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[Transforming Financial Access Through AI: An Empirical Study in Pakistan]

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ABSTRACT

Artificial Intelligence (AI) integration in emerging economies like Pakistan presents a transformative opportunity to advance financial inclusion. This study investigates the influence of AI on financial inclusion through key mediating variables—financial literacy, user adoption, financial behavior practices, government support, and AI-based risk mitigation—using a quantitative methodology. Data from 250 financial service users were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings indicate that financial literacy ($\beta = 0.558$, $p < 0.001$) and user adoption ($\beta = 0.368$, $p < 0.001$) significantly mediate the relationship between AI and financial inclusion, with financial literacy showing the strongest effect. In contrast, financial behavior practices ($p = 0.250$), government support ($p = 0.268$), and risk mitigation ($p = 0.111$) were found to have no significant mediating influence. Theoretically, the study extends existing literature by integrating the Technology Acceptance Model (TAM), Financial Inclusion Theory, Diffusion of Innovation Theory, and Social Cognitive Theory, offering a multidimensional understanding of how AI adoption interacts with user behavior and systemic access. It challenges conventional assumptions about the sufficiency of institutional support, emphasizing instead the centrality of financial literacy and user readiness in AI-driven inclusion. Methodologically, the study demonstrates the value of PLS-SEM in validating complex structural models with multiple latent constructs in emerging market contexts. The results offer valuable insights for researchers and policymakers aiming to design AI-enabled strategies that improve financial literacy, boost user adoption, and foster inclusive financial ecosystems.

Keywords: Artificial Intelligence, Financial Inclusion, Financial Literacy, User adoption, AI-Based Risk Mitigation, Financial Behavior Practices, Government Support.

Introduction

Financial inclusion is providing financial services to excluded groups for economic development and poverty alleviation (Klapper et al., 2017). However, a high majority of the Pakistani population remains financially excluded, and this creates difficulty for the country to achieve this goal. Through facilitating innovative and low-cost solutions to financial inclusion, AI growth offers a great chance to end this problem (Fazal et al., 2023). The incorporation of AI will certainly provide new competencies to businesses, which may be tied to technology itself, with all the benefits that come from AI offers in the industry (Canina and Orero-Blat, 2021).

The low rates of financial inclusion in Pakistan, which makes it the least financially inclusive country in South Asia, evidenced by 21% of adults had formal bank accounts (SBP, 2021) poor infrastructure, insufficient digital literacy, and cultural barriers. According to Recent studies, severe barriers remain with the growing adoption of digital banking—equilibrium in Pakistan. For instance, the lack of digital literacy continues to inhibit the utilization of financial services, especially in rural areas where people are not well familiar with digital technologies and tools. This problem is made worse by gender inequality, which disproportionately excludes women from formal banking systems (Zia, 2024).

AI leads a group of emerging technologies that revolutionize how financial institutions handle their obstacles. The use of AI-based solutions enables cost-effective service delivery while strengthening personalized customer interactions along with educational programs related to finance (Gisbert, 2024). By integrating AI into the financial system, decision-makers and institutions enhance inclusion, particularly in rural areas (Kaur, 2024).

AI stands out as a developing solution to address financial access problems by generating board organizational interest for its contribution to financial inclusion enhancement. AI integration within the Pakistani financial sector faces challenges related to the ethical distribution of responsibilities as well as data protection issues and a potential tendency to create a gap between the urban and rural financial service landscape.

The study (Mahmood, 2022) establishes that financial inclusion is important for improving the disposable income of poor households, although current implementation barriers remain significant. Another study (Razzaq, 2024) highlights that gender inequality is an important determinant of financial inclusion in Pakistan while pointing out that AI may help decrease and possibly increase existing disparities between genders. This research assesses the potential benefits and barriers present within the implementation of AI technologies for Pakistan's financial inclusion programs. to investigate the prospects and obstacles associated with AI integration in Pakistan's financial inclusion initiatives.

Artificial intelligence has emerged as a breakthrough in numerous fields and is being used in every organization, this study aims to determine how AI improves financial inclusion. Focusing on factors, i.e., financial literacy & awareness, the extent of integration of AI into the financial sector, the impact of regulatory frameworks on the AI industry, and how it can redirect the underserved population to a documented economy. Furthermore, it analyzes the societal and economic consequences of incorporating AI into financial services, with a focus on its capacity to empower disadvantaged communities and stimulate economic growth

Literature Review

Artificial Intelligence is a groundbreaking financial tool that promises to bridge the loopholes of inaccessibility to finance by allowing such services as electronic payments, credit scoring, and personalized financial services. The literature collectively highlights AI's transformative potential in addressing barriers to financial inclusion, particularly among underserved populations (Fazal et al., (2023).AI in Financial Access Studies Show AI Can Overcome geographical and digital barriers to financial services in developing nations (Kumar, 2024; Dhiman, 2024).

Government policies and Fintech adoption, Akhtar et al. (2024) reveal that while government policies can aid AI adoption, poor implementation may hinder inclusion efforts. Hamadou (2024) contributes insights from Islamic banking, showcasing how AI integration can uphold ethical banking standards while promoting inclusion. Machine learning and financial system AI and machine learning enhance service personalization, with PRISMA-reviewed studies affirming their role in enabling financial transactions (Anam et al., 2023). According to Anam et al. (2023), financial inclusion enables the delivery of necessary services and products to the community at reasonable costs. This paper reveals how AI supports financial inclusion and provides a systematic literature review based on database articles, including Emerald and Science Direct. The PRISMA technique assists a systematic literature review that leads to articles being screened and research articles showing proof that ML and AI are essential in research work. The deployment of AI should prioritize two main challenges which include solving barriers to financial inclusion as well as policymakers' needs to identify problem areas.

AI solution for Marginalized Groups Ritika (2023) proposes a Strategic AI-driven solution to reduce exclusion by improving service delivery in rural and underserved areas.

Theoretical Connectivity & Hypothesis Development

This study is therefore grounded in the thematic perspectives of financial inclusion, post-Occidental ethic of technology, and artificial intelligence. Financial inclusion, until recently, meant to deliver simple and affordable products and services to customers who can't get them from the conventional financial system. AI can revolutionize financial inclusion through the automation of processes, enhanced datasets, and prototype financial solutions.

Technology Acceptance Model (TAM):

This model investigates the processes through which individuals and organizations incorporate technology into their operations based on its perceived ease of use and perceived usefulness. Regarding the utilization of AI solutions in financial inclusion, the teams and employees must ensure an understandable interface and compliance with ethical criteria.

In the context of AI-driven financial inclusion, institutions need to develop user-friendly systems like mobile apps and AI chatbots. For instance, AI-based credit scoring simplifies loan approval processes, addressing Pakistan's unbanked population. Addressing perceived complexity, especially for low-literacy users, is key to achieving broader adoption.

Financial Inclusion Theory

This theory aims to make sure that individuals and businesses have access to financial services more easily meet their goals and achieve social and economic benefits. This theory is appropriately linked with the improvement of individuals in financial services. Financial inclusion theory focuses on increasing access to financial services for underserved populations. (Ozili, 2020), categorizes the theory into supply-side and demand-side aspects, emphasizing its role in reducing poverty and inequality.

Diffusion of Innovation Theory

This theory explores how innovations spread within a community. (Rogers, 2003) defined how, why, and how quickly new concepts and technologies proliferate across civilizations. Rogers distinguished five types of adopters: laggards, innovators, early adopters, early majority, and late majority. This theory also describes elements that affect adoption, including trialability, observability, complexity, compatibility, and relative advantage. AI in financial inclusion, early adopters (e.g., fintech startups) play a significant role in demonstrating the benefits of AI tools such as predictive analytics. The technology's success hinges on its compatibility with users' values and the accessibility of platforms like AI-powered wallets. Trialability, such as free or subsidized initial use, can accelerate adoption rates, especially in underprivileged areas.

Social Cognitive Theory
This theory explains that human behavior is influenced by personal factors, environmental influences, and behavior itself. This theory has been combined with various models in recent research to better explain how people use technology (Hassan et al., 2024). For financial inclusion, it highlights how people's self-efficacy and environmental factors like digital literacy impact their adoption of AI-enabled financial services.
Hypothesis Development
By utilizing cutting-edge algorithms and inclusive data analytics, AI-driven financial inclusion can reconcile the conflict between the exclusion of marginalized communities and the requirements for economic progress. Thus, we propose the following hypothesis:
H1: AI integration improves financial literacy through personalized platforms and accessible learning (Khan, 2023).

Financial literacy will rise dramatically as AI is incorporated into financial services. According to (Khan, 2023), AI-powered platforms can offer tailored educational resources to assist people in understanding complex financial products. Each person's needs are catered for in financial resources and counsel which also enhance comprehension and promote wiser financial choices. In support of this, the report by (Akhtar et al., 2023) emphasizes how AI-powered platforms promote sound financial practices and close knowledge gaps in the financial sector.
H2: AI transforms financial behavior practices by optimizing budgeting and investment decisions (Noor Al Mazrouei, 2024).

Researchers claim that AI technologies are bringing about a dynamic transformation in traditional approaches to investment and budgeting (Noor Al Mazrouei, 2024). The integration of AI enables personal financial management to benefit from significant advancements in budgeting techniques and other saving and investment procedures.
H3: AI Integration Positively Impacts Government Support:
The effective adoption of AI in the financial services sector requires government backing. The adoption of AI can be encouraged by government laws, according to (Khan, 2023). Governments should encourage innovation and guarantee that AI-driven financial services promote wider economic and social inclusion by putting in place a supportive legislative framework and purchasing infrastructure for technology.
H4: AI Integration Positively Impacts AI-based Risk Mitigation:
(peng et al., 2019) investigates contemporary methods and assessment and measurement techniques of financial systemic risk that utilize machine learning technologies with their components of big data analysis network analysis and sentiment analysis. The advanced methods demonstrate that AI integration produces enhanced systemic risk detection abilities which affect financial sector practices for management and understanding of risks.AI model focuses on credit risk assessment applied to peer-to-peer lending platforms. Such a method improves both the clarity and operational efficiency of AI systems used for risk reduction measures (Giudici et al., 2021).
H5: AI Integration Positively Impacts User Adoption:
(Ryu, H. S., 2018) in his study investigates the variables that affect fintech service

adoption through an analysis of both people who join quickly and those who join eventually. Users determine their adoption actions through a balance of felt advantages and risks during the adoption stage. The introduction of AI technology improves both the advantages and protection elements of fintech applications which subsequently raises the number of users who embrace these services.

H6: AI Integration in Financial Literacy Enhance the Financial Inclusion.

Financial literacy is the mediator between AI integration and financial inclusion. A study by (Mehmood et al, 2023) demonstrates that AI-powered platforms enhance financial literacy and make financial services easier and more efficient to use. Educating individuals about financial instruments with the help of AI removes the literacy obstacles and enhances the financial goods users.

H7: AI Integration Heightens Individual Financial Behavioral Practices of Financial Inclusion:

According to a study by Klapper et al. (2017), mobile money technology helps people become more financially capable, especially female users. The growth of small businesses and the economy has benefited from this mobile money technology. Another study by Agarwal et al. (2020) demonstrates how these improvements change consumers' financial involvement. According to research, incorporating AI improves people's financial habits, which increases financial inclusion.

H8: Government Support Facilitates AI Integration in Financial Services:

The essence of government support in AI integration in financial services is highlighted by Mishra (2024). The government can create a society that is beneficial to AI-powered advancements by offering incentives for technological adoption, infrastructure support, and legal clarity. This will encourage the widespread use of AI platforms and boost public trust in them, which will ultimately contribute to financial inclusion and economic growth.

H9: Risk Mitigation with AI serves as a bridge between AI Integration and Financial Inclusion:

Risk mitigation tackles important algorithmic and data privacy regulation issues (Lee, 2024). Furthermore, more comprehensive financial access is made possible by AI-based credit risk detection methods that enhance personalization and trust between users (Kanaparthi, 2024). Research proves that AI-based risk mitigation serves as a link between the application of AI and the growth of financial inclusion. The authors of Big Data and Cognitive Computing demonstrated how algorithmic fairness received through effective risk reduction leads to increased satisfaction and recommendation of AI-financial products. .

H10: User Adoption Enhance AI Tool Effectiveness and Boost Financial Inclusion:

The paper written by Lee (2024) analyzes how digital platforms combined with machine learning technology at digital banks allow improved service accessibility for underserved communities. AI-based personalization techniques in digital finance establish user trust, which increases both user acceptance and financial access (Kanaparthi, 2024). The adoption of users has proven to maximize AI tool effectiveness, which expands financial access opportunities for people. The Journal of Banking Regulation conducted a complete review to demonstrate that banking sector AI implementation produces operational excellence while creating better customer satisfaction levels needed for inclusive finance.

Figure 1: Theoretical Framework

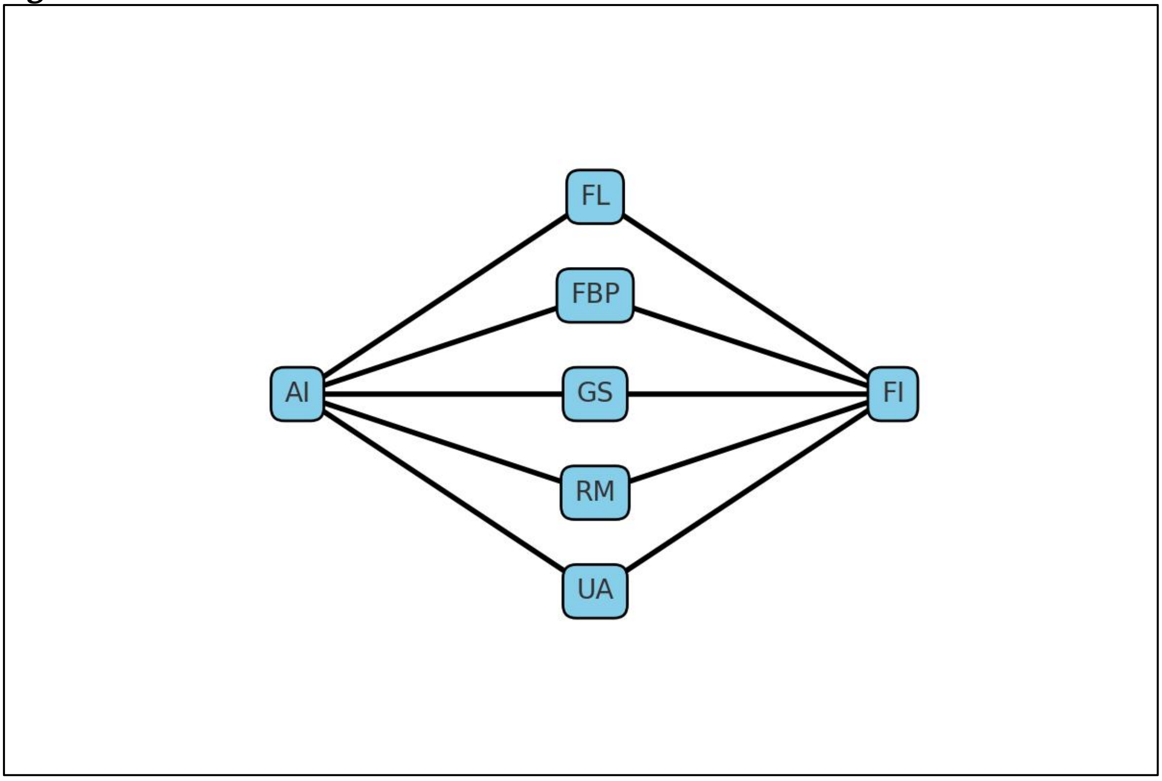

Figure: Theoretical Framework for AI Integration and Financial Inclusion

Research Methodology

A total of 270 responses were collected, of which 250 were valid and used for analysis. The study employed a convenience sampling method, and data were gathered from major cities across Pakistan using digital channels, including email, social media, and online survey platforms.

The questionnaire was self-administered and included items related to seven constructs: AI Integration, Financial Literacy, Financial Behavior Practices, Government Support, AI-Based Risk Management, User Adoption, and Financial Inclusion. All items were measured using a five-point Likert scale ranging from "strongly disagree" to "strongly agree." The instrument was developed based on previously validated constructs from existing literature.

Respondents' demographic data included age, gender, education, income, occupation, and location. Among them, 77.5% were male and 22.5% were female. Approximately 80% of the participants were aged between 20 and 35 years, a group primarily composed of students and early-career professionals. Educationally, 60% held graduate degrees, and 50.9% reported full-time, salaried employment. Regarding place of residence, 55.9% lived in urban areas, while 44.1% were from rural settings.

The data was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4. This method was chosen due to the study's complex model structure and the exploratory nature of the research.

Data Analysis and Results

The researcher utilized the PLS-SEM Partial Least Squares-Structural Equation Modeling.

Smart PLS 4 to test the hypothesis on the data after the data screening stage. According to (Joseph F. Hair et al., 2019), PLS-SEM is a second-generation multivariate data analysis approach that was utilized in this study for the following reasons: we needed latent variable scores, and the structural model is complex and contains many constructs and indicators. The researchers mostly used PLS-SEM because it allowed them to analyze both the measurement model and the structural model simultaneously. This all-encompassing strategy guarantees a deeper analysis of variable interactions and a better comprehension of the underlying mechanisms. In the research study, the researchers were able to clean up the data and find pertinent correlations between variables by using PLS-SEM for hypothesis testing. PLS-SEM's widespread use in this field attests to its efficacy and suitability, particularly when dealing with smaller datasets.

Confirmatory factor analysis (CFA) and partial least squares (PLS) were used to check the accuracy and reliability of all our measurement scales. Bootstrapping techniques were selected to assess the developed research model. The information in Table 1 shows that all items are efficiently loaded for related variables and have a low cross-loading for other measures

Table 1: Cross Loadings

Construct	AI	FBP	FI	FL	GS	RM	AU
AI1	0.716	0.216	0.280	0.409	0.090	0.093	0.242
AI2	0.858	0.278	0.345	0.481	0.218	0.235	0.297
AI3	0.846	0.282	0.352	0.463	0.184	0.273	0.346
FBP1	0.233	0.704	0.253	0.272	0.454	0.389	0.329
FBP2	0.324	0.843	0.404	0.400	0.298	0.371	0.477
FBP3	0.161	0.739	0.347	0.321	0.407	0.401	0.375
FI1	0.335	0.303	0.779	0.363	0.178	0.257	0.404
FI2	0.269	0.371	0.829	0.373	0.247	0.349	0.293
FI3	0.370	0.400	0.815	0.416	0.380	0.376	0.404
FL1	0.388	0.302	0.353	0.711	0.150	0.224	0.258
FL2	0.464	0.336	0.415	0.823	0.281	0.330	0.309
FL3	0.410	0.365	0.308	0.729	0.197	0.304	0.343
GS1	0.130	0.348	0.286	0.289	0.843	0.288	0.244
GS2	0.254	0.436	0.310	0.234	0.912	0.422	0.314
GS3	0.127	0.446	0.269	0.195	0.774	0.307	0.369
RM1	0.214	0.372	0.308	0.316	0.319	0.784	0.293
RM2	0.286	0.419	0.308	0.327	0.394	0.849	0.343
RM3	0.080	0.364	0.342	0.233	0.218	0.679	0.399
UA1	0.370	0.492	0.372	0.341	0.322	0.411	0.871
UA2	0.260	0.408	0.416	0.347	0.302	0.346	0.850

Cronbach alpha evaluated the reliability of each construct, composite reliability (CR), and AVE. They are measures of internal consistency for a scale. Cronbach's value was 0.6 to 0.7 for each construct. As a result, the reliability of a few measurement items was found satisfactory. The composite readability (rho_c) value was above 0.7 for all constructs as considered to be good reliability. The fairness of an element depends on whether it is different from other elements. For all variables, the square root of AVE was higher than its interaction with other variables. A value of 5 or more VIF values often indicates a problem in the structural model, so it is important to evaluate each construct individually for each subsection. A value of AVE above 0.50 in all constructs is considered to be good validity. The result of the collinearity assessment is summarized below.

Table 2: Reliability and Validity Statistics

Construct	Items	VIF	Cronbach's Alpha	rho_a	Composite Reliability rho_c	Average Variance Extracted (AVE)
Artificial Intelligence	I1 I2 I3	.308 .667 .584	0.736	0.758	0.850	0.655
Financial Literacy	L1 L2 L3	.183 .337 .241	0.624	0.635	0.799	0.571
Financial Behavior Practices	BP1 BP2 BP3	.238 .312 .263	0.649	0.683	0.807	0.584
Government Support	S1 S2 S3	.929 .247 .484	0.799	0.827	0.882	0.714
Risk Mitigation	M1 M2 M3	.398 .522 .181	0.661	0.676	0.816	0.599
User Adoption	A1 A2	.304 .304	0.651	0.653	0.851	0.741
Financial Inclusion	I1 I2 I3	.457 .628 .381	0.735	0.741	0.849	0.653

The latent variable descriptive statistics in Table 3 show that the data is standardized as evidenced by the zero mean and unit standard deviation for all constructs. The observed ranges also denote considerable variability in the data set, which supports robust analysis in the PLS model. All constructs with positive skewness values represent right-skewed distributions, but the fact remains within acceptable bounds and ensures that data patterns are reliable. Excess kurtosis values, especially for UA (0.892) and AI (0.898), suggest data clustering and outliers, which were retained to maintain the integrity of the dataset and sample representativeness. The results confirm that the data is appropriate for structural equation modeling.

Table 3: Latent Descriptive Statistics

Construct	Mean	Median	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness
AI	0.000	-0.339	-1.445	2.980	1.000	0.672	0.898
FL	0.00	-0.282	-1.476	3.300	1.000	0.443	0.742

	0						
FBP	0.00	-0.221	-1.628	3.336	1.000	0.340	0.629
GS	0.000	-0.327	-1.534	2.155	1.000	-0.516	0.571
RM	0.000	-0.182	-1.682	2.898	1.000	-0.250	0.441
UA	0.000	-0.171	-1.377	3.445	1.000	1.207	0.892
FI	0.000	-0.069	-1.576	2.978	1.000	0.610	0.751

Predictive relevance was established because the Q^2 predicts that the endogenous constructs have predictive relevance and that the model is well-reconstructed; the Q^2 prediction for financial literacy (FL) is 0.296, user adoption (UA) is 0.117, and financial inclusion (FI) is 0.149, all of which show that the Q^2 values for the endogenous constructs exceed zero.

Table 4: PLS predict LV Summary

Construct	Q2 Predict	RMSE	MAE
FL	0.296	0.850	0.627
FBP	0.082	0.969	0.739
GS	0.030	0.998	0.809
RM	0.053	0.986	0.786
UA	0.117	0.954	0.695
FI	0.149	0.934	0.702

The structural model analysis reveals the relationships between constructs and their role in financial inclusion. The path coefficients and their statistical significance are shown below.

Table 5: Path Coefficient

Constructs	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI -> FL	0.558	0.564	0.062	8.991	0.000
AI -> FBP	0.322	0.334	0.081	3.971	0.000
AI -> GS	0.209	0.218	0.067	3.139	0.002
AI -> RM	0.259	0.269	0.071	3.664	0.000
AI -> UA	0.368	0.374	0.078	4.749	0.000
FL -> FI	0.275	0.281	0.086	3.193	0.001
FBP -> FI	0.118	0.118	0.103	1.150	0.250
GS -> FI	0.083	0.087	0.075	1.107	0.268
RM -> FI	0.124	0.128	0.078	1.594	0.111
UA -> FI	0.200	0.197	0.090	2.219	0.027

Overall path coefficient results support 7 hypotheses (H1, H2, H3, H4, H5, H6, and H10). Three of the remaining hypotheses (H7, H8, and H9) are unsupported.

The findings reveal that hypothesis one is accepted because Table 4 below clearly demonstrates the positive coefficient between AI->FL (0.558), suggesting a strong positive relationship between Artificial Intelligence and financial literacy. The T statistic of 8.991 further supports the significance of this relationship, that AI integration enhances financial literacy, with better knowledge of financial and decision-making skills. The hypothesis that AI integration and financial behavior practices are also accepted (AI->FBP) because the findings show that a P value of 0.000 and a T statistic of 3.971 indicate a strong positive relationship. The hypothesis that AI integration and government support are also tested (AI->GS) because the findings show that a positive coefficient (0.259) and significant P value of 0.002 and T statistic 3.139 indicate a strong positive relationship. The hypothesis that AI integration and AI-based risk management is also accepted (AI->RM) because however, the findings show a T statistic of 1.549, which does not strongly support a statistically significant relationship. The hypothesis that AI integration and user adoption is also accepted (AI->UA) because the findings show that a positive coefficient (0.368) and significant P value of 0.000 and T statistic 4.749 indicate a strong positive relationship. Table 4 results show that there is a significant relationship between FL and FI due to the positive coefficient of 0.275 and the t-statistic greater than 3.193. Furthermore, the value of P below 0.001 indicates that the significance level of the relationship is accepted between financial literacy and financial inclusion. UA and FI indicate a positive relationship due to a significant coefficient of 0.200, a T-statistic of 20219, and a p-value of 0.027. Moreover, FBP and FI, GS and FI, and RM and FI show insignificant results due to a high p-value of 0.05, indicating that these variables do not mediate the relationship between financial inclusion. Therefore, the finding concludes that H1, H2, H3, H4, H5, H6, and H10 are significant and have a positive significant relationship, and H7, H8, H9, and insignificant relationship with financial inclusion in Pakistan.

Discussion

This study tries to analyze the adoption of AI for promoting financial inclusion in Pakistan, concerning mediator factors such as financial literacy, financial behavior practices, government support, AI-based risk mitigation, and user adoption. Partial Least Squares (PLS) shows the relation of dependent variables with some mediator effect on the independent variable, The analysis has demonstrated that H1, H2, H3, H4, H5, H6, and H10 are qualified and possess a strong relationship with each other and are accepted. Different studies have also examined this hypothesis and have come forward with indistinguishable results.

Prior research on the topic demonstrates how AI can increase financial inclusion by improving financial literacy and behavior patterns (Mehmood et al., 2024). AI-driven technologies, like chatbots and individual financial education platforms, improve financial literacy by making complicated financial ideas easier to understand. AI tools, such as machine learning algorithms, have been shown to encourage sound financial behaviors by providing individual financial advice.

According to (Akhtar et al., 2024), user innovativeness with the government increases fintech adoption opportunities, which allows AI-powered technologies to boost financial inclusion. The Pakistani governments demonstrate support through its National Financial Inclusion Strategy (NFIS). (Musa et al., 2024) established how emerging economies achieve financial inclusion success through technology adoption because of government support programs. Financial inclusion expands because User-friendly AI applications draw numerous types of users into their platforms. In Pakistan, AI technology in digital wallets has led to a large-scale growth of financial services usage.

The research of Khan et al (2022) supports H6 as Financial Literacy as an Intermediary Between AI Integration and Financial Inclusion, since it aligns with their findings about financial literacy being essential for financial inclusion. The research findings strengthen the hypothesis that financially literate individuals can maximize AI-driven financial services, which drives increases in financial inclusion. Financial literacy leads to improved technology adoption because it teaches positive financial conduct and attitudes (Sarwar et al., 2024). The AI-powered educational system aims to increase users' capacity to use financial services. Bridging gaps in financial knowledge has been successfully achieved through the use of AI in education.

Government support for the integration of AI for financial inclusion is insignificant (H7). The research determined that government backing failed to create meaningful support for AI integration in financial services despite what previous research indicates about the facilitative role of government intervention (Musa et al., 2024). This result shows that Pakistan faces unique environmental conditions, which may explain the difference between government policies and public awareness about state initiatives. The analysis suggests that advanced technological elements, together with market factors, seem to be more influential factors in this situation. Research conducted by Abikoye et al. (2024), supports the conclusion that well-functioning government support programs are essential for realizing successful AI adoption.

AI integration showed an insignificant effect on individual Financial Behavioral Practices, suggesting a limited role in influencing financial inclusion directly through behavior. (Sarwar et al., 2024), established in their research that technology plays a significant part in forming financial perspectives and conduct. This difference could demonstrate that Pakistani institutes face problems, such as resistance to change, along with low digital literacy levels. Furthermore, Mehmood et al. (2024) noted that although AI solutions have promise, user preparation and financial literacy frequently act as mediating factors in how effective they are at changing financial behavior. Research indicates that AI technology can support financial inclusion by offering safe, quick, and easy-to-use financial services. AI may not have a significant direct influence on changing people's financial habits, though, which suggests the need for supplementary strategies like financial education.

The existing researcher's idea that AI-based risk reduction increases the relationship between AI integration and financial inclusion is called into question by the low influence of H9 (Abikoye et al., 2024). The lack of adequate adoption of contemporary risk mitigation techniques in Pakistan's industry explains why this study finds no discernible effects. (Akhtar et al., 2024) pointed out that a robust operational and regulatory framework is necessary for AI-based risk reduction to be successful. In Pakistan's banking industry, the techniques of risk mitigation and their adoption are in short supply. Pakistan may need to create a sophisticated operational infrastructure and regulatory framework for AI-powered risk mitigation

Additionally, H10 is positively correlated with user adoption, which encourages Financial

Inclusion and improves the efficiency of AI tools. (Yang and Lee, 2024), showed how perceived justice and transparency led to a rise in the user adoption of AI systems. The research indicates that high adoption rates of AI tools in financial services contribute to their efficacy and inclusivity. Additionally, Akhtar et al. (2024) clarify that user adoption has a significant impact on the adoption of AI-driven financial services. Technology has been shown to improve access to financial services for marginalized populations, underscoring the importance of user engagement.

Overall, the discussion highlights the complex role influenced by mediating variables between financial inclusion and AI integration. The research findings are consistent with the majority of the literature currently in existence, but they offer perspectives on Pakistan's circumstances that call for new lines of inquiry and policy requirements.

Conclusion

This paper has investigated the role of Artificial Intelligence (AI) integration for financial inclusion in Pakistan, with a grasp of mediating variables such as financial literacy, financial behavior practices, government support, AI-based risk mitigation, and user adoption. By providing quantitative research on how modern technologies like AI enhance financial inclusion in developing countries, this study fills a major knowledge gap.

The result demonstrates that AI technology has an intricate role in financial inclusion. AI integration was found to significantly enhance financial literacy and user adoption, though its impact on behavior practices was less pronounced. The results show that AI-driven financial education platforms, budget management software, and predictive analytics all help individuals become more financially literate and encourage prudent financial conduct.

Interestingly, some results diverged from initial expectations. The mediating roles of government support and AI-based risk mitigation in facilitating financial inclusion were found to be statistically insignificant. This suggests that while AI technologies provide robust tools for risk management and regulatory compliance, their direct role in broadening access to financial services might be limited. Market-driven initiatives and financial literacy programs may act as an important contribution to top-down government support in enhancing financial inclusion.

Overall, this study offers both academic and practical contributions, underscoring the need for a balanced strategy that combines AI-driven innovation with inclusive education and policy reform.

Recommendations

As a result, this study reaches several actionable recommendations for policymakers, financial institutions, and researchers. Investment in digital and communication infrastructure must focus on both rural and underbanked territories because this will facilitate full demographic access to AI-driven financial services. Policies should prioritize AI innovation investment for its technologies, consumer rights protection, data security, and privacy safeguards.

The national development of educational and community programs should integrate AI-based financial education solutions for enhancing financial literacy and inclusion for all citizens. Fin-tech companies should work together to develop modern solutions that solve financial exclusion problems within remote and underserved areas. You should build AI-based applications with intuitive design and multilingual support, and accessibility functions to serve broad user sections, including groups with minimal digital abilities. Advanced AI algorithms should be used to fight fraud while conducting credit risk assessment and processing compliance, so the system becomes more reliable and increases financial access for the population. The segmentation of specific underbanked consumer needs allows companies to create microloans and low-cost insurance solutions while using AI risk evaluation to facilitate these products.

Limitations

This study possesses several limitations and is open to different future lines of research. Firstly, this research was conducted on a sample of 250 respondents using a mixed-methods approach with a primary focus on quantitative methodology so that future studies can be conducted on a larger size of sample size with both quantitative and qualitative approaches used for in-depth findings. Furthermore, research was conducted in a short time frame, which may not adequately capture the long-term impact of AI integration on financial inclusion. This study does not focus on any specific industry and not any specific AI applications, however, future studies can implement this study on specific applications and industries to determine the unique impacts of financial inclusion. AI adoption in the financial sector is still in its early stages, and further study is required to understand its effectiveness in achieving financial inclusion.

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Appendix: Visualizations and Updated Data Tables

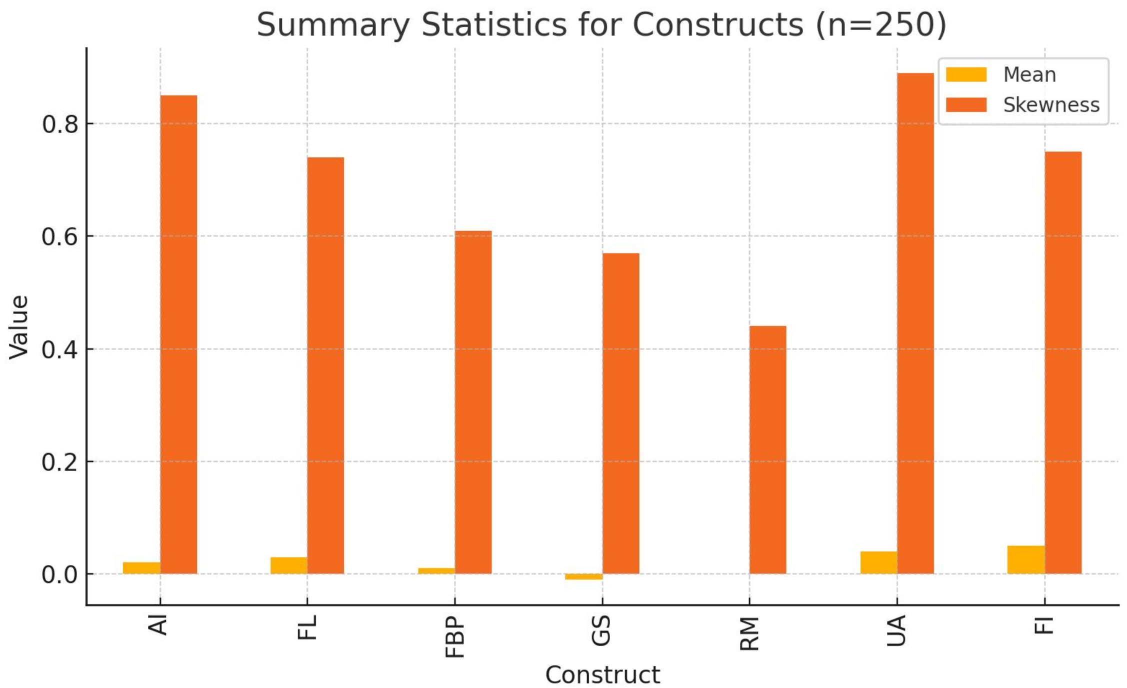

Table A1: Summary Statistics for Survey Constructs (n=250)

Construct	Mean	StdDev	Skewness	Kurtosis
AI	0.02	1.0	0.85	0.67
FL	0.03	1.0	0.74	0.44
FBP	0.01	1.0	0.61	0.34
GS	-0.01	1.0	0.57	-0.51
RM	0.0	1.0	0.44	-0.25
UA	0.04	1.0	0.89	1.2
FI	0.05	1.0	0.75	0.61

Summary of Hypothesis Results

Hypothesis	Supported
H1: AI -> FL	
H2: AI -> FBP	
H3: AI -> GS	
H4: AI -> RM	
H5: AI -> UA	
H6: FL -> FI	
H7: FBP -> FI	✕
H8: GS -> FI	✕
H9: RM -> FI	✕
H10: UA -> FI	

Figure: PLS Bootstrapping Results

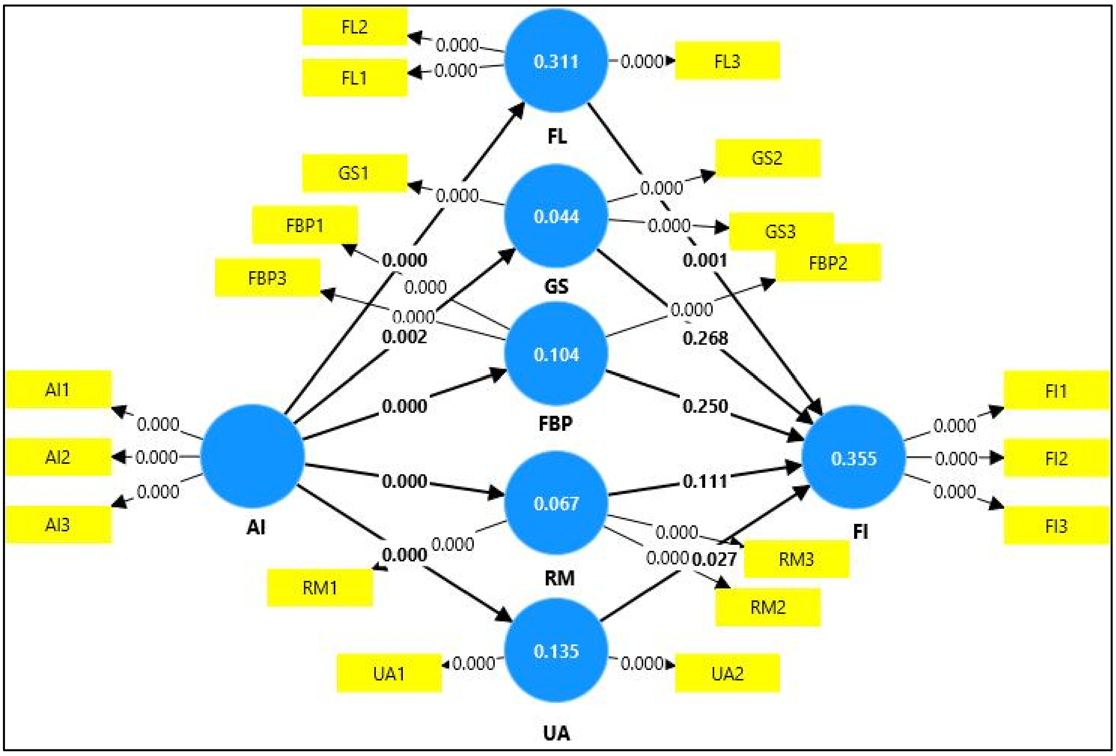

Figure 3: Path model with bootstrapped coefficient values. For actual publication, export this from SmartPLS.