable AI and audit systems play a critical role in mitigating bias, enhancing transparency, and ensuring accountability (Dwivedi et al., 2021; Saheb et al., 2022).

P6: Ethical AI Practices and Customer Trust

Ethical AI practices positively influence customer trust and long-term engagement in financial services.

When AI systems are perceived as fair, transparent, and secure, customers are more likely to engage with and rely on such technologies (Gomber et al., 2018; Rai, 2020).

P7: Lifecycle-Based Ethical Management and System Reliability

Integration of ethical considerations across the AI lifecycle enhances system reliability and decision quality.

Embedding ethical checks at each stage—from data collection to monitoring—ensures continuous evaluation and reduces the likelihood of harmful outcomes (Boukherouaa et al., 2021).

Ethical Governance and Sustainable AI Adoption

Strong ethical governance frameworks positively influence the sustainable adoption of AI in financial services.

Regulatory compliance, stakeholder oversight, and ethical standards contribute to long-term sustainability and societal acceptance of AI technologies (OECD, 2019; European Commission, 2021).

DISCUSSION

This study contributes to the growing discourse on AI in financial services by offering **a** holistic conceptual framework that integrates ethical challenges, lifecycle stages, and governance mechanisms. The findings highlight that ethical concerns are not isolated issues but are deeply interconnected and embedded across the entire AI adoption process. A key insight emerging from the analysis is that algorithmic bias remains one of the most critical barriers to ethical AI adoption. Consistent with prior research, biased data and models can reinforce existing socio-economic inequalities, thereby undermining fairness and inclusivity (Mehrabi et al., 2021; Fuster et al., 2022). This finding reinforces the need for financial institutions to move beyond performance-driven AI models towards fairness-aware systems. The study also underscores the importance of transparency and explainability in fostering trust and acceptance. While AI systems offer efficiency and predictive accuracy, their opaque nature often creates scepticism among users. The propositions suggest that enhancing explainability is not merely a technical requirement but a strategic necessity for improving user confidence and regulatory compliance (Rai, 2020; Guidotti et al., 2019).

Although this study adopts a conceptual research design, the proposed framework is supported by prior empirical evidence in the literature. For example, Yang (2024) found that perceived algorithmic fairness significantly enhances user satisfaction and trust in AI-enabled financial inclusion services. Similarly, Chang et al. (2026) demonstrated that transparency and explainability positively influence consumer trust in AI-based financial advisory systems. In addition, Fuster et al. (2022) empirically revealed that machine learning models in credit markets may create unequal outcomes, thereby negatively affecting fairness perceptions and trust. These empirical findings provide preliminary validation for the relationships proposed in this study and strengthen the practical relevance of the conceptual framework.

Another significant contribution of this study is the identification of data privacy as a central ethical concern. The increasing reliance on alternative data sources raises questions about consent, surveillance, and data ownership. This aligns with emerging literature emphasising the tension between innovation and privacy protection in AI-driven financial systems. Importantly, the study highlights the role of governance mechanisms as a mediating force between ethical risks and AI outcomes. Governance tools such as explainable AI, ethical audits, and regulatory frameworks are shown to mitigate risks and enhance system reliability. This finding extends existing research by demonstrating that ethical AI adoption is not solely dependent on technological design but also on institutional and regulatory structures (Dwivedi et al., 2021).

AI ethics regulations differ considerably across countries and regions, shaping how financial institutions implement and govern AI systems. The European Union follows a risk-based regulatory approach through the Artificial Intelligence Act and the General Data Protection Regulation (GDPR), with a strong emphasis on transparency, accountability, and data privacy. In contrast, the United States adopts a more sector-specific and market-driven approach, relying on agency-level guidelines from institutions such as the Securities and Exchange Commission (SEC), Federal Trade Commission (FTC), and Consumer Financial Protection Bureau (CFPB). China employs a state-centric governance model, focusing on algorithm registration, cybersecurity, and state oversight of digital platforms. Meanwhile, countries such as India are gradually strengthening their data protection and AI governance through the Digital Personal Data Protection Act and emerging AI policies. In the Gulf region, including Oman, AI-specific regulations are still evolving, often embedded within broader digital transformation and financial governance initiatives. These variations indicate that ethical AI adoption in financial services is strongly influenced by the regulatory environment of each jurisdiction.

Region/Country	**Key Regulation/Framework**	**Primary Focus**
European Union	AI Act, GDPR	Privacy, transparency, accountability
United States	FTC, SEC, CFPB guidelines	Consumer protection and fair practice
China	Algorithmic Recommendation Regulations	State oversight and cybersecurity

India	DPDP Act, NITI Aayog AI Strategy	Data protection and innovation
Oman/GCC	Emerging AI and digital governance frameworks	Digital transformation and compliance

Furthermore, the integration of ethical considerations across the AI lifecycle provides a dynamic perspective on AI governance. Rather than addressing ethical issues reactively, the framework advocates for a proactive and continuous approach, ensuring that ethical principles are embedded from data collection to post-deployment monitoring. Overall, the study advances the literature by bridging the gap between fragmented ethical concerns and practical implementation strategies, offering a comprehensive understanding of how ethical AI can be operationalised in financial services.

Implications

This study offers significant theoretical, practical, and societal implications for the adoption of ethical AI in financial services. Theoretically, it contributes by integrating key ethical dimensions—such as bias, transparency, privacy, and accountability—into a unified framework, while introducing a lifecycle-based perspective that extends beyond static models of AI ethics. It further bridges the gap between technology-driven and governance-oriented research and provides a proposition-based foundation for future empirical validation, thereby fostering a more holistic and theory-driven understanding of ethical AI adoption. From a practical standpoint, the findings offer actionable insights for multiple stakeholders. Financial institutions are encouraged to implement fairness-aware models, invest in explainable AI tools, and establish continuous ethical auditing systems. Regulators and policymakers should focus on developing adaptive regulatory frameworks, promoting standardised ethical guidelines, and strengthening accountability mechanisms. Meanwhile, technology developers must embed ethical considerations into AI design, ensure privacy-preserving data practices, and engage with stakeholders to enhance trust and usability. At a broader level, the study underscores that ethical AI adoption is not merely a technical or organisational concern but a societal necessity, with the potential to enhance financial inclusion, reduce systemic inequalities, and strengthen public trust in financial systems.

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