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The Role of Explainable AI in Enhancing Trust and Decision-Making in Financial Services

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Abstract

The use of AI in the finance sector is rapidly becoming essential to its key operations, including risk management, fraud detection, and investment analysis. This study examined the application of Explainable AI (XAI) to enhance transparency, trust, and informed decision-making in the financial sector. The research employed a mixed-methods approach, as it was appropriate given the quantitative data collected through the Likert survey and the qualitative data collected through academic literature, case studies, and regulatory documents. Quantitative data were analyzed using JASP (independent t-tests, correlation analysis, and regression analysis) and JAMOVI (Exploratory Factor Analysis). The qualitative data were analyzed through taguette in order to determine the themes. The findings of this study indicated that XAI was viewed as a significant tool in the decision-making process, and the level of trust in the finance sector increased. Transparency advances the quality and level of decisions made by finance professionals, which subsequently boosts the trust and quality of the AI systems. The qualitative analysis revealed the themes of the role of XAI in fostering trust, the importance of transparency in enhancing interpretability, and the constraints to XAI application, including the trade-off between complexity and explainability.

Keywords: Explainable Artificial Intelligence (XAI), Interpretability, Regulatory compliance, Transparency, Trust in AI systems, XAI Principles, XAI Techniques.

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1. Introduction

Technological innovation has always been popular in the financial sector, and artificial intelligence (AI) is one of the most revolutionary aspects of its development. Financial services are increasingly adopting AI apps in decision-making, operational performance, and customer engagement (Alt et al., 2018). Although the use of AI in the financial context has undergone significant changes in recent years, the history of introducing AI into this sphere dates back to the 1960s, when the idea of applying Bayesian statistics to auditing and the stock market was initially proposed (Rius, 2023). The concept of pioneer researchers, such as Louis Bachelier, who introduced statistical modeling in finance, and Robert Schlaifer, who introduced Bayesian decision theory, has inspired the AI-based analytics that are now beginning to emerge in financial practice. In the 1980s and 1990s, AI was increasingly applied commercially, particularly in expert systems and neural networks. Financial institutions have introduced knowledge-based systems in personal financial planning, market analysis, and fraud detection. In another example, the FinCEN Artificial Intelligence System (FAIS) enabled the detection of money laundering by inspecting over 200,000 transactions per week, demonstrating how AI can improve financial management (Pokhariya et al., 2022). With the advancement of AI technologies, not only is cash flow forecasted with the help of AI, but also control over regulatory aspects and financial reporting is offered through machine learning, natural language processing, and optical character recognition (Singh et al., 2023). Irrespective of such developments, issues persist, the most prominent of which is the black box problem. The models involved in deep neural networks, random forests, and support vector machines are too complex and often lack transparency; therefore, their rationale remains unclear. This lack of transparency compromises accountability, criticism of bias, and adherence to rules and regulations, including the European Union's General Data Protection Regulation (GDPR), which requires accountability in automated decision-making (Rudin, 2019). Biased or non-transparent models can discriminate unintentionally in credit scoring or loan issuance, which is detrimental to both financial institutions and their customers.

To address these issues, Explainable AI (XAI) has emerged as a framework to enhance the explainability of AI systems. Based on early expert systems of the 1980s and 1990s, which were characterized by rule-based explanations, XAI provides transparency by explaining the process by which models generate their outputs (Swartout & Moore, 1991). Post-hoc interpretability of complex models can be provided by these approaches, such as Local Interpretable Model-agnostic Explanations (LIME) and Shapley Additive exPlanations (SHAP). In contrast, simpler algorithms can be understood through approaches like feature importances in decision trees (Arrieta et al., 2020). XAI allows gaining confidence, enhancing decision-making, and ensuring adherence to ethical and regulatory norms by enhancing the comprehensibility of AI models (Adadi & Berrada, 2018). The issue underlying the present research is that AI models are opaque in the financial sector, which limits their applicability and usefulness in situations where accountability is required. Although deep learning and sophisticated statistical techniques achieve a high rate of accuracy, they are often too complex to be understood by many financial experts and clients. Such increases pose important questions of how institutions can balance between performance and transparency, especially when the outcomes of decisions directly relate to both financial stability and personal welfare.

The purpose of this research is to investigate the role of XAI in enhancing trust and informed decision-making within the financial services sector. Specifically, it examines how XAI techniques influence stakeholder confidence, the principles and methods most effective in finance, and the challenges professionals face when interpreting insights generated by AI. The research also examines the impact of XAI adoption on customer-facing applications, regulatory compliance, and ethical practices. The research questions guiding are as follows:

i. How does Explainable AI influence trust and decision-making processes in the financial services industry
ii. What are the fundamental principles and techniques of Explainable AI that could enhance decision-making in underexplored areas such as risk management and customer services?
iii. How do financial institutions currently implement AI, and where are the gaps in adopting XAI?
iv. What challenges do financial professionals face when interpreting AI-generated insights, particularly in high-stakes decisions such as credit risk assessments?
v. How does integrating XAI into customer-facing applications influence customer trust and satisfaction?
vi. What are the regulatory and ethical challenges in adopting XAI, and how can XAI assist in meeting compliance standards?
vii. What are the experiences and outcomes of financial institutions that have successfully implemented XAI in decision-making processes?

2. Theoretical Framework

The two theories underpinning the study are the Theory of Trust in Automation (TiA) and the Model Interpretability Framework. TiA) highlights the role of trust when humans rely on AI-driven systems in fields like finance, where tasks such as credit risk assessment and fraud detection are increasingly automated. Trust becomes essential because automation introduces uncertainty into the decision-making process. Muir (1994) identifies three key elements of trust in automation: performance (the system's reliability in meeting user goals), process (the transparency and consistency of how the system works), and purpose (the alignment of system design with user needs). Users are more likely to trust AI systems when they are dependable, understandable, and aligned with their intended goals, mirroring how interpersonal trust develops in human relationships.

The Model Interpretability framework focuses on making AI models comprehensible to humans. While definitions vary, this study emphasizes Mueller et al (2019) view that interpretability means explaining models in terms understandable to users. Criteria such as clarity (a single, unambiguous rationale) and parsimony (simplicity) help determine understandability. Interpretability techniques include post-hoc methods (e.g., LIME, SHAP, PDP, Anchors) that explain complex models, as well as inherently interpretable models designed for transparency from the outset (Ahmad et al., 2018).

3. Methodology

This research employed a mixed-methods research design, integrating quantitative and qualitative approaches to capture both measurable patterns and contextual insights on Explainable AI (XAI) in the financial services sector. Mixed methods were chosen because quantitative or qualitative data alone would not provide a sufficient understanding of both trends and underlying explanations. Guided by the principle of pragmatism, the design emphasized "what works" in addressing the research questions (Creswell, 1999; Creswell & Plano Clark, 2023).

Quantitative methods involved a structured survey distributed through Jotform. A Likert-scale questionnaire measured professionals' perceptions of trust, familiarity, transparency, reliability, decision-making, challenges, regulatory compliance, and user experience with XAI. Demographic questions provided context for analyzing responses by role and experience level. Specific sections assessed trust in AI systems, perceived transparency, the role of XAI in financial decision-making, barriers to adoption, and ethical or regulatory concerns. The Likert design allowed nuanced responses, supporting both descriptive and inferential analyses.

The qualitative phase complemented the survey by analyzing academic literature, case studies, and regulatory documents. A systematic literature review (SLR) was conducted using databases such as IEEE Xplore, Google Scholar, and ScienceDirect, applying strict inclusion and exclusion criteria. Search terms aligned with survey themes, ensuring coherence across phases. Selected studies were coded using Taguette, and thematic categories were developed to link XAI applications to specific financial areas. Case studies were then cross-analyzed to identify implementation strategies, challenges, and outcomes, while regulatory documents provided insights into compliance frameworks, transparency requirements, and ethical guidelines shaping XAI adoption.

The participants were professionals in the financial services industry with experience in AI or XAI. The target population was 100 individuals (50 technical, 50 non-technical), but 230 surveys were distributed to increase representation and minimize sampling error. Ultimately, purposive and stratified sampling were used to ensure participants had relevant expertise. Purposive sampling targeted those with knowledge of AI, while stratification by technical versus non-technical roles enabled comparisons between groups. Recruitment was conducted via LinkedIn, where profiles were manually screened for suitability, enhancing the quality of responses.

Data analysis followed a two-stage process. Quantitative data were analyzed using independent-sample t-tests to compare technical and non-technical groups, correlation analyses to examine relationships among trust, familiarity, transparency, and decision-making, and regression analysis to test predictors of trust in AI systems. Exploratory factor analysis (EFA) was used to examine the interrelationships between variables further. All analyses were conducted in JASP and JAMOVI. Qualitative findings were triangulated with quantitative results, offering contextual explanations for numerical trends and strengthening validity.

Ethical considerations were strictly observed. Participants were contacted via LinkedIn with informed consent forms outlining the purpose of the study, voluntary participation, and confidentiality measures. Withdrawal was permitted at any time, and anonymity was preserved unless disclosure was legally required. Transparency and honesty were prioritized, ensuring no deception occurred during the process.

4. Results

4.1 Quantitative Results

Demographics: A total of 228 participants completed the survey, split between non-technical (n = 116) and technical (n = 112) roles. Most had 3–5 years of professional experience (56.6%), with fewer reporting over five years (18.9%) or less than one year (6.1%). Respondents expressed very high trust in AI (M = 9.15, SD = 1.204) and strong familiarity with AI concepts (M = 9.48, SD = 1.159). They rated XAI highly for transparency (M = 4.79, SD = 0.511), decision-making support (M = 4.79, SD = 0.499), ethics (M = 4.83, SD = 0.396), and overall user experience (M = 4.86, SD = 0.424) as in Figure 1 below.

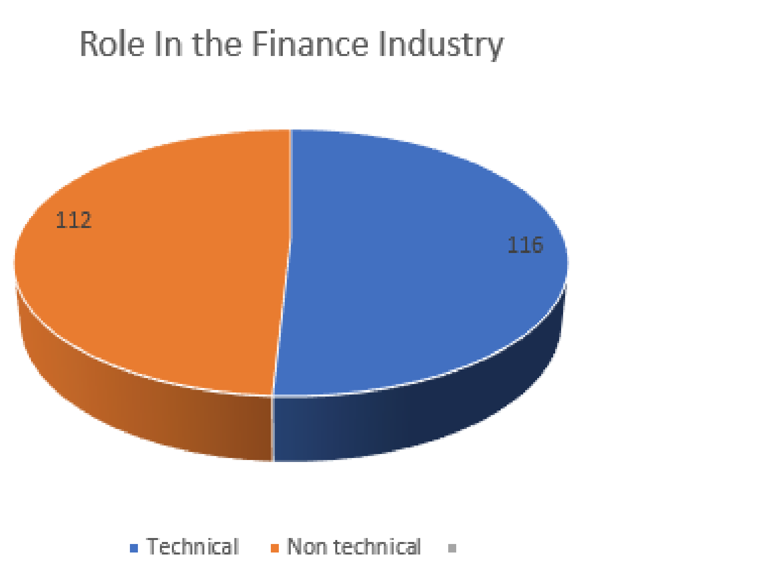

Figure 1: Summary of Demographics

Independent t-tests: Independent t-tests revealed significant differences between technical and non-technical respondents. Technical participants perceived XAI as offering more explicit guidance ($p = 0.004$), expressed higher levels of trust ($p = 0.012$), and rated the decision quality more positively ($p = 0.035$). They also felt better able to interpret AI outputs ($p = 0.008$), though were less convinced that XAI addresses broader challenges ($p = 0.009$). Non-technical respondents reported lower confidence ($p = 0.006$) and greater ethical skepticism ($p = 0.018$). No significant differences were found for understanding AI functionality, actionability of decisions, or overall user experience, with both groups generally positive.

Correlation Analysis between Variables: Correlation analysis showed that familiarity with AI concepts strongly predicted trust in AI ($r = 0.662$, $p < 0.001$). Familiarity was also positively linked to perceptions of transparency, including the belief that XAI provides clear explanations ($r = 0.368$, $p < 0.001$) and helps users understand AI conclusions ($r = 0.283$, $p < 0.01$). Trust in AI correlated with confidence when XAI was applied ($r = 0.359$, $p < 0.01$) but not with decision-specific confidence. Transparency perceptions related to improved decision quality ($r = 0.396$, $p < 0.01$). Interestingly, higher trust in AI was negatively associated with the perceived necessity of XAI for ethical practices ($r = -0.233$, $p < 0.01$).

Regression Analysis: Regression models identified multiple predictors of trust in AI systems. Transparency and understanding significantly explained variance in trust ($F(2,225) = 21.559$, $p < 0.001$). Adding reliability factors increased the explanatory power, followed by variables related to decision-making, challenges, ethics, and user experience. The strongest predictors included clarity of explanations ($\beta = 0.199$, $p = 0.004$), improved decision-making quality ($\beta = 0.222$, $p = 0.001$), and increased trust when XAI techniques were used ($\beta = 0.207$, $p = 0.002$). Barriers such as difficulty interpreting AI without XAI were also significant ($\beta = 0.149$, $p = 0.032$) as in Figure 2 below. Overall, transparency, reliability, and decision-making emerged as the most consistent contributors to trust.

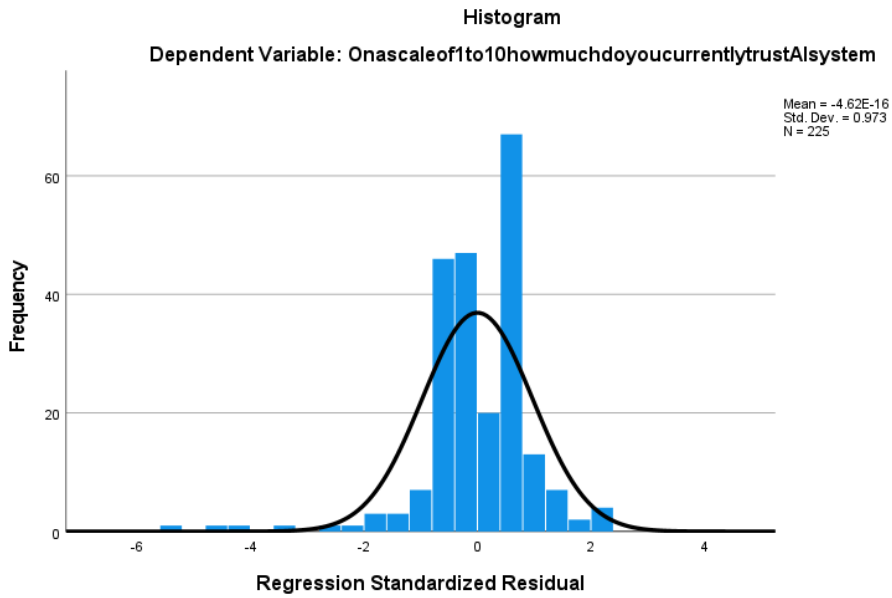

Figure 2: Summary of predicting factors for "Trust In AI Systems"

Exploratory Factor Analysis (EFA): The EFA revealed four underlying dimensions of user perceptions of XAI. Factor 1 combined trust, decision-making, and familiarity, indicating that individuals with greater understanding perceived higher trust and better decision outcomes. Factor 2 reflected confidence, ethical considerations, and satisfaction, linking XAI to improved confidence and ethical safeguards. Factor 3 emphasized user experience and ethical benefits, showing XAI's role in enhancing overall interaction with AI systems. Factor 4 highlighted transparency, trust, and understanding, underscoring the importance of clear explanations for building confidence. The KMO value (0.713) and Bartlett's test ($p < 0.001$) confirmed that the dataset was suitable for factor analysis. These findings are summarized in Table 1 below.

Table 1: Summary of Factor Loadings

Likert Scale Items	Factor Loading			
	1	2	3	4
Factor 1: Trust, Decision-Making, and Familiarity with AI				
SectionCDecisionMakingXAIimprovesthequalityofdecisi	**.766**	-.074	.025	-.101
Onascaleof1to10howmuchdoyoucurrentlytrustAIsystem	**.737**	.062	.002	.303
Onascaleof1to10howfamiliarareyouwiththeconceptand	**.711**	.011	.105	.421
SectionATransparencyandUnderstandingXAIprovidesclear	**.675**	-.040	.305	-.125
SectionDChallengesandBarriersInterpretingAIgenerated	**.613**	-.290	-.126	.199
Factor 2: Confidence, Ethical Considerations, and User Satisfaction				
SectionBTrustandReliabilityXAIincreasesmyconfidence	.213	**.691**	-.121	-.340
SectionERegulatoryandEthicalConsiderationsTheuseofX	-.398	**.640**	-.150	.003
SectionFUserExperienceIfeelmoresatisfiedwithAIdriv	-.162	**.631**	.465	.007
SectionCDecisionMakingAIdrivendecisionsaremoreactio	.147	**.576**	-.293	.221
SectionDChallengesandBarriersXAIaddressesthemajorch	-.137	**.563**	-.094	.085
Factor 3: User Experience and Ethical Benefits of AI				
SectionFUserExperienceXAIenhancesmyoverallexperience	.052	-.068	**.833**	.014
SectionERegulatoryandEthicalConsiderationsXAIhelpsfi	.204	-.300	**.585**	.052
Factor 4: Transparency, Trust, and Understanding of AI				
SectionATransparencyandUnderstandingIunderstandhowAI	.056	.170	-.042	**.788**
SectionBTrustandReliabilityItrustAIsystemsmorewhen	.358	-.295	.135	**.516**

4.2 Qualitative Results

General Overview: The review of XAI in finance highlights rapid growth, with over 70% of articles published in 2023–2024, reflecting increasing transparency demands driven by policymakers. Most studies employed theoretical models applied to financial datasets (n = 32), such as credit risk assessments using enhanced logistic regression (Lee, 2020). Systematic reviews (n = 12) evaluated techniques like LIME, SHAP, and counterfactuals (Tiwari, 2023). Case studies (n = 6), algorithm reviews (n = 2), and experimental models (n = 4) complemented the evidence. Findings suggest XAI research is data-driven, application-focused, and published mainly in lower-ranked outlets, as summarized in Figure 3 below.

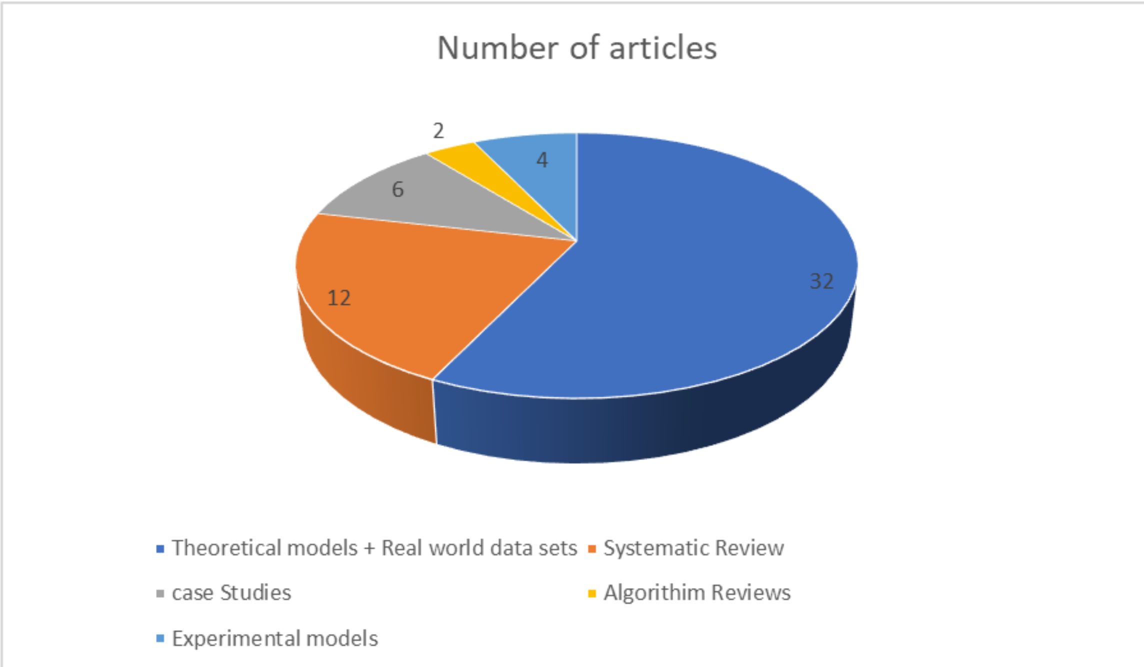

Figure 3: Summary of the methods used in XAI research

Thematic Summary: This study identified four themes on the role of Explainable Artificial Intelligence (XAI) in finance. First, XAI enhances trust and decision-making, especially in credit and risk management. Approaches such as decision trees, linear models, and model-agnostic techniques, including LIME and SHAP, have been widely studied for their ability to clarify AI predictions, improve transparency, and support high-stakes tasks like credit scoring and fraud detection. Second, transparency and interpretability emerged as central to fostering trust. While model-agnostic frameworks and counterfactuals increase accountability and regulatory compliance, studies emphasized the importance of balancing explanation detail to avoid information overload and trust miscalibration. Third, XAI improves customer experience by delivering understandable, tailored explanations. User-friendly interfaces and context-sensitive communication increase consumer acceptance of AI-driven services, fostering trust and engagement. Finally, challenges and barriers remain significant. The complexity of advanced models, trade-offs between accuracy and interpretability, fast-changing financial markets, and diverse stakeholder needs complicate adoption. Limited expertise and institutional resistance further hinder implementation.

Case Studies and Regulatory Documents: The cross-synthesis of case studies revealed that institutions adopting Explainable AI (XAI), such as JPMorgan Chase, Wells Fargo, and HSBC, achieved improved fraud detection, transparency in loan approvals, operational efficiency, and stronger customer trust. In contrast, institutions like BlackRock and Ant Financial, which lacked XAI integration, faced risks including regulatory scrutiny, privacy concerns, reduced investor confidence, and potential loss of user trust. Complementing these findings, six regulatory documents , OECD.AI, GDPR, EU AI Act, Ethical Guidelines for Trustworthy AI, the U.S. AI Bill of Rights, and the EBA discussion paper, emphasize transparency, interpretability, accountability, and fairness as essential for the ethical deployment of AI.

5. Discussion

Primary Research Question, RQ1: XAI enhances credibility and precision in financial decision-making by increasing transparency and interpretability. Both quantitative and qualitative findings show that users trust AI systems more when explanations are provided (Xu et al., 2019). Familiarity with AI strongly correlates with confidence, though non-technical users often struggle to assess fairness. Model-agnostic techniques, such as LIME and SHAP, enhance interpretability, aligning with regulatory and ethical demands for accountability (Ribeiro et al., 2021). Trust was therefore found to depend on technical comprehension, actionable explanations, and transparency, reinforcing XAI's vital role in finance.

Sub Question 1: Transparency, trust, and interpretability emerged as the most significant principles. Findings indicate that tailored explanations enhance user satisfaction, particularly among technical users (Gunning et al., 2019). Post-hoc techniques, such as LIME (Ribeiro et al., 2021) and SHAP, enhance interpretability by highlighting contributory features. Decision trees and rule-based models remain valuable for credit scoring and fraud detection due to their simplicity (Elton, 2020). However, trade-offs exist between accuracy and interpretability, as complex models like Random Forests lack clarity. Scholars emphasize the development of advanced methods that strike a balance between transparency and performance (Torky et al., 2024).

Sub question 2: AI is widely used in fraud detection, credit risk assessment, mobile payments, and portfolio management. Institutions such as JPMorgan Chase and HSBC utilize AI to minimize fraud and compliance costs (Levi & Reuter, 2006). Ant Financial applies AI in credit scoring, expanding access to underbanked populations. However, challenges persist: balancing complexity with interpretability, ensuring regulatory compliance, and addressing data privacy (Belle & Papantonis, 2021). Deep learning models, although accurate, remain opaque, which undermines trust (Holzinger et al., 2020). Findings suggest that broader adoption of XAI could address regulatory gaps, strengthen accountability, and foster user trust.

Sub question 3: A significant barrier lies in the opacity of complex AI models like deep neural networks, which hinder explainability (Rudin, 2019). Professionals struggle to justify AI-driven outputs to stakeholders and regulators. Ethical issues also emerge when opaque systems fail to meet compliance standards (Von Eschenbach et al., 2021). The technical skills gap further exacerbates interpretability challenges, forcing dependence on specialists (Zednik, 2021). Moreover, AI-generated insights often lack immediate actionability in real-world financial contexts (Wadden, 2022). Thus, limited interpretability, regulatory scrutiny, and inadequate technical expertise jointly impede effective adoption of XAI in finance.

Sub question 4: XAI improved customer experience by providing real-time, understandable explanations of AI decisions, empowering users in processes such as loan approvals or fraud detection. Findings show that over 80% of participants reported higher trust when explanations were transparent and context-sensitive, particularly for high-stakes services. Tailored explanations enhanced satisfaction, as customers preferred detailed reasoning for critical financial decisions and simpler explanations for routine interactions (Gao et al., 2022). By reducing mistrust in algorithmic processes and fostering accountability, XAI fosters stronger customer relationships, ultimately improving both trust and loyalty in financial services.

Sub question 5: XAI addresses concerns over opacity, bias, and accountability in AI decision-making. Findings indicate that users perceive XAI as essential for compliance with transparency-focused regulations such as GDPR and the proposed EU AI Act (Gao et al., 2022). Scholars highlight that ethical frameworks demand fairness and explainability in AI systems. Participants emphasized XAI's ability to clarify decision-making, aligning with Mowbray et al.'s (2023) argument that transparency strengthens accountability. Thus, XAI supports both regulatory compliance and ethical governance, ensuring fairness while fostering user trust, critical in sectors like finance, where trust and compliance are paramount.

Sub question 6: Case studies highlight measurable benefits. JPMorgan Chase's COIN reduced fraud losses, cutting false positives by 50% and saving $150 million annually. Wells Fargo's LIFE model automated loan processing while providing clear rejection explanations, strengthening customer trust. In contrast, institutions like BlackRock and HSBC face challenges where a lack of XAI hinders interpretability, and Ant Financial encountered regulatory scrutiny over opaque credit-scoring practices. These examples confirm that XAI strengthens transparency, trust, and operational efficiency (Wadden, 2022). Successful adoption illustrates the transformative role of XAI in aligning financial decision-making with accountability, compliance, and consumer satisfaction.

6. Conclusion

Implications of the findings: The research reveals that Explainable AI (XAI) plays a significant role in enhancing user confidence and decision-making in the financial sector by addressing issues of transparency and interpretability. In theory, the results confirm the theories of trust and accountability, as the more the users can see explanations of AI output, the more they become convinced, especially in high-stakes situations, such as credit approvals and risk management. XAI helps to minimize the black box effect and promote ethical behavior as it allows professionals to be aware of the possible paths of decision-making and promotes accountability because decisions can be explained to clients and regulators. In practice, institutions may use these lessons to increase customer trust, compliance with regulatory practices, and the quality of decisions. The adoption of user-friendly dashboards, application of techniques like LIME and SHAP, and balancing model complexity with interpretability are some of the approaches that can be used. Moreover, educating specialists to interpret AI-generated insights would enable staff to make informed, ethical, and constructive decisions based on these insights. A combination of these steps will establish the basis of a transparent, equitable, and responsible AI application in finance.

Limitations of the study: Due to the study's narrow scope in the financial sector, its findings cannot be generalized to other sectors of the economy, such as healthcare or education, which may pose varying ethical and technical concerns. The qualitative step was based on searches using keywords within the limited scope of databases and time periods, potentially excluding recent or pertinent studies. Moreover, Likert scales used during the quantitative stage may have introduced an element of bias in responses, as respondents were inclined to provide neutral or socially acceptable answers. Such constraints imply there is a need to continue to expand the sampling and include a wider variety of data sources, and the use of mixed-response survey techniques in future studies.

Recommendations: Future research should extend the study of XAI to other industries, such as healthcare, manufacturing, and education, to explore sector-specific benefits and challenges. Investigating user-centric design principles will also be crucial for creating XAI tools accessible to both technical and non-technical users. Studies should further analyze how XAI supports regulatory compliance by mitigating risks of bias and legal liability in financial decision-making. Research into professional training programs can address skills gaps by improving the interpretability and application of AI insights. Ultimately, examining the customer-facing applications of XAI can reveal how transparent explanations enhance trust, satisfaction, and client loyalty.

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