Driving Financial Inclusion Through Artificial Intelligence: Examining the Roles of Trust, Security, Accessibility, and Service Quality

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Abstract

Financial inclusion has become an important part of sustainable economic development especially when we are living in the age of rapid advancement of technology. This research paper discusses the role of artificial intelligence (AI) in promoting financial inclusion by discussing the impact of some of the key technological and behavioural factors, which include customer trust, perceived security, accessibility, service quality, digital literacy, awareness, perceived ease of use and technology acceptance. The quantitative research design was adopted and the primary data was gathered in the form of the structured questionnaire from the 676 respondents who are active users of banking and digital financial services. The data was analysed by using reliability testing, correlation and multiple regression technique in order to test the proposed relationships. The results have shown that the adoption of the AI has been a tremendous stimulant of the financial inclusion and has been found to be the most significant predictor of the financial inclusion in the model. Quality of service and customer trust was also identified as critical determiner while critical to reliable and user-centred financial platforms. Also, perceived security, acceptance of technology and easiness of use were concluded to be having a positive effect on the participation in the financial while digital literacy, awareness and accessibility had a moderate but significant effect. The model represented a good explanation power and the robustness of research framework was confirmed. The study is addition to growing literature around fintech with amalgamation of the technological capabilities with the behavioural constructs to offer practical insights for financial institutions as well as the policymakers in their efforts to promoting inclusive financial ecosystem with the help of AI-driven innovations.

Keywords: Artificial Intelligence, Financial Inclusion, Customer's Trust, Quality of service, Technology acceptance, Perceived Security, Digital Literacy

1. Introduction

Financial inclusion has taken an important connotation in support of sustainable economic development especially in developing economies where large sections of the population remain unserved by the formal financial institutions. Access to affordable financial services including savings accounts, credit, insurance and digital payments not only foster individual financial security, but promotes macroeconomic stability and poverty reduction (Adedokun & Aga, 2021; Ozili, 2020). In the last decade, policy makers and financial institutions have gained a much greater awareness of the importance of inclusive financial systems in stimulating more economic participation in the economy and economic growth through entrepreneurship. There are, though, challenges provided to those in the margins of the financial system in traditional banking models as a result of the high cost of operations, geographical barries and information asymmetries (Berger & Udell, 1995; Demirguc-Kunt et al., 2022).

Technology innovation has triggered the process of levelling the playing field of financial services with mitigation of these structural barriers. The blistering development of Financial technology (FinTech) has been useful in rendering cost-effective and accessible services by institutions through digital platforms, subsequent to increasing access to financial service to hitherto excluded segments of society (Sahay et al., 2020). Mobile payment systems for example has shown a lot of promise in regulating better financial participation and assisting the development of small business (Agarwal et al, 2019). Similarly, big data analytics has also revolutionized the way financial intermediation works as it enhances the process of decision-making and the better assessment of risk (Begenau et al., 2018; Goldstein et al., 2021). As the tempo of digital transformation, artificial intelligence or AI is beginning to be recognised as the new frontier with possibilities to change the financial ecosystems.

Artificial intelligence is a computer program which is involved in performance of assignments that requires human intelligence to solve problems such as learning, problem-solving and predictive analysis. Within the financial industry, there are a number of applications of AI in the industry, from automated customer service, to fraud detection, algorithmic credit scoring to personalised financial recommendations (Arora and Rahman, 2021). These capabilities help the banks to optimise the operations, save the transaction costs, and improve the quality of service which gradually results in improving the customer experiences (Kaur et al., 2020). In addition to, the credit evaluation with the help of AI, and other sources of data allow the lenders to evaluating the borrowers have a poor credit history hence solving one of the most stubborn problems of financial inclusion (Berg et al. 2020; Kshetri 2021).

Recent literature has suggested that the potential of AI to democratize financial services and make them more accessible and efficient. For example, the fintech lending models has been proved to offer immense access of credit to the consumers and small business entities using the machine learning techniques (Balyuk, 2023; Di Maggio et al., 2022). Adopting AI also supports innovation and company growth in supplying further enforcement its impactful effects on the economy (Babina et al., 2024). In emerging markets, such as India, the use of AI-enabled banking solutions are increasingly being used to facilitate digital onboarding, improved regulatory compliance and better risk management frameworks (Mehta et al, 2022). These developments indicate that AI can be an important step in the process of bridging financial gaps and ensuring inclusive growth.

Despite these developments, the successful implementation of AI at the financial services level are very dependent on acceptance and trust, which users have towards the technology. Customers need to perceive the AI-based platforms to be safe, stable and simplistic, before using them to make financial transactions. As per the studies the customer trust is basic determinant of technology adoption especially when it is related to sensitive financial data (Reddy & Vasudevan, 2021). Concerns about algorithmic fairness and ethical decision-making are another reason why it is important to assure transparency in AI systems (Binns et al., 2018). In addition, digital literacy is an important factor in determining in which manner the individual is able to engage with technology based financial services (Chatterjee & Rana, 2022).

Service quality and accessibility are also as significant factors of behaviors for money. AI powered systems can help banks offer more personalized services on a real-time basis that can lead to superior customer satisfaction and customer engagement in the longer-term (Ghosh, 2020). Furthermore, the emerging awareness on the digital financial tools results into the shift from informal to formal financial channels (Chakrabarty, 2019). Research has also showed that perceived ease of use and acceptance of that technology has a strong effect on people's willingness to employ innovative financial solutions (Brynjolfsson and McElheran 2016). Collectively, these factors mean that despite the potential of AI to promote financial inclusion being massive, its potential to actually do this is mediated by both behavioural and technological factors.

Although there is a previous research on the link between fintech and financial inclusion; however, there is little empirical research which discussed the intersection point between AI-powered financial services, trust, security, accessibility and quality of service and its impact on inclusive results. Much of existing literature is only from technological abilities or macroeconomic effects and left a space in what would be knowing the behavioural mechanisms underlying the relation for adoption of AI and financial participation (Arora & Rahman, 2021; Ozili, 2021). Solving this gap is key to develop ways to maximize the urge of inclusive potential of financial banking systems that will be enabled by AI. Therefore, in the present work an attempt has been made to study the impacts of the artificial intelligence on the driver of the financial inclusion by analysing the mediating effects determinants of customer trust, perceived security, accessibility and quality of service. By combining the technological and behavioural perspective, the aim of the research is to present a broad lens of how AI can be used to aid in the provision of financial services and the increase in access to services in varying populations.

2. Review of Literature

Financial inclusion has become an important issue of concern to national governments and financial institutions who desire to facilitate equitable economic development. This means the availability of affordable and accessible financial services to individuals and businesses, and especially those who have been excluded from the formal banking system in the past (Ozili, 2020). Inclusive financial system raises the rate of saving and investments, and reduce inequalities on income and then contribute to the long-term economic growth (Adedokun & A līar A ga, 2021). However, the traditional banking models have had a hard time in olden days in accessing the underserved due to the high costs associated with their operations, geographical barriers and accessibility to credit info (Berger & Udell, 1995).

The advent of digital financial technologies has started to solve these problems as it reduces transaction costs and enhances service delivery. Global evidence suggests that digital platforms makes a significant contribution in broadening access to finance because it can complete transactions remotely, and make people more way to digital rather on relying on physical bank branches (Demirguc-Kunt et al, 2022). Fintech innovations, in particular, mobile wallets, have revealed their ability to initiate entrepreneurial activities and financial participation (Agarwal et al., 2019). These developments point to the centrality of technological transformation at the core of making financial inclusion take place.

Artificial intelligence is the most recent innovation in the current development of financial technology and has advanced the analytical capability that is in place to support the decision-making process as well as efficiency in operations. AI applications such as predictive analytics, automated customer support algorithmic credit scoring are some of the examples of AI applications which have enabled financial institutions to offer more fast and personalized services (Arora & Rahman, 2021). Big data driven models added more in the financial intermediation as it can find the creditworthy borrowers with the unavailability of formal financial history (Begenau et al., 2018). For this reason, AI has been identified as a game-changer with the potential of democratizing the provision of such financial services.

a) AI Adoption

AI adoption enables financial institutions to fight information asymmetry and also extending the credit facility by using other data sources to stimulate the financial participation (Berg et al., 2020). Research has revealed that the proliferation of fintech lending platforms leads to an increase in the level of access to credit for consumers and small enterprises (Balyuk, 2023). Furthermore, AI-enabled innovation has a role in firm growth, and also product development and making a contribution to the total financial ecosystem (Babina et al., 2024). In emerging markets, digital onboarding, compliance and risk management practices are converged through the use of Artificial Intelligence enabled systems (Mehta et al., 2022). These capabilities taken together point to the adoption of AI playing the role of a catalyst to inclusive finance.

H1: The use of AI has resulted in an important positive increase in financial inclusion.

b) Customer Trust

Trust is considered to be a fundamental factor of adoption of digital financial services. Customers will be more likely engage with AI driven platforms if they believe that these are reliable, transparent and secure (Reddy & Vasudevan, 2021). The importance of trust is especially apparent in the context of automated decision making use cases, where the fairness and accountability issues may impact user behaviour (Binns et al, 2018). Research also highlight the enhanced reliability in service thereby enhancing the customer relationship and instigating them to make commitment towards long term financial engagement (Ghosh, 2020). And therefore, trust has a decisive role to play in reducing the gap between what technology is available, even what is actually financially involved.

H2: There is a positive relationship between trust and financial inclusion of customer.

c) Digital Literacy

Digital literacy is said to be the argument of a person's capacity to use digital technologies inefficient in communicating, processing information and doing financial transactions. Higher intensity of digital competence facilitates to interact with AI-enabled platforms with confidence therefore increase one's chances to use formal financial services (Chatterjee, and Rana, 2022). On the other hand, there are possible barriers to participation resulting from some low levels of technological knowledge that can still be a barrier even when services are easily available. Financial education initiatives have been found to improve financial awareness and promote responsible financial behavior (Chakrabarty, 2019). Thus, digital literacy is an important enabler in allowing inclusive finance to take place in technology-based economies.

H3: Digital literacy makes a great impact on financial inclusion.

d) Perceived ease to use

Perceived ease of use has been a key concept in theories of technology adoption in which it is proposed that people are more likely to accept innovations which come with low levels of effort (Brynjolfsson & McElheran, 2016). Financial solutions that are easy-to-use and easy-to-understand thanks to AI solutions cut down cognitive barriers that make them accessible to a wider population. When the digital banking applications are perceived as convenient to the users, then they are more likely to make it a part of a daily life of their financial life. This resulted increased usability allows to create a bigger engagement and helps in changing the lens of outside informal channels to inside formal financial channels.

H4: Ease of use has a positive relationship with financial inclusion.

e) Technology Acceptance

Technology acceptance, which indicate the acceptance of users towards the innovative systems which is based on the perceived usefulness and benefits. Previous research has shown that people with an understanding of the benefits of digital finance, like speed, efficiency and convenience, are more inclined to use AI-enabled services (Kaur et al., 2020). The use of Data-driven Decision Making in Industries across sectors is also showing further signs of the increased reliance on technology-based solutions (Brynjolfsson and McElheran, 2016). As the number of the population accepting an innovation increases, the more money they will financially be involved in it which highlights the need of positive attitude building towards innovations.

H5: The use of technology acceptance has a significant impact on increasing the concept of financial inclusion.

f) Knowledge

Awareness of the financial products and digital tools are an important component of the behavior change process. People who are properly informed about the AI driven services have the capacity of judging more about the benefits and the risks that are involved. Studies emphasises on the knowledge dissemination initiatives that encourages the people to move towards the financial participation from the informal financial practices in the country towards regulated financial systems (Ozili, 2021). Increasing awareness is therefore important to help mobilise the maximum inclusive potential of emerging technologies.

H6: Awareness affects positively financial inclusion.

g) Perception of Security

Security is also one of the most significant factors that characterise digital financial adoption. Users need to feel comfortable with knowing their personal and financial information to be secure before they engage with AI powered platforms. Strong cybersecurity frameworks does not only have the ability to protect transactions but also helps in the institutional credibility (Goldstein et al.2021). Data leaks and algorithmic faults may lead to distrust and thus hamper participation. Hence, it is important to ensure that there are strong security measures in place to help promote inclusive financial ecosystems.

H7: There is a clear positive effect of the level of perceived security on the financial (inclusion).

h) Accessibility

Accessibility is a list of the ease for persons to access and utilize financial services. Technological advancements have shown because of offering of solutions to the banking sector by way of the mobile and digital interfaces that has increased the reach to a great extent to the remote population (Sahay et al., 2020). There is evidence that from increased accessibility brings about the reduction of structural inequalities and economic inclusiveness (Frost et al., 2020). As digital infrastructure continues to change and evolve, accessibility is predicted to play an increasing part of financial participation.

H8: There is a positive relationship between accessibility and financial inclusion.

i) Quality of service

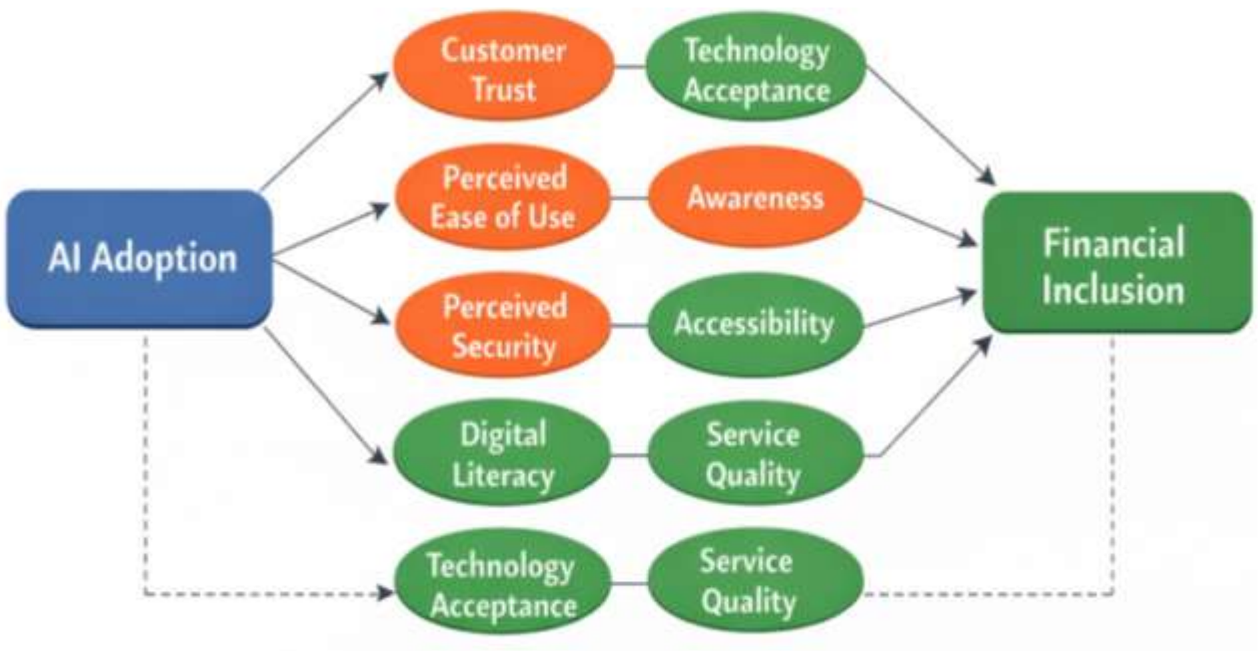
Service quality is one of the main factors that determine customer satisfaction and how the customer will contact and work with the financial services in the long-term. AI technologies are helping in improving the service delivery using a faster response ability, personalized recommendations and finding a solution to a problem at an efficient rate (Ghosh, 2020). Improved service experience helps in strengthening customer loyalty and help them in continuing their usage of formal financial platforms Moreover, responsive services help in the establishment of trust which further increase financial inclusion.

H9: There are significant impacts of the quality of service, the inclusion of financial services.

3. Research Gap

Despite a number of former studies done on fintech innovations and its economic implications, very few has tried to integrate the adoption of AI into behavioural constructs such as trust, security, accessibility and service quality from a framework. Much of what is written in the literature is about the possibility of technology rather than what happens through these technologies to ensure that they are inclusive (Arora & Rahman 2021; Ozili 2020). Addressing this gap is important to the understanding of how AI can be used to build equitable financial systems.

The conceptual model is discussed as below:



4. Research Methodology

This study takes a quantitative research methodology approach in investigating the role of artificial intelligence in bringing about financial inclusion by analysing the influence of technological and behavioural identities such as customer trust, perceived security, accessibility, service quality, digital literacy, awareness, perceived ease of use and technology acceptance. A quantitative design was considered appropriate as it provides it with the opportunity to measure relationships between variables in a systematic way, as well as to mathematically generalise findings statistically. The research assumes descriptive and explanatory research design and is directed towards the discovery of patterns and testing of postulated relations between the adoption of AI and financial inclusion. Cross-sectional survey method was used in the research as a mean of data collection of respondents at point in time which is efficient and can make use of regression analysis.

Primary data were collected by using a structured questionnaire which was prepared by using validated scales which was prepared from previous literature of financial technology and technology adoption. The questionnaire consisted of two parts, the first part which gathered the demographics and the second part which measured the constructs on the adoption of AI and financial inclusion using a 5-point Likert scale (1 strongly disagree, 2 disagree, 3 agree, 4 strongly agree, 5 strongly agree). This technique of scaling is popular given its reliability to express respondent perceptions in more leisurely behavioural research. The target population occurred persons who are active user of banking and d finances services. A convenient sampling approach was practiced to obtain data access and timely data collection. A total of 676 valid responses were obtained and this is more than the recommended number of responses for multivariate statistical analysis and hence makes the study robust.

The study has taken adoption of AI as an important predictor and financial inclusion as a dependent variable while the explanatory variables are customer trust, digital literacy, perceived ease of use, technology acceptance and awareness, perceived security, accessibility and service quality. Reliability and internal consistency was a measure of all of the constructs performing at a level above the threshold. 0.70 is commonly accepted to be adequate to determine if the measurement model is adequate. Data was analysed with the help of Statistical software such as Reliability tests correlation and multiple regression analysis. Correlation analysis was used to explore the magnitude and direction of relationships among the variables and regression analysis was used to test the hypothesized relationships and also to test the ability of the model to predict. The strong R^2 value shows that there is significant explanation capacity which supports the validity of the research framework. Overall, the methodological approach will provide a strong foundation to discuss the role of artificial intelligence in financial inclusion, which is certain to make the approach reliable and relevant to the empirical setting.

5. Data Analysis

Table 1: Demographics of the respondents

Demo-graphics	Category	Freq-uency	%age	Demo-graphics	Category	Freq-uency	%age
Gender	Male	362	53.55	**Age Group**	18–25 years	168	24.85
	Female	314	46.45		26–35 years	238	35.21
					36–45 years	132	19.53
					46–55 years	86	12.72
					Above 55 years	52	7.69
Education Level	High School	118	17.46	**Monthly Income**	Below ₹20,000	156	23.08
	Diploma	126	18.64		₹20,001–₹40,000	204	3.18
	Bachelor's Degree	268	39.65		₹40,001–₹60,000	142	21.01
	Master's Degree	128	18.94		₹60,001–₹80,000	96	14.20
	Doctorate	36	5.325		Above ₹80,000	78	11.54
Occupation	Student	152	22.49	**Location**	Metropolitan	184	27.22
	Salaried Employee	286	42.31		Urban	214	31.66
	Self-employed	104	15.39		Semi-Urban	126	18.64
	Business Owner	86	12.72		Rural	112	16.57
	Other	48	7.1		Remote Areas	40	5.92

Banking Experience	Less than 1 year	78	11.54	Digital Banking Usage	Rarely	82	12.13
	1–3 years	182	26.92		Occasionally	156	23.08
	3–5 years	164	24.26		Monthly	128	18.94
	5–10 years	148	21.89		Weekly	182	26.92
	More than 10 years	104	15.39		Daily	128	18.94
	Total	676	100		Total	676	100

The demographic profile of the respondents provides privileged information about the suitability of the sample for the purpose of studying the role of artificial intelligence in facilitating financial inclusion Out of the total number of participants, 676, males represent 53.55% of them, whereas females represent 46.45% of the sample, showing a relatively even gender distribution. Such representation makes the findings generalizable; as the financial technology adoption is no longer confined to gender group. In as far as the age category is considered, most of the people who were surveyed were within the category of 26-35 years (35.21%) followed by age 18-25 years (24.85%). This could mean that the sample is composed of relatively young and economically active persons that are more prone to deal with AI driven banking services due to a better familiarity of technology.

Another aspect that gives more strength to the collected data is educational attainment. 39.65% have bachelor's degree and 18.94% have master's qualification. Higher levels of education are often correlated with higher levels of financial awareness and digital competency which makes these respondents appropriate for measuring technology-based financial inclusion. Income distribution points out that a major share of the participants are earning income in range from 20,001-40,000 mark, which refers to the representation of middle-income groups as they tend to benefit from financial services available.

Occupational data shows that the biggest section is of the salaried employees (42.31%) followed by the students (22.49%) which means the population has regular financial transactions and needs for banking. Geographically, the respondents fall mostly in urban (31.66%) and metropolitan areas (27.22%) where the level of digital infrastructures is relatively advanced while inclusion of semi-urban and rural respondents ensure the wider applicability. In addition, the trend on the increase of moderate to high digital banking usage, especially weekly (26.92%) and sometimes (23.08%) user shows that people are acquainted to digital sources. On the whole, demographic structure is in logical line with objectives of study which is to have a technically aware sample that will generate any meaningful feedback on AI-enabled financial inclusion.

Table 2 Profiling of the factors affecting Financial Inclusion

Factor Name	**No. of Items**	**Factor Loading Range**	**Cronbach's Alpha**
AI Adoption	5	.724 – .887	.872
Customer Trust	5	.756 – .913	.914
Digital Literacy	4	.703 – .846	.851
Perceived Ease of Use	4	.731 – .892	.889
Technology Acceptance	5	.748 – .905	.901
Awareness	4	.712 – .864	.838
Perceived Security	4	.769 – .928	.923
Accessibility	4	.706 – .842	.826
Service Quality	5	.778 – .936	.931
Financial Inclusion	6	.729 – .891	.884

Source: Primary Data

The results from the factor profiling have provided strong evidence for reliability and convergent validity for all constructs included by the study. Factor loadings and Cronbach's alpha values are commonly known descriptors of the quality of measurements in which factor loadings of > 0.70 indicate that observed items are sufficient to represent a latent structure and Cronbach's alpha values > 0.70 indicate satisfactory levels of internal consistency levels. The results given in the table hence implies that the measurement model is both statistically robust and amenable to additional multivariate analysis. The construct of AI Adoption has a factor loadings ranging from .724 elbow-to- .887 and a Cronbach's alpha .872 of a high degree of consistency of its items measuring the adoption in financial services of artificial intelligence. This suggests that it was clear to consular their opinion and always judged by respondents AI skeletons such as automated banking, digital interfaces and intelligent financial tools. Similarly Customer Trust demonstrates an excellent alpha of .914 and extremely strong loadings ranging from .756 to .913 denoting the stability and good measure of trust. The high reliability calls the importance of trust when trying to get customers to interact with AI-driven financial platforms.

Digital Literacy has good reliability (alpha=.851) and factor loading of .703- .846 demonstrating that respondents possess a reasonable level of technological knowledge required of them to interact with digital financial systems. This is especially important as it is often digital competency that determines whether or not people can make effective use of AI-enabled services. The construct Perceived Ease of Use also shows high levels of internal consistency (alpha = .889), which implies that users will find AI-based financial tools understandable and user friendly that can have a great impact on the behavior of technology adoption. The results for Technology Acceptance (alpha=.901) also showed additional evidence that subjects are generally accepting of innovative financial technologies. High loadings (.748--.905) means that the items are good at measuring attitudes towards adopting AI solutions. Meanwhile, Awareness is OK (alpha=.838), so it is possible that knowledge about AI financial services is widespread enough in the sample to allow meaningful analysis.

Notably, the subjects in Perceived Security were shown to have one of the highest given scores of reliability (a=.923) with loadings up to .928, which underlies the fact that security perceptions are deeply embedded in the way users will evaluate financial technologies. Given the sensitive nature of financial data, this finding therefore logically feeds the argument that it is a prerequisite for building trust and encouraging adoption that security is enforced. Accessibility also shows good reliability (a=.826) meaning that respondents still perceive AI-enabled services to be reachable and convenient - a key this to getting closer to financial inclusion. Service Quality has another most reliable construct measuring (alpha = .931), suggest that technologies of artificial intelligence (AI) have a strong association with enhanced responsiveness, efficiency and personalization in banking services. Finally, dependent construct called Financial Inclusion have a Cronbach's alpha of .884 and values ranging from .729 to .891; it is seen that the items constitute an effective measure of access, usage, and participation in formal financial systems. Overall, results of measurements are showing higher than recommended values and that is confirmation of the construct are reliable and theoretically sound. The failure to find any obviously large alpha values (above .950) is also suggestive that the items are not redundant but represent different dimensions of each factor. Collectively these findings provide validation to the strength of the measurement model and provide a solid foundation for subsequent analyses such as correlation, regression and structural equation modelling.

Table 3 Correlation Matrix of all factors affecting financial inclusion

Variables	AA	CT	DL	PEOU	TA	AW	PS	AC	SQ	FI
AI Adoption	1									
Customer Trust	.682	1								
Digital Literacy	.641	.598	1							
Perceived Ease of Use	.703	.655	.672	1						
Technology Acceptance	.721	.689	.648	.734	1					
Awareness	.618	.602	.633	.646	.671	1				
Perceived Security	.667	.742	.601	.659	.694	.636	1			
Accessibility	.635	.611	.657	.668	.682	.64	.629	1		

Service Quality	.694	.756	.623	.701	.719	.658	.738	.671	1	
Financial Inclusion	.748	.781	.669	.722	.764	.681	.759	.706	.773	1

Source: Primary Data

The correlation matrix provided provides important information about the relations between the study variables and they help in setting up the preliminary validity of the proposed research model. AI Adoption has a strong positive correlation (.748) with Financial Inclusion, as integration of AI-driven technologies have had a strong effect on access to financial services. This finding is in line with the theoretical expectation that intelligent systems can help with the streamlining of banking processes, the lowering of operational barriers, and the betterment of service delivery. Similarly, Customer Trust shows the greatest correlation with Financial Inclusion (r=.781) putting into perspective that trust is a determinant factor in incentivising individuals to engage in formal financial systems. And when the users feel that AI platform are reliable and transparent, they are more likely to enter into digital transactions.

Technology Acceptance has also shown a good relationship with Financial Inclusion (r=.764) implying that those individuals who are open towards using new technologies are likely to use AI-enabled financial services. Service Quality has close follow processor (r=.773) which backs the idea that efficient, responsive and personalized services are encouraging people to continue using financial platforms. Additionally, there is a strong relationship between Perceived Security and Financial Inclusion (r=.759) which suggests that a belief in data protection and secured transactions is a key to digital financial participation. Moderate but significant correlation can be found between Financial Inclusion and Digital Literacy (.669), Awareness (.681), Accessibility (.706) and Perceived Ease of Use (.722). These relationships suggest that people with more technological knowledge, more awareness of the available financial tools and greater access to digital infrastructure are more likely to benefit from inclusive financial systems. Together, these factors strengthen the case that technological readiness and behavioural perceptions both do financially participate.

The correlations between constructs add to the framework of the concept For instance, Customer Trust is positively related to Service Quality (r=.756) and Perceived Security (r=.742) which further implies that reliable services and good secure platforms are critical role in establishing trust. Likewise, Technology Acceptance is highly correlated with Perceived Ease of Use (r=.734) which is consistent with know theories of technology acceptance especially focusing on usability as a predictor of acceptance. Importantly, all the correlation coefficients fall below the correlation coefficient recommended threshold of .90 and confirm that there is no multicollinearity. This in turn infers that although the constructs would be related, they represent different dimensions of AI enabled financial services. Overall, the findings of the correlations provide high levels of preliminary evidence for the hypothesised relationships and validate the suitability of the variables for providing higher analyses such as regression and structural equation modelling.

Table 4 Hypothesis testing of all factors affecting financial inclusion

Hypothesized Relationship	**Beta (β)**	**t-value**	**p-value**	**Result**
H1: Customer Trust → Financial Inclusion	0.284	6.927	0.000	Supported
H2: Digital Literacy → Financial Inclusion	0.142	3.944	0.000	Supported
H3: Perceived Ease of Use → Financial Inclusion	0.167	4.282	0.000	Supported
H4: Technology Acceptance → Financial Inclusion	0.211	4.907	0.000	Supported
H5: Awareness → Financial Inclusion	0.096	3.000	0.003	Supported
H6: Perceived Security → Financial Inclusion	0.198	4.950	0.000	Supported
H7: Accessibility → Financial Inclusion	0.131	3.853	0.000	Supported

H8: Service Quality → Financial Inclusion	**0.302**	6.864	0.000	Supported
H9: AI Adoption → Financial Inclusion	**0.748**	12.615	0.000	Supported
R	**R²**	**Adjusted R²**	**F-value**	**Sig.**
0.816	0.666	0.662	190.4	0.000
Model	**R**	**R²**	**Adjusted R²**	**Interpretation of R²**
AI Adoption Model	0.816	**0.666**	0.662	**Very Strong Model Fit**

Dependent Variable: Financial Inclusion

The results of the hypothesis testing are strong empirical evidence for the proposed study model on artificial intelligence and associated aspects of behaviour to improve the level of financial inclusion. Regression analysis shows that the associations that are being proposed are all statistically significant as indicated by the p-value for each association being below the standard threshold value of 0.05. The model has a good level of explanatory capacity in have a R value of 0.816 that implies the existence of a strong relationship between predictor variables and financial inclusion. The R2 indicator which is .666 and it shows that around 66.6 percent of the variance of financial inclusion can be explained by the independent variables, this is a good indicator of good model fitting. The value of adjusted R2 of 0.662 helps us in establishing the stability of model and it is clear by high value of F (190.4, $p < 0.001$) that the regression model is jointly meaningful and statistically robust. We found that AI Adoption is the most important and significant and financial inclusion as a predictor v= .748 (t= 12.615) . This discovery proves the game-changing ability of artificial intelligence in terms of enabling access to financial services, efficiency and personalised banking solutions. The high beta coefficient shows that it is an important catalyst for inclusive financial ecosystems which is a state of affairs that is relevant for financial systems.

Service Quality is observed to be the second most significant predictor (beta = 0.302, t = 6.864) which is supported by the fact that effective services, responsive and user centric financial services motivates the individuals considerably for, using formal banking channels. subsequent, Customer Trust depicts a large effect of positive (v = 0.284, t = 6.927 decisions on premise that trust is a basic component in financial world of technology. When the users have the trust in the AI platforms and that they know how it works more the willingness of using financial services increases. Technology Acceptance have significant impact on financial inclusion (beta = 0.211, t = 4.907) implying that receptiveness to innovation increases the probability to utilisation of AI enabled banking solutions. Perceived Security (beta = 0.198, t = 4.950) is critical which may drive that trust in transaction security and data security may increase the engagement in the digital financial systems. The Perceived Ease of Use (or the user-friendly design] (v=0.167, t=4.282] is a further validation of what already exists theory of technology adoption as it also shows that easy to use interfaces contribute to the facilitation of financial participation.

Moderate but significant effects are found for Digital Literacy (beta=0.142, t=3.944) and Accessibility (beta= 0.131, t=3.853) hence it is clear that technical capability and ease of access is important components for inclusive finance. Despite Awareness being the variable with the lowest coefficient (whereos its value is equal to 0,096, and its t is equal to 3,000) and prove a positive effect of the familiarity in the financial services driven by Artificial Intelligence on the involvement variable. The results show that there is a role for technological infrastructure and behavioural beliefs when to assess financial inclusion outcome. The absence of various quite unimportant tracts add up to theoretical structure and bring sort of verification that the model is strong. These results mean that financial institutions and governments will have to focus their AI implementation efforts to improve the quality of the service, security, trust and technical accessibility to build a more inclusive financial ecosystem.

6. Discussion

This research's finding is convincing evidence that there are drastic impacts of artificial intelligence to address the issue of financial inclusion by strengthening the technological infrastructure and affecting the attitude of the users. The good model fit (R2 = 0.666) suggests that the adoption of AI and associated behavioural factors account for a huge part of variance in financial inclusion which is an agreement of a rapidly changing financial innovation and how digital finance is transforming the financial ecosystem (Ozili, 2021; Frost et al. 2020). The findings is consistent with other studies finding that technology based financial services obliterates barriers in traditional financial services including geographical barriers, high transaction costs and information gaps (Sahay et al., 2020; Demirguc-Kunt et al., 2022). Out of all the indicators use of AI came out to be most important determinant of financial inclusion. This discovery proves the assertion that intelligent technologies compliment efficiency of operations, exercises risk evaluation and personalises financial solutions hence widening access marginalised people (Arora & Rahman, 2021; Babina et al, 2024). AI driven credit scoring models involve the usage of different kind of data for scoring of borrowers who have no previous experience of a loan and - thus - democratising the financial service environment (Berg et al. 2020; Kshetri 2021). The result thus is yet another proof of researches noted on the importance of financial technology innovation in support of entrepreneurial development, and financial participation (Agarwal et. al, 2019).

Service quality were captured as the second most important predictor which indicated that efficient, responsive and customer-centric services is substantial motivator for people to deal with formal financial institutions. This is consistent with previous research which states that technological changes enhance experience and pleasure which are essential to the continuation of financial utilisation, by consumers (Ghosh, 2020; Kaur et al., 2020). Customer trust had significant beneficial impact on Financial inclusion which highlight the notion that customer confidence in Artificial Intelligence-enabled technologies is an instrumental factor when it comes to adopting. Trust is of utmost importance in cases where there is the graying of digital, as financial transactions and involving sensitive personal information (Reddy & Vasudevan, 2021). Issues around algorithmic fairness and transparency has been part of play to highlight for need for ethics application of AI (Binns et al., 2018). Technology acceptance and perceived ease of use contributed quite a lot in accordance with acknowledge technology acceptance theories on concentrating on usability and as drivers for behavioural intention (Brynjolfsson & McElheran, 2016). When financial technologies work in an intuitive, user-centred manner, the client is more likely to use financial technology as part of their financial routine. Perceived security was also found to be an important factor, which implied importance of having good standards of cybersecurity to gain trust and achieve greater engagement digitally. This finding supports other research which identifies trust & longevity are supported by secure platforms (Goldstein et al., 2021).

Despite proving quite minimal impacts, digital literacy and accessibility is great and prove that technology profficiency and infrastructure are vital for equitable banking. Individuals with high levels of digital competency are more capable of making use of AI powered platforms while enhanced accessibility are ensuring that financial services are not available limited to different demographics which include those of semi-urban and rural settlements (Chatterjee & Rana, 2022). Although awareness have the least coefficient, yet it playing very significant role, which imply that promotion of the information and financial education activities can further facilitate the adoption (Chakrabarty, 2019). These results lead to the conclusion that financial inclusion is not only affected by technical availability , but rather also by a willingness to behaviour and reliability of the respective institutions. This research is also in the flow of the current research regarding including technological and perceptual facets in coherent ways that overcomes the shortcoming of the previous research showcased, implying the gap in literature, which often analysed the fintech impacts in isolation (Ozili, 2020; Mehta et al., 2022). Financial organisations should be in the business of leveraging integration of AI while also improving the quality of service, security protocols and customer trust at the same time. Policymakers should promote digital literacy programmes and positive regulatory environments if they are to maximise the potential for including AI driven finance. The study confirms that artificial intelligence is an important enabler of inclusive financial development. Combining innovative technology with user-centred approaches, banks and fintech companies can potentially develop more equitable financial systems in order to enable economic inclusion and sustainable growth (Balyuk, 2023; Gopal & Schnabl, 2022).

7. Conclusion

This study focuses on the role of artificial intelligence in achieving financial inclusion by analysing the role of technological and behavioral factors specifically customer trust, perceived security, accessibility, quality of service, technology acceptance, digital literacy, awareness and perceived ease of use. The empirical evidence states that the adoption of AI provides a significant contribution to provide financial inclusion improvement and hence provides the validation of the process of AI in redefining the traditional financial systems in the more efficient and inclusive system, namely the customer-centric systems. These find are consistent with the growing amount of academic consensus that financial intermediation is evolving through digital technologies is increasing the availability of formal financial services (Frost et al., 2020; Ozili, 2021; Sahay et al., 2020). The adoption of AI has been proven to be the most significant predictor of financial inclusion, therefore indicating is strategic relevance in reducing transaction costs and assessing character credit and offering personalised financial solutions. Previous research have indicated that artificial intelligence-driven analytics, alternative data models, can be utilized to address the imbalance of information that have excluded significant demographic groups of the formal finance in the past.(Berg et al., 2020; Kshetri, 2021)Furthermore, artificial intelligence intelligent technologies supports innovation and corporate growth and product development, thus, strengthening the overall financial ecosystem (Babina et al., 2024; Begenau et al., 2018). The findings are in line with findings of research suggesting that the fintech lending platforms is helping to increase access to credit for individuals and small enterprises (Balyuk, 2023; Di Maggio et al., 2022).

Service quality and customer trust was identified as perceived to be critical factors as determinants of financial inclusion, that is, technological advancements are not sufficient with a lack of reliability and user trust. Trust is also an important factor in the digital banking especially where the transactions involve personal information that is sensitive (Reddy & Vasudevan, 2021). Transparency of AI algorithms and accountability are both ethical considerations which makes transparent and accountable AI systems a necessity (Binns et al., 2018). In accordance with the results of the previous research, more, responsiveness in terms of services and personalized have a major impact on customer satisfaction and long-term engagement (Ghosh, 2020; Kaur et al., 2020). Technology acceptance and perceived ease of use showed significant positive effects for the support of the recognised theories of innovation adoption fruitful with usability as a aspect influencing behavioral intention (Brynjolfsson & McElheran 2016). The perception of financial technologies to be intuitive leads to a multiplicity to increase the likelihood of adoption of these technologies by the user. In addition, perceived security has become a major precondition to digital engagement, and contribute to previous findings of safe systems giving rise to a confidence and continued financial behavior (Goldstein et al., 2021).

Digital literacy, awareness and accessibility showed moderate but significant contributions indicating that technology preparedness and infrastructure are essential elements into acquisition of equitable finance. Those with digital skills have a better access to the AI enabled services and as a result of the increased accessibility the financial instruments become available to the marginalised communities (Chatterjee & Rana, 2022; Chakrabarty, 2019). These results are consistent with research and studies that have been conducted across the globe and have estimated the positive impact of inclusive financial systems in helping to reduce economic participation and inequality (Adedokun and Ağa, 2021; Demirguuc-Kunt et al., 2022). This study has contributed value to the literature by combining the technological capacities and the behavioural gears in a coherent pattern hence bridging the gap which in most cases in the literature, it has been seen that the previous research had at times made the implication of fintech by analysing it on its own (Arora & Rahman, 2021; Mehta et al., 2022). Moreover, the development of financial services using AI make it possible to develop entrepreneurism and economic sustainable which enables its development significance (Agarwal et al., 2019; Hau et al., 2024). Progress in ML & big data- The continuously evolving impact on decision making for the corporation and the corporation financial framework, thus substantiating the transformative purpose of Artificial intelligence (AI) (Easley et al, 2021; Goldstein et al., 2021).

Financial institutions are required to pay attention to the correct use of AI and on the other hand improving the standards of cybersecurity, internalizing the quality of services and growing customer trust. Regulatory frameworks to support innovation while ensuring ethical safeguards are necessary to be supported by policy makers (Philippon 2016; Vives and Ye 2025). Collectively these initiatives can help to establish strong financial systems in attaining inclusive economic growth (Ozili, 2020; Telukdarie and Mungara, 2023). In conclusion, artificial intelligence is a powerful force that can enable financial inclusion. By combining technological innovation with user-centred approaches financial institutions can contribute to addressing persistent inequalities in the financial system and help to support fair and inclusive economic participation (Fuster et al., 2019; Gopal & Schnabl, 2022).

8. Future Scope

Notwithstanding its contributions, however, there are a few opportunities for future investigation in this work. The cross sectional nature of this study, it is challenging to test for long term dynamics and in future, studies should use longitudinal approaches to measure the effects of the adoption of AI on financial inclusion over time (Livshits et al., 2016). This research is potentially capable of rendering significant revelations on the subject of digital financial ecosystem sustainability. Secondly, the geographic area could be made wider so that the generalizability would be increased. Comparative assessment between established and emerging markets may point out the existence of structural disparities in the technology adoption and financial behaviour (Desmet et al., 2017; Falck et al., 2012). Furthermore, there is need for research to be done from the point of view of rural communities so that there will be an understanding of how AI will help to solve the problems that financially marginalised groups face. Third, future studies should include moderating factors such as regulatory quality, wealth inequality and technological readiness in order to better understand the variation in outcomes of adoption (Cong et al., 2025). A competitive analysis of information technology on the lending markets could give better theoretical model (Liberti & Petersen, 2019; Petersen & Rajan, 2002).

A further avenue of interest is to devise the ethical and governance implications for AI. Algorithmic bias, transparency and privacy of data are all major issues that need to be scrutinised by academics to ensure that the access to financial opportunity is not begun limited at all (Mihet et al., 2025). Similarly, generative AI can be expected to affect the corporate valuation and the market setup and provides them with new study opportunities (Eisfeldt et al. 2025). Subsequent research may also benefit from the more sophisticated analytical methodologies including: structural equation modelling, effects of mediation and moderation, machine learning based predictions and mixed method approaches. Examining the influence of AI in the credit market, evaluation of corporate culture, automated decision making processes could provide an improvement to the existing literature (Li et al, 2021; DeMiguel et al, 2023). It is necessary that the scholars study the role big tech loan models and cashless payment models on the financial engagement, particularly on rapidly digitalised countries (Liu et al., 2022; Ouyang, 2023). As financial technologies continue to develop, knowledge on the socioeconomic implications of the developments will be critical to the development of inclusive, transparent and sustainable financial institutions. The future of financial inclusion is related to the development of artificial intelligence. On-going research from multiple disciplines will help to translate the transformation from technological advances into broader and more widely-spread economic empowerment rather than downsizing existing differences (Aghion & Bolton, 1992; Berger & Udell, 1995).

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