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AI-Enabled Personalized Financial Services: A Systematic Review of Customer Outcomes and Adoption Factors

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ABSTRACT

Artificial intelligence has been used to build personalized financial offerings that are improving customer experiences in the banking, insurance, fintech, and investment industries. A systematic literature review of 62 peer-reviewed articles using Scopus, Web of Science, IEEE Xplore, and Google Scholar was done to examine customer outcomes and determinants of adoption. Quantitative methods prevailed (54.8%), followed by qualitative (25.8%), and mixed-method (19.4%) researches giving more insight into ethics and transparency. The most used AI technologies were machine learning algorithms and recommendation systems, where NLP and deep learning were used moderately. The most prominent of them were customer satisfaction (45 studies), trust (38), engagement (34), loyalty (29), and decision quality (22). Perceived usefulness, ease of use, trust, data privacy, ethical perception in AI, and regulatory assurance were all factors that affected adoption. Explainable, transparent, and ethical AI practices proved to be critical to long-term adoption and engagement principles to make responsible AI applications in financial services.

***Keywords**: AI-Enabled Personalization, Financial Services, Customer Outcomes, Adoption Factors, Trust, Ethics, Machine Learning.*

Introduction

Artificial intelligence (AI) is changing the financial services sector by allowing a very personalized customer experience. Financial services with AI combine machine learning, natural language processing, and recommendation systems to offer personalized guidance, deploy AI support, and initiate proactive interaction and satisfaction, increase trust, and decision-making (Ashrafuzzaman et al., 2025; Zungu et al., 2025). The AI-based self-service solutions eliminate operational inefficiencies and enhance customer urgence such as customer loyalty and customer engagement (Swamy, 2025).
Available empirical research points to the implementation of AI in banking across the world. Byambaa et al. (2025) established that customer trust and perceived usefulness are some of the drivers of adoption in Mongolia. Ikhsan et al. (2024) documented that perceived trust is a substantial intermediate in Indonesia, and Lopes et al. (2025) have indicated that, in mobile banking, the AI solutions perceived to have an impact on engagement with mobile banking are transparency and usability. According to other researchers, AI assists with personalization in real-time and provides proactive financial advice and automated credit ratings, enhancing customer satisfaction and retention more (Ali et al., 2025; Nivedha et al., 2025).

Nevertheless, ethical uses of AI, data privacy, and regulatory compliance are the primary sources of challenges in adoption (Vuković et al., 2025; Wang et al., 2025). To fill these gaps, this research aims to determine the important AI technologies used in personalized financial services and their effects on customer outcomes, examine the effects of factors that determine customer uptake, including usefulness, ease of use, and privacy, and compare the functions of trust, transparency, and ethical aspects in the acceptance and uptake of AI-driven financial services.

Literature Review

AI has taken center stage in personalized financial services as an instrument to improve the customer experience, engagement, and operational efficiency. According to Ganesan (2024), AI is used in the contact center to enhance query response and customized financial recommendations, whereas Vandanapu (2024) notes that AI can be used in banking services to simplify the work and tailor it. According to Kumar and Sinha (2024), generative AI has transformed the world of finance, making it quicker to make a decision and more receptive to customers.

Chatbots that utilize AI are also changing the interaction with customers. According to Nguyen and Le (2024), AI chatbots enhance behavior and satisfaction, and also Gupta et al. (2025) present frameworks that can examine the conversational AI to improve user experience. According to the research, trust, empowerment, and loyalty form the core of digital finance promotion through the use of AI-based personalization, which are reported by Singh et al. (2025) and Arora et al. (2023). Artificial intelligence improves ownership service in the context of financial advisory areas (Singu, 2024; Yang and Lee, 2024). According to Chang et al. (2025), there is the aspect of trust that includes algorithmic reliability and transparency, which affects adoption.

Human-centric AI strategies also guarantee the support of UX design during adoption and satisfaction (Adedoyin and Dogan, 2025). Another application of AI is in financial inclusion and digitalization of bank transformation strategies (Prajapati and Baheti, 2025; Alsobai and Aassouli, 2025). The systematic reviews in other areas, including tourism, strongly support the idea that AI personalization enhances engagement and satisfaction; therefore, it can be applied across sectors (Żyminkowska & Zachurzok-Srebrny, 2025). Lastly, adoption in FinTech cannot be attained without government support, financial knowledge, and user innovativeness (Akhtar et al., 2024). Altogether, these studies explain that customer experience, engagement, and adoption are enhanced by AI personalization; however, ethical, regulatory, and design factors are of critical importance.

Methodology

- **Research Design**

This paper uses a systematic literature review (SLR) to Xplore AI-based personalized financial services and their subsequent adoption by customers. The SLR approach is perfect since it allows rigorous, structured, and replicable synthesis of both empirical and conceptual research, making complete use of all secondary data. This enables the study to make an analysis of the trends, research gaps, and methodological approaches adopted in various studies without necessarily collecting primary data. The SLR would be appropriate, especially to represent the multidimensionality of AI-enabled personalization, comprising the types of technologies used, outcomes on the customer side, driving factors to adoption, and trust or ethical considerations. Moreover, the approach guarantees transparency, objectivity, and reliability to improve the relevance and credibility of findings in academic research and also in the application of financial services.

- **Data Sources and Literature Search Strategy**

Several academic databases were searched thoroughly, such as Scopus, Web of Science, IEEE Xplore, and Google Scholar, which were chosen based on their broad range of peer-reviewed literature in the field of computer science, business, finance, and management. Peer-reviewed journal and conference papers were only included to make sure that the methodological rigor and relevance were maintained. Working papers, non-peer-reviewed sources, gray literature, and other sources that are not peer-reviewed were eliminated to ensure a stable level of quality.

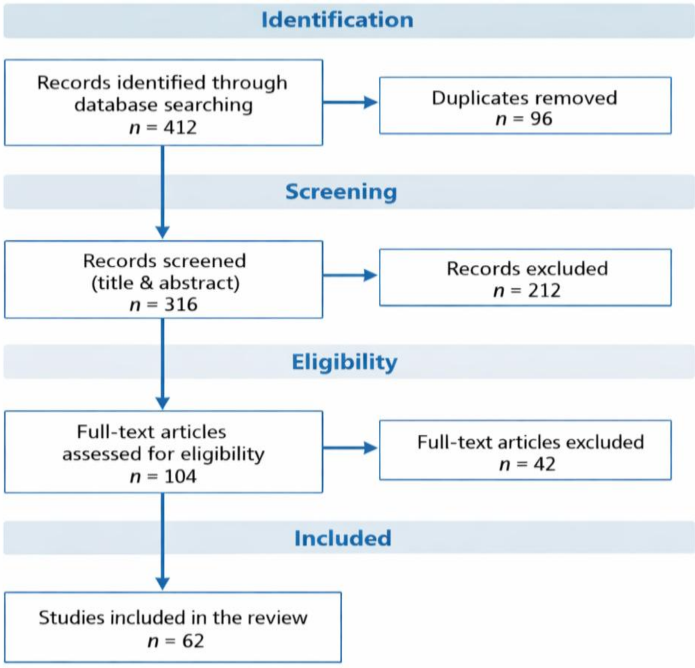
The search strategy was a set of preset keywords and Boolean operators that comprised terms like artificial intelligence, AI-enabled personalization, financial services, customer outcomes, technology adoption, trust in AI, and ethical AI. There were also no limitations on the publication year because the authors wanted to take both the historical studies and the latest ones, which would present the entire picture of the field's evolution. In the PRISMA, the first search found 412 records, which defined the largest foundation for further selection and screening.

- **Inclusion and Exclusion Criteria and Study Selection**

The studies had to include an emphasis on AI-based personalized financial services and had to cover at least one of the following: customer results, determinants of adoption, or trust and ethical implications. Filtering of the studies excluded those that were not related to the financial service, did not have a customer perspective, and did not have AI-enabled personalization. Furthermore, non-peer-reviewed and duplicate sources were eliminated, as well as non-English articles.

Upon elimination of 96 duplicate recordings, 316 investigations were vetted according to name and Abstraction to estimate the restrictions to the inquiry of AI applications, customer results, curiosity about adoption, and trust or moral concerns. 104 studies were evaluated at the complete-text phase, and 62 investigations were considered all-inclusive of the ultimate dataset (Figure 1). This stringent selection procedure guaranteed results that were methodically correct and complete that would satisfy all the research goals but not the outcomes of the research at this point.

Figure 1: PRISMA flow diagram showing the systematic selection of studies



- **Data Extraction and Analysis**

The data extraction framework was standardized and applied to the chosen studies and included year of publication, country, research methodology, applied AI technologies, financial service setting, customer outcomes, determinants to adoption, and trust or ethical concerns. The data extracted was then synthesized using a thematic analysis approach. The results were divided into categories that represented AI technologies, customer outcomes, factors of adoption, or trust or ethical implications. The thematic coding allowed finding patterns and trends as well as methodological approaches to the research, which offered a systematic synthesis in accordance with the aims of the research and retained the distinctness of the results.

- **Quality Assessment and Ethical Considerations**

The methodological quality of included studies was determined by the clarity of research design, the appropriateness of a methodology, and analytical rigor, with each of the studies being measured in terms of transparency, consistency, and relevance to the research objectives. Because the research is based on secondary data only, no ethical issues related to human subjects are involved in the research. Ethical integrity and transparency were also maintained in the course of the review by citing all the sources properly, and the standards of academia were followed.

Results and Discussion

- **Overview of Selected Studies and Database Distribution**

This systematic literature review (SLR) identified 62 peer-reviewed papers that have satisfied the inclusion criteria of the topic of AI-enabled personalized financial services, which can be considered the current research. Those studies cover a variety of financial industries, such as banking, insurance, fintech, and investment services, which implies that AI personalization can be applied across various industries productively. Most of the publications date back to after 2018, which is indicative of the extremely high rate of AI use in the financial sector, as well as an academic interest in customer-oriented results.

The international spread of the literature suggests the applicability of the AI-facilitated personalization under varying regulatory, technological, and cultural contexts, although the developed economies prevail in the research environment. This data can be a good base for technological, behavioral, and ethical aspects of AI personalization in the financial services.

- **Database-Wise Distribution of Studies**

The studies were considered according to the academic databases on which they were based. The greatest number was added by Scopus (24 studies) and Web of Science (18 studies), and indicates a very broad coverage of interdisciplinary studies in AI, finance, and management. The IEEE Xplore database added 11 technical AI model studies, and Google Scholar added 9 studies that were of emerging or interdisciplinary research not indexed in the other databases (Table 1).

Table 1. Database-Wise Distribution of Included Studies

Database	Number of Studies	Percentage (%)
Scopus	24	38.7
Web of Science	18	29.0
IEEE Xplore	11	17.7
Google Scholar	9	14.6
Total	62	100

- **Research Methodology of Included Studies**

The methodological analysis showed that quantitative research is the most prevalent (54.8%), which is comprised of qualitative research (25.8%) and mixed-method research (19.4%) (Table 2).

Table 2: Methodological Approaches in Reviewed Studies

Research Methodology	Number of Studies	Percentage (%)
Quantitative	34	54.8
Qualitative	16	25.8
Mixed Methods	12	19.4
Total	62	100

Discussion: The lack of qualitative research underscores focus on measurable constructs, including customer satisfaction, customer trust, and customer adoption intentions, in line with the proven models, including TAM (Technology Acceptance Model) and UTAUT (Unified Theory of Acceptance and Use of Technology). Qualitative research can help to comprehend ethics and explain ability or transparency, which are needed to engage in responsible AI implementation. Mixed-method research can be more informative, as it triangulates quantitative and qualitative results and proves the multidimensionality of the AI-based personalization.

- **AI Technologies Used in Financial Services**

The literature review revealed that there is a vast array of AI technologies used in financial personalization. The most common included machine learning algorithms and recommendation system which were later followed by NLP and deep learning models (Table 3). NLP improves customer interaction with the help of catboats and virtual assistants, whereas deep learning can be used to detect fraud and apply it to risk assessment and predictive analytics. The AI based on rules, as well as expert systems, were less common, which is indicative of the transition towards data-driven, adaptive models that can be used to give customers real-time recommendations.

Table 3: AI Technologies Identified in the Reviewed Literature

AI Technology	Frequency of Use
Machine Learning Algorithms	High
Recommendation Systems	High
Natural Language Processing	Moderate
Deep Learning Models	Moderate
Expert Systems / Rule-Based AI	Low

- **Customer Outcomes of AI-Enabled Personalization**

Customer satisfaction, trust, engagement, loyalty, and quality of decisions were reported the most (Figure 2).

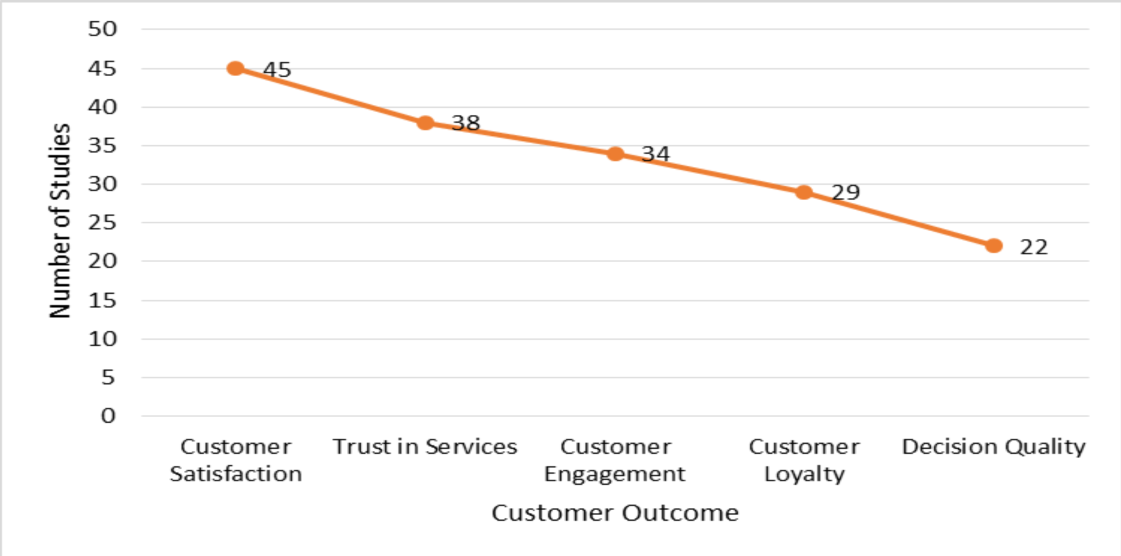


Figure 2: Customer Outcomes results

Discussion: The satisfaction and trust of the customers rule since they have a direct effect on long-term retention and adoption. The improvement in the quality of decisions is clear-cut in robo-advisory and auto credit assessment, where AI is offering recommendations to an individual, and the user does not have to think much. These results reveal that AI personalization improves service perception and behavioral results, in line with the existing empirical research.

- **Determinants of Customer Adoption**

Among the determinants of the adoption, perceived usefulness, ease of use, trust, data privacy concerns, ethical AI perception, and regulatory assurance should be noted (Table 4).

Table 4: Key Adoption Determinants Identified

Adoption Factor	Strength of Evidence
Perceived Usefulness	Very High
Ease of Use	High
Trust in AI	High
Data Privacy Concerns	Moderate
Ethical AI Perception	Moderate
Regulatory Assurance	Emerging

Discussion: Although the focus on the concept of technological performance (usefulness, ease of use) is still essential, adoption is influenced by trust, ethics, and privacy more. This is in line with the literature where sensitive financial decision-making is emphasized, with the perceptions of reliability and accountability being as important to functional efficiency. There is a sign of regulatory assurance, which implies that governance frameworks might further rise.

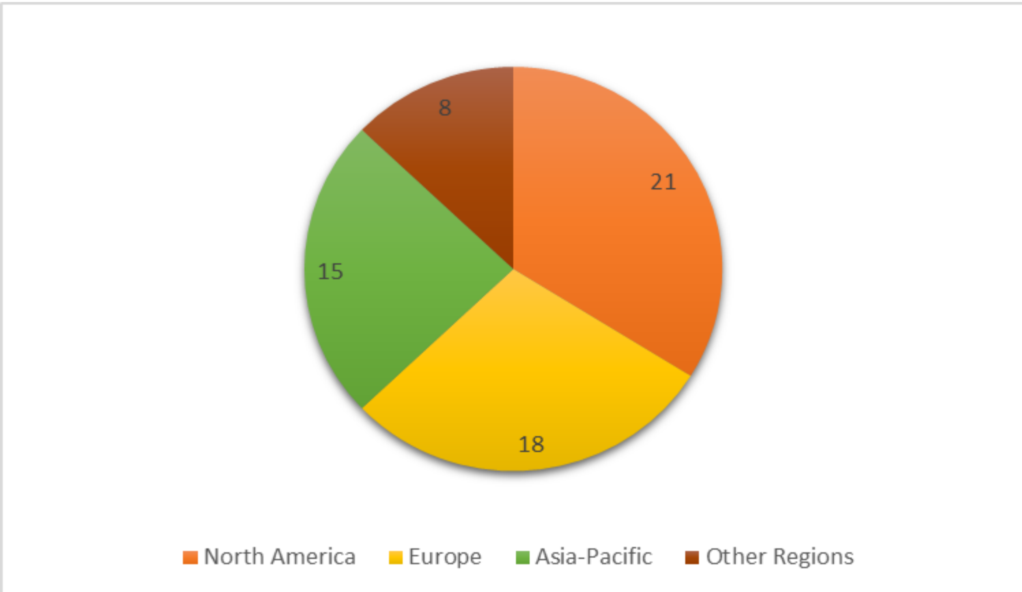
- **Trust, Transparency, and Ethical Considerations**

Figure 3: Thematic Distribution of Trust and Ethical Issues

Discussion: There must be trust and ethical practices as the prerequisites of adoption and continued engagement (Figure 3). This is supported by research which has found that clear AI systems with explainable advice confer more confidence to users, whereas the myth of bias, data abuse, or an algorithmic black box wanes trust. Such results facilitate the idea of responsible AI in financial services.

- **Geographic Distribution**

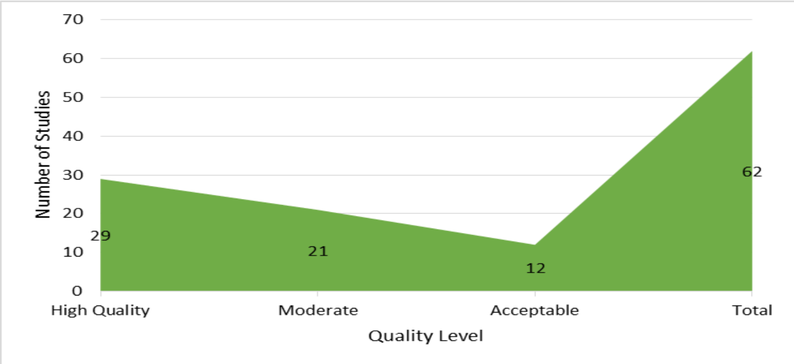
Figure 4: Geographic Distribution of Reviewed Studies



Discussion: The trend of research is focused on developed economies, indicating a developed state of digital infrastructure, greater adoption of AI, and regulatory preparedness (Figure 4). Due to global diffusion, emerging markets are increasingly represented, but research on the local adoption issues in underrepresented areas is still required.

- **Quality Assessment**

Figure 5: Quality Classification of Reviewed Studies



Discussion: The general quality of the vast majority of studies is high to moderate, which means that they present reliable evidence (Figure 5). Acceptable-quality studies are new or exploratory research, especially ethical AI, explain ability, and privacy, which offer future potential opportunities to conduct rigorous studies.

Conclusion

These systematic review findings indicate that AI-powered personalized financial services have a strong impact on positive customer satisfaction, trust, engagement, and decision-making in both banking and FinTech settings. Adoption is affected by the performance of technology, transparency, privacy of data, and ethical issues. Although AI induces operational and personalized experiences, there are issues of regulation, fairness, and user trust. These gaps should be addressed by future research to streamline adoption and make AI deployment in the world responsible and customer-centered.

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