Name of Publisher: BRIGHT EDUCATION RESEARCH SOLUTIONS

Area of Publication: Business, Management and Accounting (miscellaneous)

Let's Start!

Journal of Management & Social Science

ISSN Online: 3006-4848
ISSN Print: 3006-483X

https://rjmss.com/index.php/7/about

RECOGNIZED IN "Y" CATEGORY BY HEC

[ARTIFICIAL INTELLIGENCE INTEGRATION FOR FINANCIAL INCLUSION: A STUDY IN PAKISTAN]

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Review Type: Double Blind Peer Review

Journal of Management & Social Science
VOL-2, ISSUE-1, 2025

ABSTRACT

Purpose - Artificial Intelligence (AI) integration into financial systems has been given important attention due to its potential to enhance financial inclusion, particularly in developing economies like Pakistan. This research examines the potential of AI integration for financial inclusion through mediating variables. The primary aim of this study is to uncover AI solution benefits that improve financial inclusion when these important factors interact. This quantitative study aims to look into the role of AI integration in Pakistan's financial inclusion. Data was collected from 200 financial services users in Pakistan. Data is analyzed using statistical techniques such as PLS-SEM. PLS-SEM modeling was implied to examine the research framework of the study. The study confirms that AI integration has a positive role in mediating variables. The study has implications, that can be recognized and used by policymakers to shape targeted interventions, and policies, which improve financial access by enhancing user knowledge about financial matters and promoting the acceptance of AI system utilization. Findings enable practitioners to create better financial education programs and inclusive financial service delivery so that people can easily understand and access desired outcomes. This study enhanced the academic knowledge of the utilization of AI technology to promote economic growth in developing economies.

Keywords: Artificial Intelligence, Financial Inclusion, Financial Literacy, User adoption, Finance.

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, is evidenced by 21% of adults having formal bank accounts (SBP, 2021) poor infrastructure, insufficient digital literacy, and cultural barriers. Recent studies show 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 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 analysis of current literature confirms the extent to which AI has revolutionized financial inclusion by addressing the challenges of getting to the unbanked population (Fazal et al., 2023).

A thorough financial inclusion review is provided, featuring prominent global trends in research as reported in (Kumar, 2024). The study highlights how AI can help bridge the digital skills and geographical distance divide, especially in developing countries. Dhiman (2024) also outlines an AI deployment plan for financial contexts that prioritizes accessibility and sustainability. From the paper, education, and access to finance can be encouraged through AI solutions, which foster lifelong learning as well as social inclusion.

The paper by (Akhtar et al,.2024) explores how government policies affect fintech adoption across Pakistan, employing AI to analyze financial inclusion. The research study uncovers government policy components that both enable and hinder implementation while making recommendations for government support initiatives. Another study (Hamadou, 2024) examines Islamic banking through Bank Syariah Indonesia while analyzing AI integration challenges and opportunities This study demonstrates that AI serves as a tool to foster ethical banking operations inclusively. Artificial intelligence plays an important role in improving financial inclusion. 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.

A paper by (Ritika, 2023) in which the usage of AI to enhance financial integration among unbanked and underbanked populations. The research aims to solve financial exclusion through AI-powered solutions proposals. The analysis encompasses multiple sections about its historical development alongside operational aspects and SWOT analysis while discussing extensive implementation potential. This study investigates the digital businesses and financial organizations that have taken action in this field. The research proposed to AI-powered solution to solve marginalized problems that the unbanked and underbanked population face.

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 with 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 trial ability, 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 Positively Impacts Financial Literacy

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 Integration Positively Impacts Financial Behavior Practices

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 have 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 essential 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.

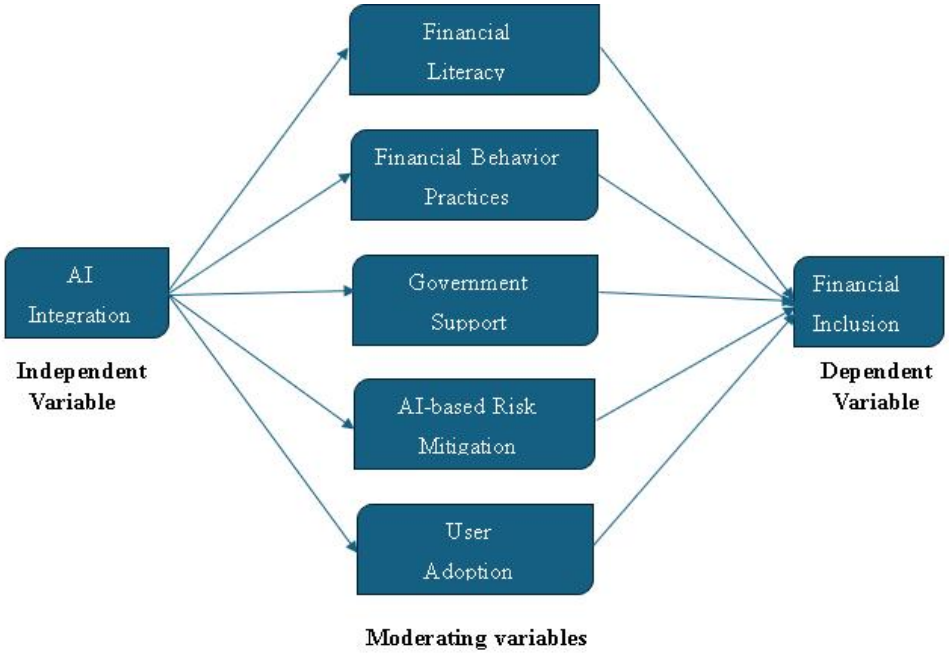

Figure1: Theoretical Framework

Research Methodology

In this research, a correlational design was chosen as the research method. sampling technique is Purposive sampling which will target individuals who are directly involved with AI technologies, such as users of financial technology to ensure that the sample includes those with relevant expertise. Additionally, the sampling technique is purposeful sampling which will focus on selecting participants from specific regions, income levels, and demographic groups that are most likely to provide insights into the impact of AI on financial inclusion. The target demographic for this survey is students, employees, self-employed, unemployed, and retired individuals who interact with banking, digital finance, and AI-driven financial solutions. Information was collected through a web-based questionnaire and distributed via email and LinkedIn to respondents. The groups are selected that represent a diverse segment of financial product users, offering valuable insights into the role of AI integration on financial inclusion. A study test size of 220 responses was collected from all sources. The questionnaires received found missing information and external sources, and 200 out of the 220 questionnaires received were used.

The respondent's demographic data include age, gender, education, income, and occupation. Among these, 75.5% of the respondents were male and 24.5% were female. 82% of those surveyed are between the ages of 20 and 30. People in this age range are most likely students or those just starting their careers. Regarding education, 66.8% of those surveyed hold graduate degrees in a variety of subjects. According to the poll, 55.9% of participants hold full-time, salaried positions. Residence distribution showed that 55.9% were from urban areas, while 45.5% resided in rural regions. Survey responses were obtained through a self-administered questionnaire The questionnaire comprises

seven variables, including AI Integration, financial literacy, financial behavior practices, government support, AI-based risk management, user adoption, and financial inclusion. A five-point Likert scale is used for all items that were graded with answers ranging from strongly agree to strongly disagree.

Data Analysis and Results

The researcher utilized the PLS-SEM Partial Least Square 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 col linearity 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	**AI1**	.308	0.736	0.758	0.850	0.655
	AI2	.667				
	AI3	.584				
Financial Literacy	**FL1**	.183	0.624	0.635	0.799	0.571
	FL2	.337				
	FL3	.241				
Financial Behavior Practices	**FBP1**	.238	0.649	0.683	0.807	0.584
	FBP2	.312				
	FBP3	.263				
Government Support	**GS1**	.929	0.799	0.827	0.882	0.714
	GS2	.247				
	GS3	.484				
Risk Mitigation	**RM1**	.398	0.661	0.676	0.816	0.599
	RM2	.522				
	RM3	.181				
User Adoption	**UA1**	.304	0.651	0.653	0.851	0.741
	UA2	.304				
Financial Inclusion	**FI1**	.457	0.735	0.741	0.849	0.653
	FI2	.628				
	FI3	.381				

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	0.000	-0.282	-1.476	3.300	1.000	0.443	0.742
FBP	0.000	-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.

Figure 3: Bootstrapping

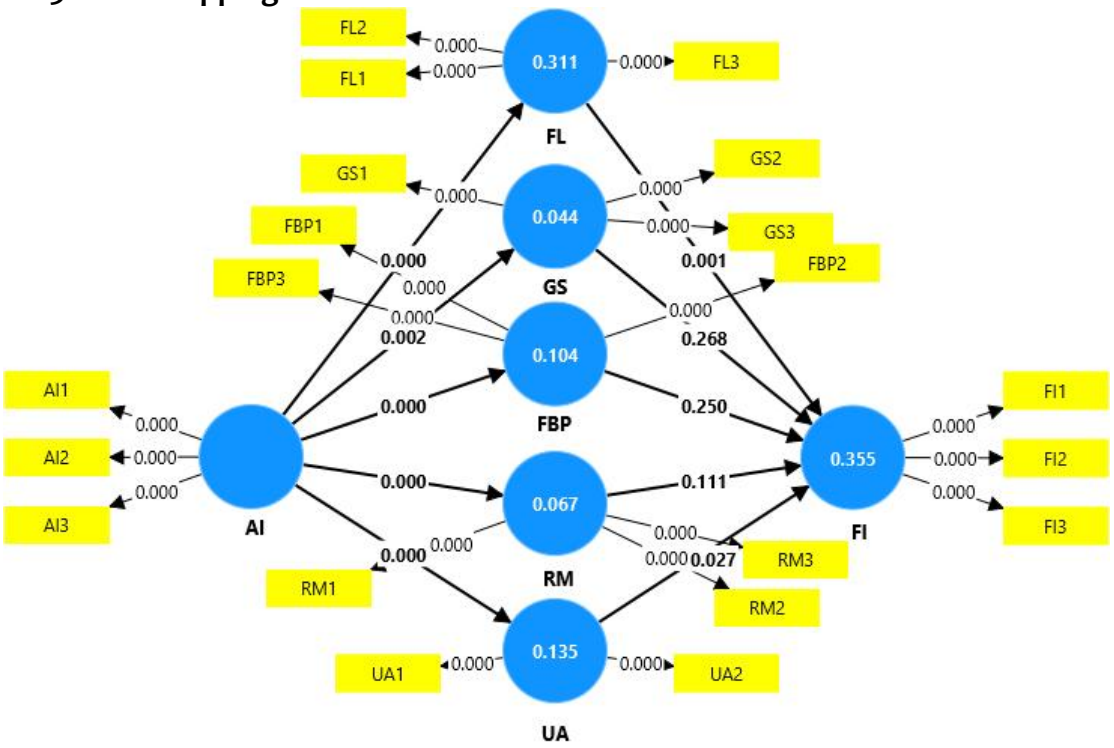

Table 4: Path Coefficient

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 not supported.

Table 5: Specific Indirect Mediator Effects

Construct	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI -> FL -> FI	0.154	0.159	0.055	2.818	0.005
AI -> FBP -> FI	0.038	0.039	0.036	1.047	0.295
AI -> GS -> FI	0.017	0.019	0.019	0.929	0.353
AI -> RM -> FI	0.032	0.035	0.024	1.331	0.183
AI -> UA -> FI	0.074	0.073	0.036	2.061	0.039

The findings reveal that hypothesis one is accepted because Table 4 below clearly demonstrates the positive coefficient between AI->FL (0.558) suggesting a positive strong 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 is also accepted (AI->GS) because the findings show that a positive coefficient (0.259) and significant P value 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 the findings show that a P value of 0.000 and T statistic of 1.549 indicates a strong positive 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 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 significant 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 analyzed 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 Analysis (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 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 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 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 amounts to an insignificant factor when measuring the role of individual Financial Behavioral Practices for Financial Inclusion. (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 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 this 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 is to be in dearth. 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 inequity and policy requirements.

Conclusion

This paper has investigated the role of Artificial Intelligence (AI) integration for financial inclusion in Pakistan, with the grasping 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. Integration of AI shows a positive role in increasing the ratio of financial literacy, financial behavior practices, and user adoption in financial services. 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.

The research shows some unexpected results in addition to the main findings. 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 an important contribution than top-down government support in enhancing financial inclusion.

Overall, the study contributes to the academic and practical understanding of how AI can catalyze financial inclusion, highlighting the need for a balanced approach that includes both technological innovations and human-centric strategies.

Recommendations

As a result, this study reaches several actionable recommendations for policymakers, financial institutions, and researchers. Digital and communication infrastructure investment 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 that focus on simple design and offer language

choices 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 the different future lines of the research. Firstly, this research was conducted on a sample of 200 respondents, and responses were mixed, quantitative methodology is measured so that future studies can be conducted on the larger size of the sample with both quantitative and qualitative approaches used for in-depth findings. Furthermore, research was conducted in a short time frame, which may not capture the long-term effects of AI integration for 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 the specific applications and industry 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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