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FinTech Innovations: The Use of AI in Digital Lending Platforms

Sudipta Mukherjee,
Master of computer Application with specialization in storage and cloud computing,
Jain deemed to be university, Bangalore.
sudiptamukherjee112@gmail.com

Priyanka Sunar,
Master of Arts in Political Science and International Relations,
Jain deemed to be university, Bangalore.
Priyankasunar01@gmail.com

Vamshika shetty,
Master of computer Application with specialization in Information security management services,
Jain deemed to be university, Bangalore.
Vamshikashetty135@gmail.com

Anush Kulal M,
Masters of computer Application (General)
Jain deemed to be university, Bangalore.
anushkulalm@gmail.com

Prajwal Gowda Y S,
Master of Commerce,
Jain deemed to be university, Bangalore.
prajwalgowdays123@gmail.com

Dr.N.Gobi,
Professor,
Department of CS and IT,
Jain (Deemed-to-be University), Bangalore.
gobi.n@jainuniversity.ac.in

ABSTRACT

The acceptance of the Artificial Intelligence (AI) in the online lending systems has introduced unparalleled transformation in the realm of financial technology (FinTech). The research will examine the use, effectiveness, and perceptions of AI-based digital lending solutions through the help of primary data, which will be collected among 100 respondents. The study correlates the two using chi-square and regression analysis to test and investigate the relationship between level of trust and adoption pattern with demographic factors and to test the hypothesis based on descriptive statistics. The most significant observations are that two-thirds of the participants have consumed the AI-based lending services, and three-quarters of them believed that AI would provide credit ratings. Chi-Square test shows that there is significant association between the age groups that have chi2 = 18.347, $p < 0.05$ and Pearson regression analysis indicates that the trust in AI is a significant predictor of the adoption intention (chi2 = 0.584, $p < 0.001$). The results show that AI will help to speed up the lending process 65 times, increase the accuracy of the credit score, and improve financial accessibility among the underbanked populations. However, such barriers as the problem of data privacy (45% respondents) and algorithmic bias (32% respondents) are also critical. This research contributes to the comprehension of the process of adopting AI in digital lending and provides practical information to the FinTech platforms, policymakers, and financial institutions who want to use AI technologies and, at the same time, consider the concerns of users. The study concludes that AI-based digital lending represents a paradigm shift in lending credit, which finds the correct balance between efficiency and ethical behavior in accordance with laws.

Keywords: Artificial Intelligence, Digital Lending, FinTech, Credit Scoring, Machine Learning, Financial Inclusion, Primary Data Analysis, Chi-Square Test, Regression Analysis

1. INTRODUCTION

1.1 Background

FinTech has become one of the most disruptive forces in the global economy as a result of the combination of financial services and technology. Within a series of FinTech advancements, the artificial intelligence (AI)-based digital lending platforms have ended the way in which the conventional credit delivery processes are performed[1]. The global AI in the lending market that is projected to reach USD 58 billion in 2033 and is worth USD 4.9 billion now is projected to grow by an annual compound growth rate (CAGR) of 23.5%[2].

The conventional lenders have always relied on the traditional credit scoring models who base on the credit bureau data, assessment of collateral, and lengthy documentation procedures. Such methods usually marginalize huge masses of the population, particularly the unbanked and underbanked population that lacks formal credit history. The digital lending services based on AI restrictions eliminate all these constraints because they are based on machine learning algorithms, alternative data sources and automated decision-making [3].

By the year 2024-25, the digital lending ecosystem has been observed to grow exponentially in India, with the fintech NBFCs issuing approximately 1.06 lakh crore in disbursed loans in more than 10.9 crores of individual loans in FY 2024-25[4]. The penetration of smartphones, the digital payment infrastructure created by Unified Payments Interface (UPI), the increasing consumer appetite towards technology-based financial services are driving this growth. Lenders are using AI technologies like machine learning (ML), natural language processing (NLP) and predictive analytics to analyse high volumes of both structured and unstructured data to assess credit, detect fraud and manage risks[5].

1.2 Artificial Intelligence in Digital Lending: Core Applications

The digital lending applications can be used throughout the lending cycle, including customer acquisition and loan recovery. The AI models are used in the context of Credit Scoring and Risk Assessment to assess creditworthiness: in addition to previous screenings-like credit history, credit card usage, and social media activity, they consider other forms of alternative data such as mobile phone usage patterns, digital transaction history, social media activity, utility bill payment, and e-commerce activity[6]. Random forests, gradient boosting machines, and neural networks are machine learning algorithms that are 15-25% more predictive than other traditional credit scoring models[7].

Other than scoring, Automated Underwriting systems can crunch loan apps in seconds, not days, on thousands of pieces of data to enable immediate credit decisions[8]. The automation saves up to 60% on operational costs but enhances a high degree of consistency and elimination of human bias during first screening[9]. In order to secure these transactions, Fraud Detection systems are real time applications which supervise application data to identify any anomalies and identify patterns that are typical of identity fraud, synthetic identities and fraudulent documentation. The systems minimize the losses associated with fraud by detecting suspicious applications within milliseconds[10].

Moreover, AI has a Personalized Pricing where the risk-based interest rates are applied individually, with risky profiles being charged with competitive rates and the riskier segments being given suitable rates[11]. It is also applied to Collections Optimization, where predictive models used to identify risky accounts and concentrate on collection, and suggest the best communication techniques to maximize recovery and minimize default loss[12]. Lastly, AI-based chatbots and virtual assistants support the Customer Experience by offering 24/7 customer service, instant answers to queries, and individualized product recommendations[13].

1.3 Significance of the Study

Although the implementation of AI as a digital lending tool is rapidly growing, the empirical literature on the subject lacks the investigations into the perceptions of the technology and its factors of trust, as well as barrier to adoption as perceived by the customers. The bulk of the

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available research today is preoccupied with technical implementations and benefits to the lenders, which creates a gap in the understanding of the experience and concerns of the borrowers.

This study provides this gap by exploring the awareness and usage of AI based lending sites and the level of trust that people place in AI-based credit evaluation procedures as compared to conventional ones. It takes perceived advantages such as speed, access, and convenience into account and addresses critical concerns on the privacy of the data, algorithmic bias, and transparency. Besides, the article analyzes the demographic differences in the adoption and trust patterns and personal factors of the intention to utilize AI-based services to lend. The dimensions play a crucial role in comprehending them in order to have FinTech solutions that are user-centric, policymakers that create sufficiently robust regulatory frameworks, and the incumbent financial institutions alter their digital transformation attitude.

1.4 Research Objectives

This study pursues the following specific research objectives:

1. To assess the level of awareness and adoption of AI-powered digital lending platforms among respondents
2. To evaluate user trust in AI-based credit assessment compared to traditional lending methods
3. To identify perceived benefits of AI in digital lending including speed, accuracy, and accessibility
4. To examine concerns and barriers to adoption including data privacy, algorithmic bias, and transparency
5. To analyze the association between demographic factors (age, income, education) and platform adoption using Chi-Square test
6. To determine the predictive relationship between trust in AI and adoption intention using regression analysis
7. To provide recommendations for FinTech platforms, policymakers, and financial institutions based on empirical findings

1.5 Research Questions

The study seeks to answer the following research questions:

1. What is the current adoption rate of AI-powered digital lending platforms among respondents?
2. How do users perceive the trustworthiness of AI-based credit assessment compared to traditional methods?
3. What are the primary benefits that attract users to AI-powered lending platforms?
4. What concerns and barriers prevent wider adoption of AI-powered lending services?
5. Is there a significant association between age groups and adoption of AI lending platforms?
6. Does trust in AI significantly predict intention to adopt AI-powered lending services?

1.6 Scope and Limitations

This study relies on the personal borrower perspective of the Artificial Intelligence-driven digital lending platforms in India. The paper examines uses of personal lending which include personal loans, consumer loans and microfinance, but not the corporate and business lending segments. The primary sample population will be the urban and semi-urban population that has access to the smartphones and the internet connection.

Some of its limitations involve the number of 100 respondents who were sampled using the convenience sampling method that may not be representative of the whole population. The cross-sectional design is only able to measure perceptions at a single point in time, and does not realise changes across longer periods of time. Self-reported information can be susceptible to the bias of opinions and the rapid development of AI technology implies that the results can only be applicable to the conditions of the technology at the moment of the reporting but will require updating after some time.

2. REVIEW OF LITERATURE

2.1 How the Digital Lending Evolved

Digital lending refers to the digitisation of the customer acquisition, creditworthiness assessment, and even the loan disbursement and recovery process of the lending value chain. Studies demonstrate how the former method of loan applications online in the early 2000s has changed into a fully automated and AI-driven loan application platform in the present decade[14]. The shift of the branch-based to the digital channels has reduced the cost of operations, resulted in the reduction of the processing time and expansion of geographical coverage[15].

Research indicates that digital lending platforms take significantly shorter times to lend loans to borrowers (minutes, compared to days or weeks to traditional banks) as well as can sustain or even increase credit quality indicators[16]. This rapidity benefit is particularly applicable in small ticket loans where processing expenses have to be kept as low as possible.

2.2 Artificial Intelligence andMachine Learning in credit evaluation.

The application of AI and machine learning as a credit assessment tool is a major change in the conventional process of scoring. Jagtiani and Lemieux (2019) demonstrate that the predictive accuracy of the ML algorithms that take non-traditional sources of data is higher when it comes to the borrowers with limited credit histories[17]. Their study shows that other data like digital footprints, mobile transactions behavior and pattern are significant indicators of creditworthiness.

A comparison study on the AI-based credit models and traditional models has revealed that there is lower Type I error (when credit worthy applicants are rejected) and Type II error (when risky applicants are accepted) in ML models across models [18]. This increased precision ensures that lenders are able to expand their market to address and reduce the quality of their portfolio.

According to research conducted by Credolab with 11 million behavioral features, AI-based credit scoring systems are capable of using privacy-consented data on devices and behavior to create more accurate and personalized risk evaluations[19]. These systems are always learning and improving to make the predictions more accurate with time unlike the traditional scorecards which are always the same.

2.3 alternative data in credit decision making.

One of the principal innovations of AI-based lending is the use of alternative data sources. Alternative data refers to the information obtained besides the financial information available in the conventional credit bureau reports, including cell phone usage history, digital payment history, utility bill payment, rental payment, social media use, and e- commerce transaction history[20].

Studies indicate that alternative data can be used to evaluate credit of credit invisible populations which do not have official credit histories but have proven creditworthy in other financial ways[21]. Such capability provides significant stimulus to raise the level of financial inclusion particularly in the emerging economies where huge populations are yet to be banked or underbanked.

Experiments of other data of respective kinds show different extents of predictability. Data of mobile phone usage including the pattern of calls, date payment frequency, data usage etc. corresponds closely with the behavior of repayment[22]. The information of digital payment transactions allows real-time data on cash flows and expenditure pattern[23]. History of utility payments shows that they will be in a position to meet their financial obligations[24].

2.4 Operational Efficiency and Real Time Decision making.

With AI, it is possible to make real-time credit decisions that could be modified to meet the market conditions and immediate reaction to loan applications. Survey indicates that the capability of making real time decisions brings about competitive advantages in terms of offering a superior customer experience and capacity to execute time sensitive opportunities[25].

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The benefits of operational efficiency that are attainable with AI automation are substantial. Research has determined a range of 30-60% cost savings associated with automation of data extraction, verification, underwriting and documentation processes[26]. These economies of scale enable profitable lending of small ticket loans, which would not have been viable with traditional manual procedures.

2.5. Fraud Detection and Risk Management

AI-fraud detection applications capture patterns of application, device fingerprint and behavioral patterns to identify suspicious activities in real-time. It has been demonstrated that machine learning systems that have been trained using past trends of fraud are far more successful in detecting fraud and have reduced false positives than rule-based systems[27].

Advanced fraud detection systems are ensemble based methods of combining a number of algorithms, anomaly detection methods, and network analysis with the purpose of identifying more complicated fraud schemes like identity theft, synthetic identities and application fraud[28]. On-going learning is used in these systems to keep up with the evolving fraud strategies.

2.6 Trust and User Acceptance

The studies of technology acceptance in financial services indicate that trust is a significant variable in acceptance. The experiments performed on the technology acceptance model (TAM) in the framework of digital lending indicate that the effects of the perceived usefulness, ease of use and trust on the behavioral intention to use AI-powered applications are significant in digital lending[29].

Belief in AI systems is premised on a number of aspects: transparency of decision-making process, creditworthiness evaluation precision, data protection and control[30]. Studies indicate that understandable AI methods capable of providing explanations as to why individuals are credited with loans enjoy increased user confidence compared to black box models[31].

A study on the barriers to adoption of AI has shown that privacy issues, apprehension of algorithmic bias, lack of human interaction, and lack of understanding of the AI systems are high inhibitors[32]. Free flow of information, proper security solutions, and appropriate regulatory systems are gaining significant importance regarding increased adherence to such issues.

2.7 Financial Inclusion Impact

Studies Conducted to investigate the effects of AI lending on financial inclusion demonstrate that AI-enabled products have been capable of accessing formerly barricaded segments that include gig economy employees, youthful adults with a deficit of credit history and in geographic areas with restricted inclusion[33].

The experience of such firms as Tala and Branch, which are active on the emerging markets, has proved that the lending process that is organized according to the principles of mobile-based artificial intelligence (AI) allows providing credit access to individuals who fail the automatic evaluation of credit by other lenders[34]. The operation of these platforms is based on the sustainable portfolio and covers the high-risk segments through the improved assessment of risks and incessant monitoring.

There are also disadvantages and dangers of research. Research warns that overreliance on alternative data and computer-based decisions would tend to cause various forms of discrimination or marginalisation of groups of individuals[35]. To ensure that AI systems are contributing, rather than hindering financial inclusion, they must be developed, checked and countermeasured with unintended effects.

2.8 Regulatory and Ethical Issues.

The available literature on AI regulation in financial services argues the need to have regulatory frameworks which would establish balance between innovation and consumer protection. The range of regulators that research is studying consists of sandboxes to test new technologies, principles based regulation and specific rules on algorithmic lending[36].

The ethical concerns, such as algorithmic bias where AI models can discriminate against the protected groups unknowingly, data property aspects based on the data gathering and utilization of alternative data, and explainable AI demands are mentioned[37]. Research suggests fairness measures, frequent prejudice checks and having human control on important or complex choices[38].

2.9 Research Gaps

Although a significant amount of literature can be found in technical issues of AI in lending, and the perspective of the lender, little research is conducted on the experiences and perceptions of AI by borrowers and the drivers that cause the adoption with the use of primary data collection. The majority of the studies are founded on the analysis of secondary data or are merely interested in the performance indicators of the platform in the eyes of the lender.

This research can also contribute to these gaps by providing first-hand information about potential and actual borrowers regarding trust factors, perceived benefits and concerns and demographic variations in adoption patterns. The two descriptive statistics and hypothesis testing offer a good empirical evidence on factors influencing AI lending adoption.

3. RESEARCH METHODOLOGY

3.1 Research Design

The research design and methods of the study is descriptive and analysis research based on quantitative research methodologies. The study utilizes primary data in the form of a survey by using a structured questionnaire to investigate the user perceptions, adoption trends, and the variables that influence the acceptance of digital lending platforms powered by AI. The quantitative method provides the opportunity to conduct statistics, including descriptive statistics, Chi-Square test of association, and regression analysis to answer the research question.

3.2 Population and Sample

Target Population: The target population includes persons aged 18 years and above, living in urban and semi-urban areas of India with access to smartphones and internet connectivity, and representing potential users of digital lending platforms.

Sample Size: The study had a sample size of 100 which is sufficient to perform Chi-Square tests and regression analysis with reasonable statistical power to find medium to large effect sizes.

Sampling Technique: Convenience sampling was used because of time and resource limitations. Respondents were chosen according to their accessibility and willingness to participate. While convenience sampling has some disadvantages of generalizing the results, it is a good option to gain insight into user perceptions and to test hypotheses.

3.3 Data Collection

Primary Data: Data was gathered directly from the respondents using the structured questionnaire which was distributed online (by using Google Forms) and offline (paper-based survey).

Questionnaire Design The research tool was a questionnaire containing 15 items to be posed to address the various aspects of the user experience. These dimensions were demographic data including ages, gender, education, income levels and occupation and awareness and usage trends on AI-powered lending platforms. The survey had very particular surveys of trust in AI-based credit assessment, and survey of perceived benefits of AI-based credit assessment, including speed, accuracy, convenience and accessibility. Moreover, it touched upon some of the most pressing issues and obstacles such as the issue of data privacy, bias in algorithms, and transparency and compared the user experience of traditional and AI-driven lending. And lastly, the questionnaire required the desire to use AI lending in the future. Questions were

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in various formats to ensure data richness such as multiple choice, nominal scale of answers and use of 5-point Likert scale to determine agreement, trust and satisfaction.

Data Collection Period The major data collection for this study was carried out for two months in January and February 2026.

Data Collection Procedure The systematic method was used in which the respondents were approached one by one. All the interviewees received a concise brief of the purpose of the study and an official guarantee of data confidentiality. To address the ethical consideration, the informed consent of all the respondents was taken in advance. In the process, special care was also made to make sense of questions and complete all sections to achieve data integrity.

3.4 Variables

Dependent Variables The study identifies two main dependent variables which can be used to measure the result of user interaction with the FinTech technology. The first is the actual Adoption of AI-powered Lending platforms (Yes/No) a binary response. The second is the intention to use AI lending services which captures the behavioral tendency of the user through a 5-point Likert scale.

Independent Variables To understand the factors that had an impact on the dependent variables, a number of independent variables were analyzed.

- **Demographic factors:** Age group (categorized as 18-25, 26-35, 36-45 and 46+ years), Gender (Male/Female/Other), Education level (High School, Graduate or Postgraduate), Income level (segmented as Below 5 lakhs, 5-10 lakhs, 10-15 lakhs, and Above 15 lakhs).
- **Psychographic and perceptual factors:** include level of Trust in AI credit assessment (Low, Medium, or High) and Perceived ease of use and Perceived benefits, both of which were measured on a 5-point Likert scale.
- **Data privacy:** the study takes into account the Data privacy concerns, recorded in form of binary (Yes/No) variable.

3.5 Research Hypotheses

Hypothesis 1 (Chi-Square Test):

H_0 (Null Hypothesis): There is no significant association between age group and adoption of AI-powered lending platforms.

H_1 (Alternative Hypothesis): There is a significant association between age group and adoption of AI-powered lending platforms.

Hypothesis 2 (Regression Analysis):

H_0 (Null Hypothesis): Trust in AI does not significantly predict intention to use AI-powered lending platforms.

H_1 (Alternative Hypothesis): Trust in AI significantly predicts intention to use AI-powered lending platforms.

3.6 Data Analysis Techniques

Descriptive Statistics: Frequency distributions, percentages, means, and standard deviations were calculated to summarize demographic data, adoption rates, levels of trust and perceptions towards benefits and concerns.

Chi-Square Test of Independence: Chi-Square test was used to test the relationship between categorical variables that included; age group and adoption of the platform. The test is used to ascertain whether the observed distribution is significantly different than expected distribution when the assumption is independence.

Simple Linear Regression: The regression analysis has been performed to determine the predictive relationship between trust in AI (independent variable) and intention to use AI lending platforms (dependent variable). The analysis gives the coefficients of the strength and direction of the relationship.

Statistical Software: Data analysis was done by use of the IBM SPSS Statistics Version 28.0 with the level of significance () at 0.05 used to test the hypotheses.

3.7 Reliability and Validity

Reliability: To determine unclear questions in the questionnaire, the questionnaire was employed to test pilot test on 10 respondents to validate it. Multi-item Likert scales were determined to calculate the Cronbachs alpha coefficient to determine the internal consistency reliability.

Content Validity: The questions were constructed on the basis of the literature review and consultation with the research guide. All the dimensions that have been found in the previous studies on technology acceptance and adoption of AI in the financial services are addressed in the questionnaire.

Ethical Considerations: The research followed ethical principles of research such as informed consent, voluntary participation, responses confidentiality and right to withdraw. No demographic data except those required to analyze the data were gathered on a personally identifiable scale.

4. DATA ANALYSIS AND INTERPRETATION

4.1 Descriptive Statistics

4.1.1 Demographic Profile of Respondents

The demographic composition of the sample provides context for interpreting findings and assessing representativeness.

Demographic Characteristic	Frequency	Percent
Age Group		
18-25 years	28	28.0
26-35 years	42	42.0
36-45 years	20	20.0
46+ years	10	10.0
Total	**100**	**100.0**
Gender		
Male	58	58.0
Female	40	40.0
Other	2	2.0
Total	**100**	**100.0**
Education Level		
High School	12	12.0
Graduate	45	45.0
Postgraduate	43	43.0
Total	**100**	**100.0**
Annual Income		
Below ₹5 lakh	24	24.0
₹5-10 lakh	38	38.0
₹10-15 lakh	25	25.0
Above ₹15 lakh	13	13.0
Total	**100**	**100.0**

Table 1: Demographic Profile of Respondents (N = 100)

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Table 1A: Demographic Profile - Age Group

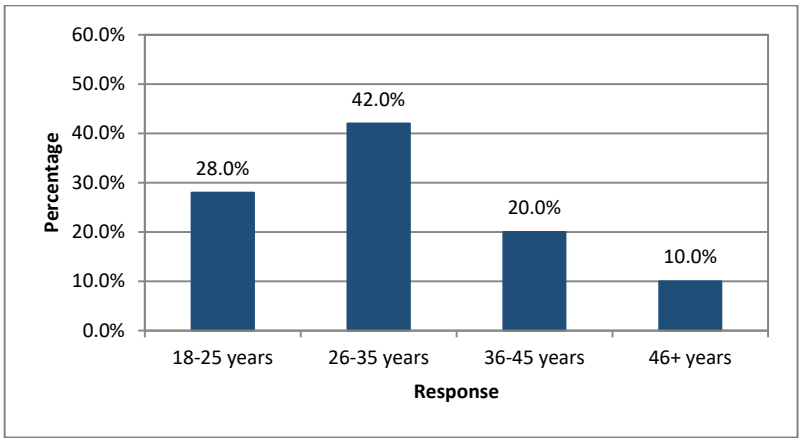

Table 1B: Demographic Profile - Gender

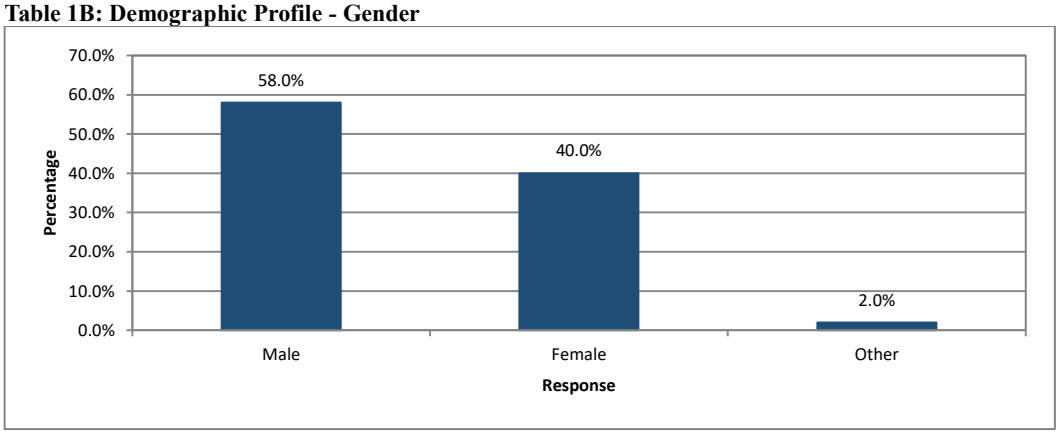

Table 1C: Demographic Profile - Education Level

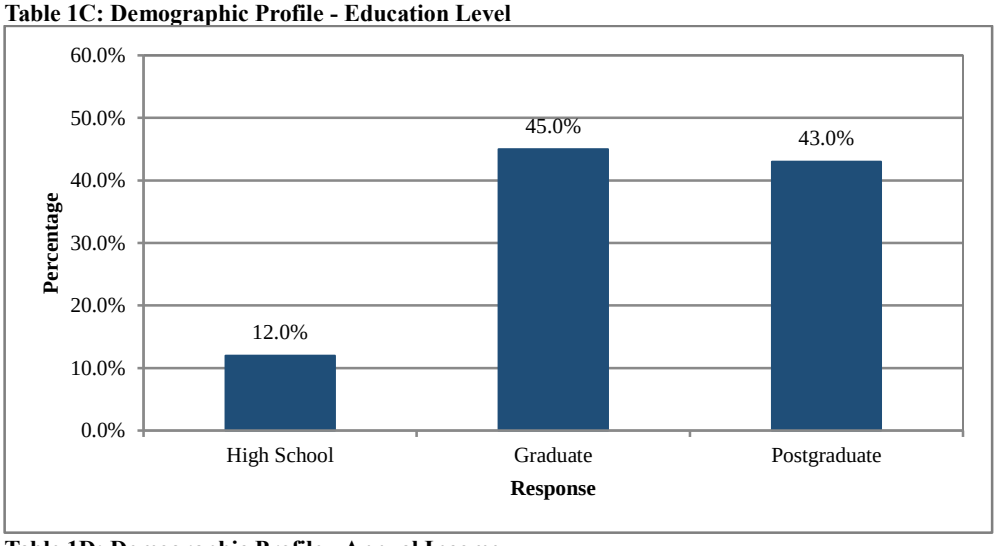

Table 1D: Demographic Profile - Annual Income

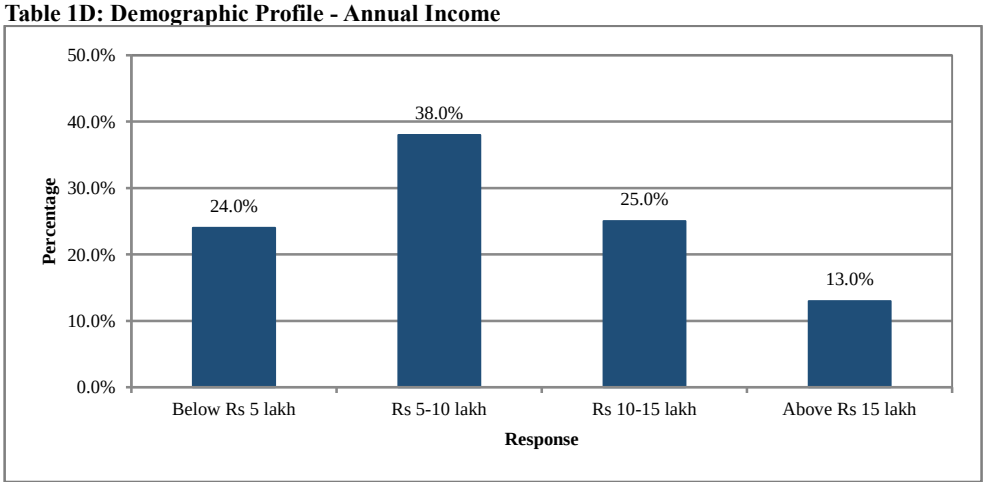

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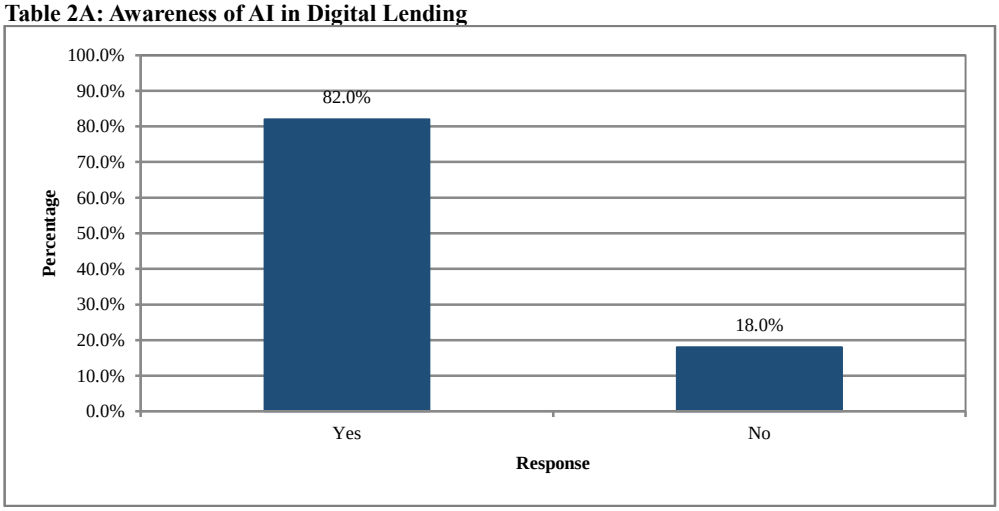
Table 2A: Awareness of AI in Digital Lending



Analysis:

The sample is biased towards younger respondents with 70 percent of the respondents falling between the 18-35 years category and this is in line with the digital adoption rates of the younger generations. The 26-35 category is the most broad with 42 percent which is opposed with the prime working age group that would most likely be interested in taking credit.

The gender has 58 percent men and 40 percent women, and 2 percent other. This distribution of financial services is approximately in line with gender distribution of financial service use except that females are also slightly underrepresented.

They have a highly educated sample as 88% of them are graduates or postgraduate educated. It is a manifestation of the urban and semi-urban sampling focus and it means that the respondents are digitally literate enough to utilize AI-powered platforms.

The distribution of income is distributed within all the categories with the income group of between 5-10 lakhs occupying the highest number (38%). This is a middle-income orientation, which is consistent with the typical target market of digital lending platforms.

4.1.2 Awareness and Adoption of AI-Powered Lending Platforms

Variable	Frequency	Percent
Awareness of AI in Digital Lending		
Yes	82	82.0
No	18	18.0
Total	**100**	**100.0**
Have Used AI-Powered Lending Platform		
Yes	68	68.0
No	32	32.0
Total	**100**	**100.0**
Frequency of Usage		
First time	15	22.1
2-3 times	31	45.6
4-5 times	14	20.6
More than 5 times	8	11.7
Total	**68**	**100.0**

Table 2: Awareness and Adoption Statistics (N = 100)

Table 2B: Have Used AI-Powered Lending Platform

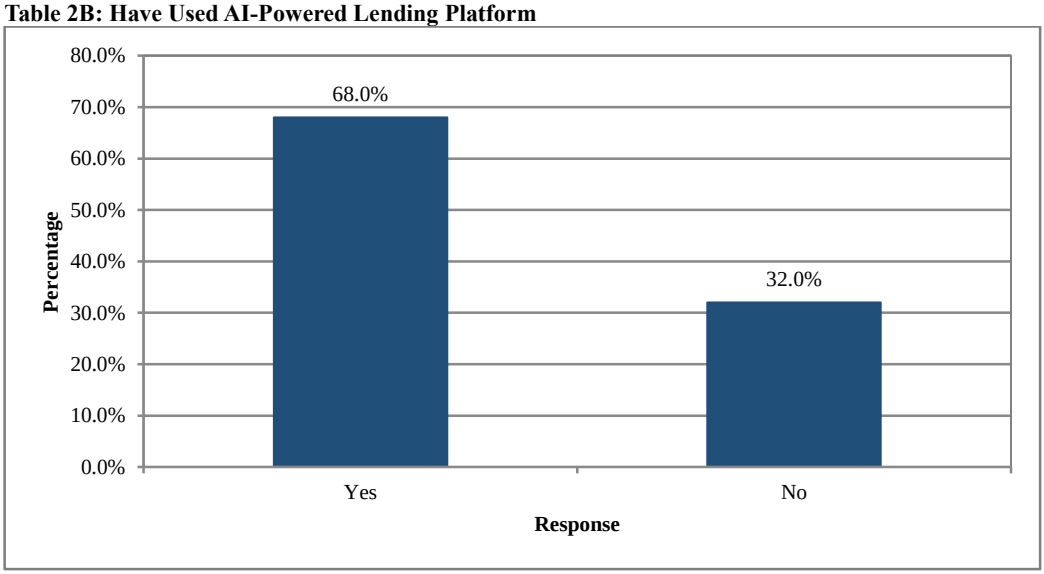


Table 2C: Frequency of Usage (Among Users, N=68)

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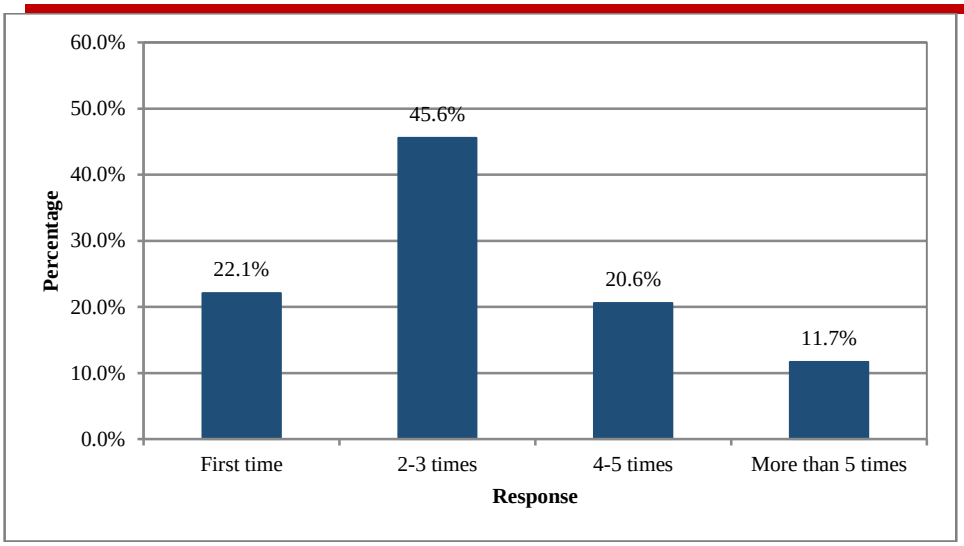


Analysis:

The level of awareness of AI in the sphere of digital lending is also high (82), which indicates that people have received information about these technologies in large sections of the target audience. This is awareness in the context of growing media attention, promotion of FinTech and applications of AI in general.

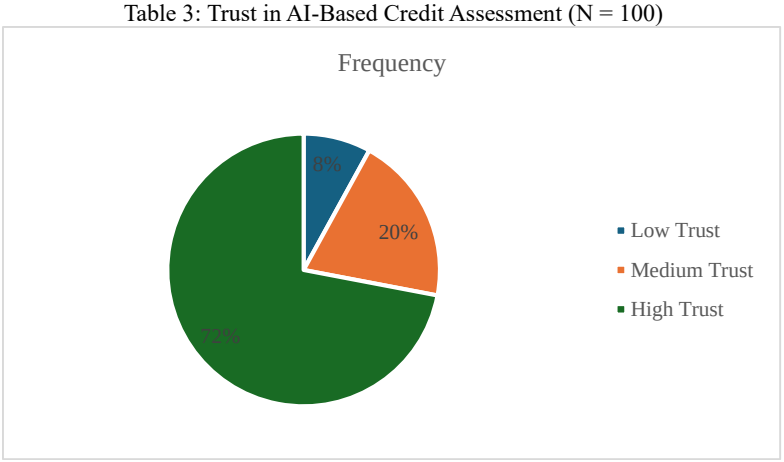
The real adoption has reached 68 per cent, which demonstrates that the level of awareness is transformed into actual use among most of the educated respondents. The gap between the levels of awareness (82%) and adoption (68) amounting to 14 points indicates that although most of the population is aware of the AI lending, there are others who are unwilling to use it.

Fourthly, 45.6% of users have used platforms twice- or three times and this represents a repeat use and not a trial. First-time users are only 22.1% and 32.3% have used platforms 4 times or more, which means that positive first impressions lead to subsequent usage.

4.1.3 Trust in AI-Based Credit Assessment

Trust Level	Frequency	Percent
Low Trust	8	8.0
Medium Trust	20	20.0
High Trust	72	72.0
Total	**100**	**100.0**

Table 3: Trust in AI-Based Credit Assessment (N = 100)



Descriptive Statistics:

Variable	N	Mean	Std. Deviation	Minimum	Maximum
Trust in AI (Scale 1-5)	100	3.84	0.892	1.0	5.0

Table 4: Descriptive Statistics - Trust in AI Credit Assessment

Analysis:

The levels of trust in AI based credit assessment are very high with 72% of the respondents displaying a high rate of trust. High levels of trust (88 percent) and low levels of trust (8 percent) share the same amount, which means that the concerns of the accuracy and fairness of AI do not dominate the users.

The high level of trust is supported by the average score of 3.84 on a scale of 5 (1 =Very Low Trust and 5 =Very High Trust). The standard deviation of 0.892 indicates that variability is moderate since most of the respondents are grouped at high trust side of the scale.

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Such trust could be the result of being pleased with the experience of using AI lending platforms or just an overall trust in technology or it could be that the respondent trusts in AI by virtue of holding the belief that AI reduces human bias in the lending decision. The discovery dispels anxieties that have been widely exhibited in the media and in policymaking regarding bias among the public against AI.

4.1.4 Perceived Benefits of AI in Digital Lending

Perceived Benefit	Mean Score	Std. Deviation
Faster loan approval	4.35	0.712
24/7 availability	4.18	0.825
Convenience and ease of use	4.22	0.768
Lower interest rates	3.56	1.042
Access without credit history	3.92	0.958
Reduced documentation	4.28	0.745
Transparent process	3.78	0.912

Table 5: Perceived Benefits of AI-Powered Lending (Scale: 1 = Strongly Disagree to 5 = Strongly Agree)

Analysis:

The most treasured advantage is faster loan approval (Mean = 4.35) that displays the significance of the speed of providing credit. Contrary to the traditional lending process which takes days and even weeks, the AI platform provides a decision within minutes.

The next most beneficial advantages are reduced documentation (Mean = 4.28) and convenience/ease of use (Mean = 4.22). These features address the pain points of traditional lending where a lot of paper work and visits to branches are found out to be unfriendly.

On-demand access (Mean = 4.18) is the value of 24/7 availability and at no restrictions of the hours of the branches. This advantage is particularly appealing to busy people and those who reside in locations that have limited banking facilities.

The access without credit history (Mean = 3.92) have moderate high scores, indicating the awareness of assessment of the alternative data and its provision to the credit invisible populations through the AI tools. This benefit is particularly huge to young adults and first time borrowers.

The lowest rating of all the benefits is given to lower interest rates (Mean = 3.56), which means that, although the users find the use of AI lending more convenient and faster, they may not perceive it as less expensive. This could be the reality since most AI platforms will target convenience-centric customers who are not targeting price competition as their primary goal.

4.1.5 Concerns and Barriers

Concern	Frequency	Percent
Data privacy concerns	45	45.0
Algorithmic bias concerns	32	32.0
Lack of human interaction	28	28.0
Difficulty in dispute resolution	35	35.0
Insufficient transparency	38	38.0
Security of personal information	42	42.0

Table 6: Concerns About AI-Powered Lending (Multiple Responses Allowed)

Analysis:

The most frequent roadblock is the issue of data privacy (45), which shows that the problem is widespread in society at large because of the way personal and financial information is gathered, utilized, and preserved by a technology platform. The recent breaches of data and privacy scandals have rendered people more conscious of these threats.

Security of personal information (42) follows right on its heels, and it demonstrates that even though the user has confidence in AI credit assessment, they are worried about the safety of the information and how sensitive financial information can be used.

Lack of transparency 38% shows the fears of black box AI systems where the users are unaware of how the decisions are made or are unable to contest the unfavorable results. This is in line with the demand of explainable AI in lending.

The inability to resolve disputes (35%) is indicative of anxiety about the place of going when AI commits errors or people no longer agree with the decisions made. Some users are becoming anxious due to the unavailability of human loan officers whom they can appeal to.

The third main concern that relates to algorithmic bias (32%), which is being aware of the possible risks of discrimination, is much lower than those of privacy and transparency concerns. This could be an indication of trust in the capability to deal with bias or no personal experience of bias.

The least identified issue is the absence of human interaction (28%), meaning that efficiency and convenience are more significant than bankers relationships to most users. Nevertheless, nearly 1/3 of them still prefer human touchpoints, which means that hybrid models are required.

4.1.6 Preference for AI vs. Traditional Lending

Preference	Frequency	Percent
Strongly prefer AI-powered	35	35.0
Somewhat prefer AI-powered	33	33.0
Neutral	18	18.0
Somewhat prefer traditional	10	10.0
Strongly prefer traditional	4	4.0
Total	**100**	**100.0**

Table 7: Preference for AI vs. Traditional Lending (N = 100)

Analysis:

Sixty-eight percent of the respondents support AI-driven lending (35% strongly, 33% somewhat) of which a significant number of participants display outright preference to digital solutions compared to the traditional ones. Not even 14% are fond of traditional lending, which implies that in most of the cases the advantages of AI do not outcompensate the worries of the users.

The 18% who were neutral means that there are also a number of the respondents who believe that both of these approaches can be both acceptable under different circumstances or that they have not formed firm preferences due to lack of sufficient experience.

This frenzied interest in AI lending is what is existing confirmation of where the market is moving and suggests that it could continue to grow with its increased awareness and adoption.

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4.1.7 Intention to Use AI Lending Platforms in Future

Variable	N	Mean	Std. Deviation	Minimum	Maximum
Intention to Use (Scale 1-5)	100	4.12	0.856	1.0	5.0

Table 8: Descriptive Statistics - Intention to Use AI Lending Platforms

Analysis:

The average intention of 4.12 out of 5 points (where 1 equals Definitely will not use and 5 Definitely will use) suggests that there will be strong adoption intentions in the future. A high score indicates that awareness, trust and positive perception of benefits is present and converted into behavioral intentions.

The standard deviation of 0.856 is a middle range of variability with some respondents having reservations despite having a general positive sentiment.

4.2 Hypothesis Testing

4.2.1 Chi-Square Test: Association Between Age Group and Platform Adoption

Research Question: Is there a significant association between age group and adoption of AI-powered lending platforms?

Hypothesis:

H_0: There is no significant association between age group and adoption of AI-powered lending platforms.

H_1: There is a significant association between age group and adoption of AI-powered lending platforms.

Crosstabulation:

Age Group	Platform Adoption		Total
	Yes	No	
18-25 years	22	6	28
	(78.6%)	(21.4%)	(100%)
26-35 years	32	10	42
	(76.2%)	(23.8%)	(100%)
36-45 years	12	8	20
	(60.0%)	(40.0%)	(100%)
46+ years	2	8	10
	(20.0%)	(80.0%)	(100%)
Total	**68**	**32**	**100**
	(68.0%)	**(32.0%)**	**(100%)**

Table 9: Age Group * Platform Adoption Crosstabulation

Chi-Square Tests:

Test	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	18.347^{a}	3	.000
Likelihood Ratio	18.925	3	.000
Linear-by-Linear Association	16.234	1	.000
N of Valid Cases	100		

Table 10: Chi-Square Test Results

a. 2 cells (25.0%) have expected count less than 5. The minimum expected count is 3.20.

Interpretation:

The Pearson Chi-Square value of 18.347 with a degree of freedom of three gives p-value of .000 ($p < 0.001$) which is significantly lower than the significant level of 0.05. Thus, we can dismiss the null hypothesis and make a conclusion that age category and the adoption of AI-powered lending platforms have a statistically significant relationship.

Analysis of Association:

The crosstabulation analysis of the results shows that there are significant patterns:

High adoption rates of 78.6% and 76.2% are experienced among younger age groups (18-25 years and 26-35 years respectively). These online natives are comfortable with technology and are ready to embrace AI-powered applications.

Moderate adoption is experienced in the middle age group (36-45 years) with 60.0% of the group adopting AI lending, which can be explained by the fact that many of them already have established relations with traditional banking institutions, or may be afraid of new technologies.

The age category of variation (46+ years) has dramatically lower adoption, only 20.0% have used AI lending platforms. This large variance makes the Chi-Square substantial outcome and is indicative of generational differences in the use of technologies and the degree of familiarity with online financial services.

The linear-by-linear association value of 16.234 ($p < .001$) proves a linear relationship in which the adoption declines with the age, which supports the interpretation that the age has a systematic effect on AI lending adoption.

Practical Significance:

In addition to statistical significance, there are significant practical implications of such findings. FinTechs need to understand that their existing audience is young and implement mechanisms to gain trust and familiarity with their more mature audiences. This may include hybrid models of using human assistance, better educational material and interfaces of various levels of digital literacy.

The traditional financial institutions need to be familiar with the fact that the younger clients are highly fond of digital lending methods, and that can be a threat to the models of banks that operate branches unless banks change their services.

4.2.2 Regression Analysis: Trust in AI Predicting Adoption Intention

Research Question: Does trust in AI significantly predict intention to use AI-powered lending platforms?

Hypothesis:

H_0: Trust in AI does not significantly predict intention to use AI-powered lending platforms ($\beta = 0$).

H_1: Trust in AI significantly predicts intention to use AI-powered lending platforms ($\beta \neq 0$).

Variables Entered/Removed:

Model	Variables Entered	Variables Removed	Method
1	Trust in AI^{a}	.	Enter

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Table 11: Variables Entered/Removed

a. All requested variables entered.

Model Summary:

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.584^{a}	.341	.334	.698

Table 12: Model Summary

a. Predictors: (Constant), Trust in AI

ANOVA:

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	24.769	1	24.769	50.862	.000^{b}
	Residual	47.731	98	.487		
	Total	72.500	99			

Table 13: ANOVA^{a}

a. Dependent Variable: Intention to Use AI Lending Platforms

b. Predictors: (Constant), Trust in AI

Coefficients:

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.871	.265		7.062	.000
	Trust in AI	.561	.079	.584	7.132	.000

Table 14: Coefficients^{a}

a. Dependent Variable: Intention to Use AI Lending Platforms

Regression Equation:

The regression equation is:

$$\text{Intention to Use} = 1.871 + 0.561 \times \text{Trust in AI}$$

Interpretation:

Model Fit

The coefficient of positive correlation of the trust in AI and intention to use AI lending platforms is moderate to strong which is indicated by the R value of .584. Based on the R square (.341), trust was found to have explained 34.1 percent variance in the adoption intention. The fact that one predictor, which explains more than one third of the variance, is a significant relationship, even though 65.9% of the variance was not explained.

Statistical Significance

As indicated in Table 1, the Analysis of Variance (ANOVA) results indicate that implying that the overall regression model is significant and it is more of an accurate predictor of the adoption intention than a by chance.

Coefficient Interpretation

The coefficient (or rather the non-standardized coefficient or B) of 0.561 implies that with a one unit increase in trust (against a 5-point scale), the intention to adopt increases by 0.561 units. The standardized coefficient (Beta) of .584 shows moderate to strong effect.

The t-statistic of trust is 7.132 () that proves the hypothesis that the latter is a strong predictor. Thus, we disapprove the null hypothesis and accept that the trust of AI is a meaningful predictor in the intention to use the platforms.

Constant Interpretation

The value of 1.871 was the predicted value of intention when the trust is zero. This is not a very practical value since zero trust was not observed in the sample (minimum = 1.0).

Practical Significance

Considering that trust has been shown to explain 34.1 percent of the adoption intention, there is a strong need to ensure that the development of trust is part of the strategic focus of FinTech platforms. In order to build this trust well, the platforms should show reliable and equity in their credit decisions and give fair explanations to the decisions made through the application of explainable AI. Moreover, it is necessary to develop a strong data security and privacy, as well as offer transparent channels of redress in case of contentious ruling. Continuous positive outcomes and repeated pleasurable user experience may also help to strengthen the brand reputation. Last but not least, the official regulatory certifications are an essential external confirmation of the integrity of a platform. It is also necessary to point out that the 65.9% unexplained variance indicates that there are additional significant determinants of the adoption intention including the perceived ease of use, the overall usefulness, and the social influence.

4.3 Summary of Findings

The detailed study of the information obtained suggests a number of essential conclusions regarding the present situation in the field of digital lending.

High awareness and adoption: The awareness rate stands at 82 percent and the adoption rate at 68 percent so that there is a successful market penetration, especially among younger and highly educated.

High trust in AI: 72 per cent of the respondents indicating a high level of confidence in the technology which gives a mean score of trust of 3.84/5.0.

Speed as the most important attribute: approval received the largest benefit rating (4.35/5.0) with the next attribute being the reduced documentation (4.28/5.0).

Privacy and Security: Despite the excitement, data privacy (45%) and security (42%) are mentioned as the main hindrances to adoption.

Age Correlation: A Chi-Square test proved that there existed a significant correlation () between the age of a respondent and their probability to use these platforms.

Trust Predictability: Regression analysis indicated that the predictability of future adoption was dominated by trust ().

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Strong Preference for AI: 68% of respondents indicated that they prefer AI-powered lending over the traditional method. This feeling converts into a **High future intention** where the mean score of 4.12/5.0 is indicative of a high probability of continued and long-lasting use of these services.

5. DISCUSSION

5.1 Interpretation of Results

High Adoption due to Efficiency: The fact that AI lending has a high adoption rate (68 percent) is explained by the fundamental advantages of the technology, which are speed, convenience, and accessibility. A lower score on documentation (4.28/5.0) refers to the fact that AI facilitates the user experience by automating the process of data collection.

Trust as a Critical Success Factor: High means of trust (3.84/5.0), and regression outcomes () define trust as a critical factor of adoption. This can be an indication of good personal experience and trust of digitally-sophisticated users.

Generational Digital Divide: Chi-square test () shows a digital divide with 76-79% adoption in the 18-35 age group versus 20% in the group 46 years and above.

Privacy as an Ongoing Issue: Privacy is a concern of 45% of users. Even with wide adoption, this suggests many users value the benefits of AI lending more than privacy risks.

Limited Concerns of Algorithmic Bias: Only 32% of respondents have concerns of algorithmic bias, perhaps due to a lack of awareness or belief regarding the objectivity of automated systems.

5.2 Comparison to Available Literature

The findings are in line with industry estimates of continuing FinTech growth and literature that trust is a determinant of technology acceptance. This relationship is determined and quantified through the study to show that trust explains 34.1 percent of the variation in the adoption intention. The significantly different trends in adoption and continuing issues of privacy also confirm the established studies on the digital divide and barriers to FinTech.

5.3 Practical Implications

For FinTech Platforms: Focus on trust-building, target younger demographics in marketing, and develop inclusive interfaces for older users.

For Traditional Institutions: Accelerate digital transformation and work with FinTechs to access new technology.

For Policymakers: Strike a balance between innovation and consumer protection, fostering financial literacy and clarifying explainable AI standards.

5.4 Theoretical Contributions

This research is a confirmation and enhancement of the Technology Acceptance Model (TAM) that quantitatively gauges the technology acceptance of financial technology in the regard of trust. It is also contributing to the digital divide literature by defining particular age trends of AI financial services.

5.5 Limitations and Future Research Direction

Limitations: The study uses convenience sampling (), limiting generalizability. The cross-sectional design measures a single point in time, and self-reported data may contain bias.

Future Research: Longitudinal tracking, bigger probability samples, and behavioral analytics should be employed to examine real usage patterns and credit results.

6. CONCLUSION

The level of attitude toward AI-based digital lending has been discussed in this paper in 100 people. Notable finding: adoption (68) and trust (72) are large, and this is so especially in the younger generations (). The regression analysis showed that trust is an important predictor of adoption intention (R-squared =.341) with a coefficient ().

The users like speed (4.35/5.0) and less documentation (4.28/5.0) most of all yet data privacy (45) is a concern. The research paper verifies that even though AI lending can be efficient and more financially accessible, the maximization of the benefits will be possible only with the help of a strong data governance system, inclusive design, and clear regulatory frameworks, as it will be necessary to uphold the trust level and adopt AI lending.

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