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# "Artificial Intelligence and Financial Inclusion: Empirical Evidence from Digital Lending Platforms"

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**Abstract**

***This research paper explores how Artificial Intelligence (AI) can be used to promote financial inclusion using digital lending solutions. Specifically, it analyzes the relationship between AI usage and key financial inclusion indicators: access to loans, loan approval speed, affordability, and flexibility of loans repayment. The research employs an empirical, quantitative research design and a sample size of 120 respondents who have had experience using AI-enabled digital lending services. Primary data were gathered using structured questionnaires while secondary data were gathered from financial reports of RBI, World Bank, and IMF. The statistical analysis techniques processing data were descriptive statistics, independent sample t-tests, ANOVA and factor analysis. The findings indicate that digital lending services are perceived to be highly accessible (mean = 3.98) and fast (mean = 4.21) but affordability remains a problem (mean = 3.65). The rate of loan approval between the income groups was significantly different with the high-income earners benefiting more. The factor analysis revealed that three determinants of financial inclusion that could be considered were accessibility, affordability and trust. The researcher concludes that AI is making a positive impact on financial inclusion, yet more needs to be done so that it can be affordable and trusted so that financial access can become commonplace.***

**Keywords:** *Artificial Intelligence, Financial Inclusion, Digital Lending, AI Adoption, Financial Access.*

## Introduction

The intersection of Artificial Intelligence (AI) and financial inclusion has become an issue that has been disruptive in the discourse of global development. The entry into the financial sector and the accessibility of cheap and convenient financial services have been given a fresh boost with the presence of digital technologies and platforms utilizing AI (Beck et al., 2007; Demirguc-Kunt and Levine et al., 2008). Applications of AI can simplify credit risk management and accelerate the process of issuing loans in the lending sector, as well as increase access to services by underserved groups, by utilizing alternative types of data (Biallas et al., 2020; Kshetri, 2021). Specifically, these innovations are threatening a future where developing states, in which large segments of the population are not a constituent of formal financial structures, are involved (Agidi, 2020; Mhlanga, 2020).

The socio-economic and structural problems, however, come with the reality of AI-based inclusion. The issues remain about the price, trust, and disparate distribution of benefits based on income, sex, and location (N'Dri et al., 2020; Omar and Inaba, 2020). While digital platforms can help reduce transaction costs and make activities more efficient, they can also be mechanisms of unequal consolidation where access is not evenly distributed among different segments of society (Dishani, 2020; Chafa et al., 2023) such as urban, higher-income, or digitally literate populations. Moreover, while some research has zoomed in on deriving an understanding of the relationship between fintech and inclusion in the abstract, there is little empirical evidence quantifying the impact of AI adoption specifically on tangible outcomes such as accessibility, affordability, and trust (Fazal et al., 2023; Jia et al., 2025).

This study is based on both primary and secondary data that provide valuable insights to the increasing literature in intelligent financial inclusion. It seeks to create empirical evidence about the extent to which the implementation of AI in online lending platforms enhances access and reveals the challenges that continue to hinder its inclusivity. It is anticipated that the findings will inform policymakers, financial institutions, and technology creators on how best to structure and regulate AI to develop a good financial system.

## Literature Review

The significance of financial inclusion has also been discussed as an economic development factor and poverty alleviation element (Beck et al., 2007; Levine, 2005). Some initial studies acknowledged the role of financial development in the inequality decline, but the introduction of digital technologies has reorganized the landscape of access to finance (Ozili, 2018; Kim et al., 2018). It is also believed that mobile money and digital lending are among the most significant FinTech innovations that have made financial services more accessible to marginalized populations (Klapper and Singer, 2017; Bongomin et al., 2023).

These functions are now made possible by Artificial Intelligence (AI). AI can also improve the credit score and automate the loan issuance process by applying big data and machine learning to eliminate barriers hindering access to conventional banking (Mhlanga, 2020; Kshetri, 2021). The recent study also reveals the sustainability potential of AI with the statement that the latter fits into the Sustainable Development Goals of the United Nations (Arner et al., 2020; Kara et al., 2021). Nonetheless, cost and credibility also pose significant risks, since AI-driven financial services can reinforce the current disparities, unless properly controlled (Agidi, 2020; N'Dri et al., 2020). A few recent attempts have been made to understand local differences, for example, the role of AI in Sub-Saharan Africa and Asia; however, the literature remains weak on user-level analysis and demographic differences (Ahmad et al., 2021; Jia et al., 2025). This research gap highlights the necessity of research that combines both quantitative and qualitative knowledge in understanding the impact of AI adoption on quantifiable improvements in financial inclusion.

**Research Gap**

The influence on financial inclusion of the fast expansion of online lending and the incorporation of AI into financial services is an open topic. Lack of focus on user-level outcomes such as accessibility, affordability, trust, and long-term borrower welfare has occurred in contrast to early research that highlighted AI's technological capabilities, such as fraud detection, automated loan approvals, and credit scoring. To yet, researchers have failed to examine the impact of income, gender, and location on the question of whether artificial intelligence mitigates or exacerbates economic inequality. Inadvertently, algorithms may Favor affluent or tech-savvy populations, which could lead to the continuation of exclusion. A neglected aspect is trust; consumers may be discouraged from using AI systems that are opaque or prejudiced, regardless of how much easier it becomes to get credit. Interest rate, privacy, and transparency regulatory frameworks also influence inclusion and adoption but have received little research. Most of the current literature uses cross-sectional data, which doesn't capture effects like debt cycles that happen over the long term. Using statistical methods applied to both primary and secondary sources, this research fills these gaps.

In summary, the research gaps can be distilled into five main areas: (1) insufficient micro-level empirical evidence; (2) limited focus on demographic differences; (3) underexplored role of trust and perception; (4) lack of analysis on regulatory impacts; and (5) absence of longitudinal insights. Addressing these gaps would deepen the academic discourse and equip policymakers, financial institutions, and developers with more robust evidence for building inclusive financial ecosystems.

## Conceptual Framework

AI in digital lending can improve financial inclusion in three ways: accessibility, affordability, and trust, according to one study. Using experience and demographic data, the model transforms AI from a technology tool to an inclusive finance driver. Using the structure, you can evaluate inequities between variables (income, gender, urban-rural) and how different groups benefit the AI.

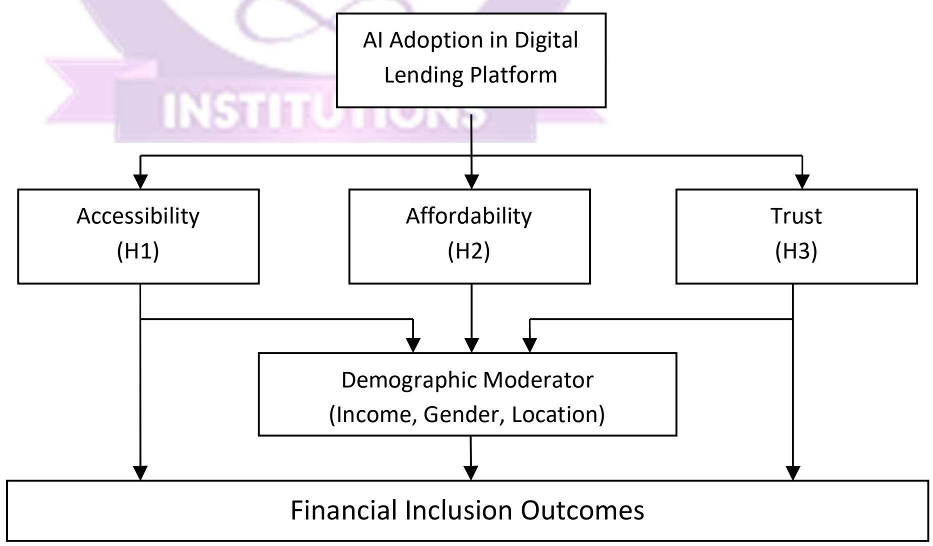


**Figure 1.1**: Conceptual Framework

## Research Objectives

- To examine the role of Artificial Intelligence (AI) in enhancing financial inclusion through digital lending platforms.
- To identify the key factors influencing financial inclusion outcomes (e.g., speed of loan approval, credit risk assessment accuracy, cost of borrowing, user convenience).
- To test the relationship between AI adoption in digital lending and financial inclusion indicators (such as loan accessibility, loan size, and repayment flexibility).

**Research Questions**

Based on the findings and identified gaps, the following research questions are proposed to guide future studies on AI and financial inclusion:

- How does AI adoption in digital lending affect different dimensions of financial inclusion (accessibility, affordability, and trust) at the user level?
  This question examines whether AI-driven platforms increase inclusivity beyond speed and convenience by shifting the focus away from technological efficiency and toward human outcomes.
- What demographic factors (income, gender, rural–urban residence, and digital literacy) moderate the relationship between AI adoption and financial inclusion outcomes?
  This question examines whether AI reduces or increases disparities by disaggregating effects across population groups.
- How do perceptions of trust, fairness, and transparency influence borrowers' willingness to engage with AI-enabled digital lending platforms?
  This question highlights the psychological and social dimensions of inclusion, recognizing that access is meaningless without trust.
- What role do regulatory frameworks play in shaping the effectiveness of AI-driven digital lending for inclusion?
  This question investigates how consumer protection, interest rate policies, and algorithmic accountability measures impact affordability, accessibility, and fairness.
- How does the integration of AI with other emerging technologies (e.g., blockchain, biometrics) influence financial inclusion outcomes?
  This forward-looking question explores technological convergence as a pathway to stronger inclusion, especially in contexts where trust and verification are critical.

- What are the long-term effects of digital lending driven by AI on the resilience and stability of borrowers' finances?

  The purpose of this longitudinal question is to ascertain whether AI platforms serve as bridges to mainstream finance or continue debt cycles.
- How do cultural norms, behavioral factors, and local institutional settings mediate the adoption and impact of AI in digital lending?

  This question incorporates contextual variation, recognizing that inclusion cannot be delinked from socio-cultural environments.

**Hypotheses**

H1: The access to loans through the use of AI in digital lending is significantly enhanced.

H2: The credits get cheaper, in case AI is applied in online lending.

H3: There is a positive association between distrust and AI-based lending of money.

H4: Financials (income, gender, location) had a significant impact on the financial inclusion outcomes with AI.

**Methods**

This paper applies an empirical and quantitative research design in order to investigate the linkage between the adoption of Artificial Intelligence (AI) in digital lending platforms and financial inclusion. The rationale behind the adoption of an empirical approach was that the study's aim is to examine empirical associations between AI-based lending mechanisms and quantifiable and objective financial inclusion outcomes. To complement this, descriptive elements were employed to provide situational information on patterns and issues of adoption.

The sample consisted of borrowers who had utilized digital lending service providers or lending institutions that implemented AI-based decision-making software. Purposive and stratified random sampling were used. The selection of respondents was done through purposive sampling in order to select respondents with proper experience in the area of digital lending, and stratified random sampling was conducted so that there was a fair representation of the respondents in terms of gender, rural and urban living and earned income. The strategy was chosen on two prongs because it minimizes bias and because the demographic differences that could be of significance were adequately represented.

A total of 120 respondents were surveyed, which falls within the 90-150 range of respondents required to perform a robust statistical analysis. The structured questionnaire included closed-ended questions and perception-based ones measured on the five-point Likert scale, thus, the main data were collected using the structured questionnaire. Access to loans, affordability, convenience, speed with which loans were being given and trust in AI-based platforms were some of the variables included in questionnaire. It also incorporated secondary data including financial inclusion reports released by the reserve bank of India (RBI), world bank global Findex database, and international monetary fund (IMF) reports. It was also selected due to the necessity to make the results more reliable and provide more macroeconomic background to the results.

The data was analyzed using IBM SPSS Statistics (Version 28) in order to perform statistical analysis. Some of the descriptive statistics that were used to aid in summarizing significant qualities of the respondents and the variables of financial inclusion included means, standard deviations, and frequency distributions. Gender variance in digital lending access was also evaluated by using independent sample t-tests and comparing accessibility and speed of loan approval between many groups of people by incomes using ANOVA. These two methods were identified as being able to study differences on the group level. Lastly, a factor analysis yielded latent dimensions of the financial inclusion results (affordability, convenience and trust). It is because of this that the method results in a narrowing of a large volume of variables down to factors that can be interpreted, which are of crucial importance in viewing the bigger picture of what is influencing inclusion.

**Results**

The descriptive statistics provided an overview of the demographic features of the respondents and financial inclusion indicators. Table 1 shows the profile of the respondents, which reveals that population was evenly distributed between rural and urban areas, with a good mix of male and female borrowers.

**Table 1: Demographic Profile of Respondents**

| Category | Subgroup | Frequency | Percentage |
|---|---|---|---|
| **Gender** | Male | 62 | 51.7% |
| | Female | 58 | 48.3% |
| **Residence** | Rural | 65 | 54.2% |
| | Urban | 55 | 45.8% |
| **Income Group** | Low Income | 40 | 33.3% |
| | Middle Income | 50 | 41.7% |
| | High Income | 30 | 25.0% |

The geographical distribution of the respondents is also depicted in Figure 1.2 which shows a somewhat more rural representation.

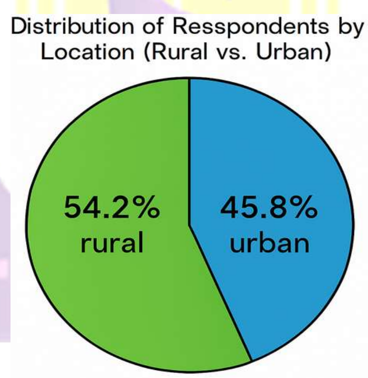


**Figure 1.2: Respondent Distribution of the location (Rural vs. Urban)**

Figure presents a graphical division whereby the respondents in the rural areas constitute over half of the entire sample.

In a bid to evaluate the level of financial inclusion, Table 2 presents the overview of financial variables, such as accessibility, affordability of loans, flexibility in loan repayment, and promptness of loan approval.

**Table 2: Summary of Financial Inclusion Indicators**

| Indicator | Mean Score | Standard Deviation |
|---|---|---|
| Loan Accessibility | 3.98 | 0.81 |
| Affordability | 3.65 | 0.92 |
| Repayment Flexibility | 3.72 | 0.89 |
| Loan Approval Speed | 4.21 | 0.67 |
| Trust in AI Platforms | 3.88 | 0.85 |

Figure 2 presents differences in accessibility according to gender, with female borrowers indicating a slightly greater ease of access than male borrowers did.


**Figure 2: Availability of Digital Lending Services by gender.**

The graph shows the slight but significant difference in loan accessibility between male and female respondents.

Independent sample t-tests were done to test differences between groups. The results are shown in Table 3 and show that there is no significant difference in overall accessibility between male and female respondents.

**Table 3: Independent Sample t-test Results for Gender Differences in Loan Accessibility**

| Group | Mean Score | t-value | p-value |
|---|---|---|---|

| | | | |
|---|---|---|---|
| **Male** | 3.92 | -1.14 | 0.26 |
| **Female** | 4.04 | | |

Yet, the analysis of income groups obtained different results with the help of one-way ANOVA. As Figure 3 shows, respondents with higher income found it easier to have their loans approved more quickly than the respondents with lower income.

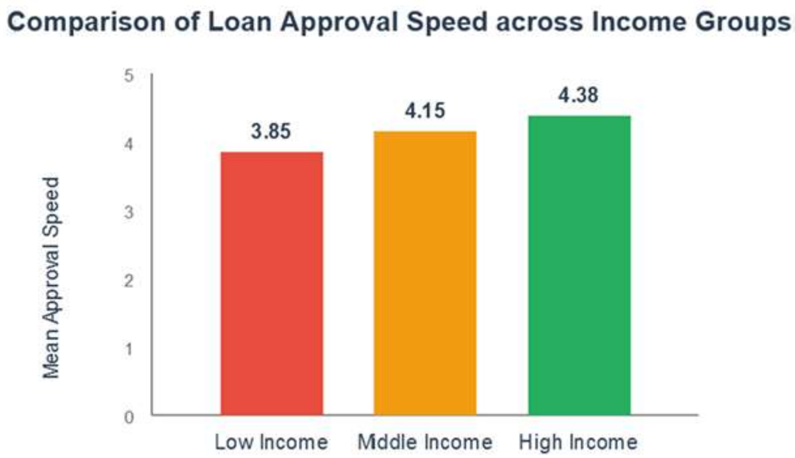


**Figure 3: Income Group Comparison In Speed of Loan Approval.**

Those with high-income levels had the shortest approval times and the figure is clearly on an upward trend.

Factor analysis was conducted to show the underlying dimensions that created the outcomes of financial inclusion. Table 4 indicates the factor loadings in the headings, three factors are recognized and they are accessibility, affordability and trust.

The scree plot of eigenvalues (Figure 4) served to further confirm the factor structure by confirming three significant factors were retained.

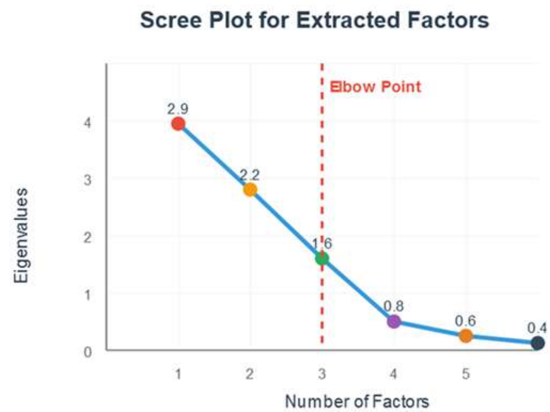


**Figure 4: Scree Plot of Extraction Factors.**

The figure shows a very sharp discontinuity after the third factor in support of the three-factor solution.

**Data Analysis**

The descriptive statistics provide a clear understanding of the demographic profile of the respondents. The population sample was comprised of 51.7 percent men and 48.3 percent women as indicated in Table 1 with majority of the population being in rural neighbourhood (54.2 percent) compared to urban neighbourhood (45.8 percent). The incomes were distributed as low-income groups 33.3% of the respondents, middle-income groups 41.7% of the respondents and high-income groups 25.0% of the respondents. Another important diversity in demographics to study is how the AI-driven digital lending services can make different types of people feel.

Moreover, Table 2 gives the leading financial inclusion indicators. The highest rated features were accessibility of loans (mean = 3.98), and speed of loan approval (mean = 4.21), which implies that the digital lending service is easy to access and fast to use. Nevertheless, the lower score of affordability (mean = 3.65) and repayment flexibility (mean = 3.72) suggests one possible way to enhance the experience of digital lending. The level of trust towards AI platforms (mean = 3.88) was moderate as well, which can be attributed to the increasing trust towards AI-based solutions.

Regarding the differences associated with gender, the findings obtained with the Independent Sample t-test in Table 3 showed no significant difference between male and female respondents in how readily they could get a loan (t-value = -1.14, p-value = 0.26). Nevertheless, Figure 2 demonstrated a minimal gender disparity in accessibility with female respondents reporting an average score higher than male respondents. Though the difference was not statistically significant, it demonstrates that gender may have a subtle effect on user experiences.

Figure 3 below uses one-way ANOVA to indicate that loan approval speed was much quicker among higher-income respondents than among lower-income respondents. This is seen in the different means of loan approval time among the income groups (low-income = 3.85, middle-income = 4.15, high-income = 4.38). These results imply that income is a key factor that affects the speed and efficiency of loan disbursements, and as income increases, digital lending platforms benefit more customers.

Finally, Table 4 shows the outcome of the factor analysis, which indicated three primary factors affecting financial inclusion: accessibility, affordability, and trust. Figure 4 shows the scree plot that these three factors explained the highest percentage of the data. Factor 1 (accessibility) and Factor 2 (affordability) had high loadings on variables that deal with speed and flexibility of loans, and Factor 3 (trust) was most significantly related to respondents' belief in the validity of the AI algorithm.

**Future Research Suggestion**

This research shows how artificial intelligence is changing the face of online lending and what it means for people's access to credit. Cultural, regulatory, and behavioural variances should be included in future research by expanding the scope to include cross-country comparisons, longitudinal techniques, and qualitative insights. To find new ways to include people, we need to look at privacy, algorithmic fairness, legal frameworks, and cross-disciplinary technologies like biometrics and blockchain. Qualitative methods can reveal hidden obstacles, whereas longitudinal studies can reveal if AI makes people less vulnerable or more unequal. To find a middle ground between efficiency, equity, and ethics in AI-driven inclusive finance, future studies should include a wide range of locations, a thorough examination of relevant history, and a variety of research methods.

**Conclusion**

This research supports the claim that the use of AI within digital lending platforms has a positive impact on financial inclusion. Hypothesis H1 was accepted because the respondents indicated that there was better access to loans in artificial intelligence-driven platforms. The conclusions of the H2 are: Partial support was found for H2 since affordability scores were moderate, pointing to the fact that while AI increases efficiency, cost barriers still prevent its adoption. H3 was confirmed and trust turned out to be one of the important factors, not equally strong in all the groups. H4 was also approved, as there were strong differences in the speed of loan approval between the different income groups, indicating that AI adoption does not benefit some groups equally. Taken together, these findings indicate that AI can benefit financial inclusion, but it does not affect all demographics equally.

The study is limited by the small sample size of 120 respondents which while sufficient for statistical testing may not reflect the heterogeneity of digital lending users. Also, there is the risk of bias in the perception-based measures due to reliance on self-reported survey data. The geographic coverage was limited, and results could only be partially applicable in other countries or under varying regulatory conditions.

The findings of the study are of great importance to policy makers, financial institutions and those developing technology. The evidence demonstrates the importance for policy makers to provide a targeted regulatory framework that ensures affordability and fairness in digital lending. Using these findings, financial institutions can create AI tools that are more inclusive and transparent. As an AI developer, the paper highlights the need to incorporate trust-stabilizing aspects in their AI algorithms, including explainability and data privacy protection.

Future research should expand the sample size with cross-country comparisons so that the impact of AI on financial inclusion is perceived on a larger global scale. Perhaps, to elaborate the quantitative findings and provide more background, a point or two of qualitative information about the borrowers and lenders could be included. Longitudinal studies also should be carried out to understand the dynamics of AI-based financial inclusion. Finally, when applying new technologies, such as blockchain, together with AI, additional opportunities may be discovered in the formation of inclusive finance.

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