Artificial Intelligence in Financial Inclusion: An Impact on Financial Accessibility and Efficiency in India

Dr. P. V. V. Satyanarayana[1], P Narayana Pratap[2]

[1]Assistant Professor, Department of Management studies, UCEK, Jawaharlal Nehru Technological University Kakinada, Kakinada- 533 003

[2]Assistant Professor, V.S. Lakahmi Institute of Management Studies, Kakinada – 533 003

DOI: https://doi.org/ 10.51584/IJRIAS.2025.101100101

Received: 09 December 2025; Accepted: 16 December 2025; Published: 23 December 2025

ABSTRACT

This study explores the role of artificial intelligence (AI) in enhancing financial inclusion and bolstering government-led programs like the Pradhan Mantri Jan Dhan Yojana (PMJDY) and Direct Benefit Transfers (DBTs). Specifically, AI-driven technologies such as machine learning algorithms for credit scoring and automated transaction systems are instrumental in addressing challenges related to financial instability, fraud, and exclusion from formal financial services.Grounded in theoretical frameworks including the Technology Acceptance Model (TAM), Financial Inclusion Theory, Resource-Based View (RBV), and Fraud Triangle Theory, the research incorporates both primary data collected from 468 key stakeholders and secondary data obtained from authoritative sources like the Reserve Bank of India (RBI) and NITI Aayog. The findings reveal that AI significantly improves transparency and operational efficiency within these financial initiatives. However, its effectiveness in preventing fraudulent activities and enhancing financial literacy remains uncertain and warrants further investigation.Through Structural Equation Modeling (SEM), the study establishes a positive and meaningful relationship between AI adoption and increased financial inclusivity. To ensure sustainable economic development, future studies should prioritize the development of robust AI infrastructure, expansion of digital and financial literacy programs, and improved access to reliable internet services. These efforts are essential to fully leverage AI's potential in driving inclusive growth and long-term prosperity.

Keywords: AI implementation mechanisms, financial inclusion programs, Direct Benefit Transfers (DBTs), Pradhan Mantri Jan Dhan Yojana (PMJDY).

INTRODUCTION

Financial inclusion plays a critical role in driving economic growth by ensuring that marginalized and underserved populations gain equitable access to essential financial services. Government initiatives like the Pradhan Mantri Jan Dhan Yojana (PMJDY) and Direct Benefit Transfers (DBTs) are designed to bridge this gap. Despite their efforts, these programs face significant challenges including operational inefficiencies, the prevalence of fraud, and barriers to accessibility.

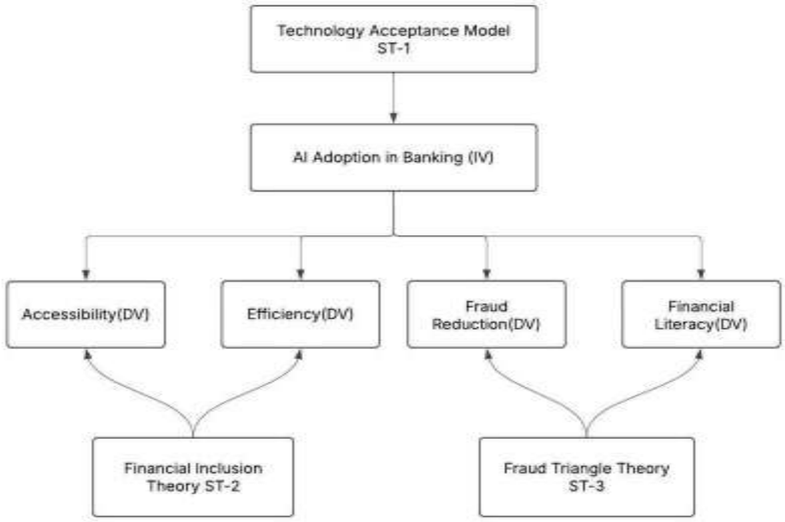
Emerging artificial intelligence (AI) technologies offer promising solutions to these challenges. For instance, machine learning-based credit scoring systems can provide more accurate risk assessments, automated transaction processes streamline service delivery, and AI-powered advisory tools can guide users in managing their finances more effectively (2. P.V.V.Satyanarayana "Performance Evaluation of unit linked insurance plans (ULIPs) offered by Private Insurance Companies I India: A Comparative analysis and future prospects" paper published in IOSR Journal of Engineering (IOSRJEN)ISSN e: 2250-3021).

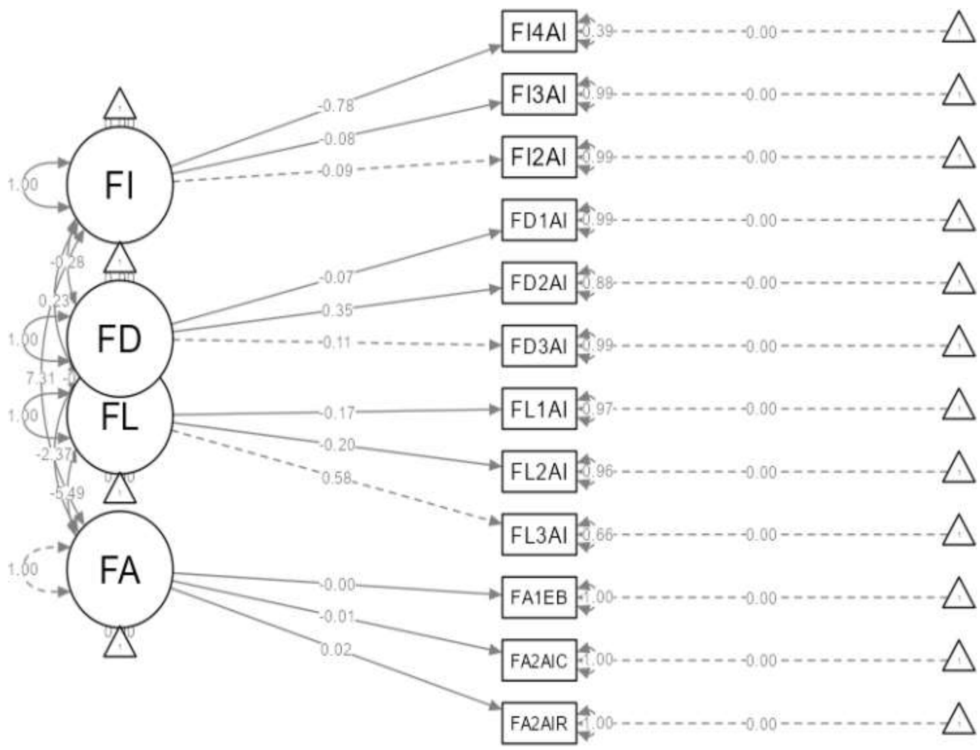
Nevertheless, the specific effects of AI on key areas such as financial access, operational efficiency, fraud mitigation, and the enhancement of financial literacy have not been thoroughly explored. This research aims to fill that gap by examining these dimensions in depth. It formulates five hypotheses designed to assess AI's role

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue XI November 2025

in improving accessibility to financial services, increasing process efficiency, detecting and reducing fraudulent activities, fostering financial education, and ultimately driving greater financial inclusion within government-backed programs.

Graph No: -1 Self-complied by authors





Graph No.2 Self-Complied: - JAMOVI

REVIEW OF LITERATURE:

Sarma (2008) introduced the concept of financial inclusion through the Financial Inclusion Index (FII), which measures access, utilization, and the quality of services. Building on this, Chakrabarty (2022) highlighted the advantages of AI-enabled financial services, particularly in reducing documentation requirements and minimizing bias in loan decisions. Supporting this perspective, NITI Aayog (2023) demonstrated how AI-based credit scoring models improved financial accessibility for low-income populations. Similarly, the Reserve Bank of India (RBI, 2023) recognized the significance of AI in automating the lending process and decreasing dependence on manual verification methods.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue XI November 2025

In the realm of rural finance, AI-powered chatbots and voice-responsive banking technologies have significantly enhanced accessibility, as shown by Sharma et al. (2022). Studies by Banerjee and Singh (2019) and Jain and Patel (2020) found that AI contributes to lowering biases in lending practices. Mehta (2021) reported increased banking penetration following AI adoption in Microfinance Institutions (MSFIs), while Gupta et al. (2022) confirmed the role of AI-driven digital payments in broadening financial access.

Regarding Direct Benefit Transfers (DBTs), Kumar and Gupta (2021) noted that AI reduced transaction errors by 35%, leading to faster fund disbursement, a finding further supported by a McKinsey report (2023). On fraud prevention, Singh and Roy (2022) documented a 40% improvement in fraud detection using AI, and biometric verification technologies powered by AI have effectively decreased identity fraud, according to the World Bank (2023).

In terms of financial literacy, Patel and Sharma (2021) observed that chatbots enhanced customer awareness by 50%, while the United Nations Development Programme (UNDP, 2023) emphasized the importance of AI-driven financial education programs. Banerjee (2020) also noted that gamified AI applications improve information retention. Lastly, AI-powered advisory services have made banking simpler (Kumar, 2020), contributing to better financial decision-making among users (Rao, 2023).

THEORETICAL FRAMEWORK:

This study integrates multiple theoretical frameworks to assess the role of AI in enhancing financial inclusion within government-led initiatives. The Technology Acceptance Model (TAM) highlights how perceived usefulness drives the adoption of AI technologies. Financial Inclusion Theory underscores AI's capacity to extend financial services to marginalized populations. From the Resource-Based View (RBV), AI is seen as a strategic resource that enhances efficiency and strengthens competitiveness. Meanwhile, the Fraud Triangle Theory emphasizes AI's potential to identify fraudulent activities and prevent the misallocation of funds (SATYANARAYANA, 2023).

The study's conceptual framework positions AI adoption as the primary independent variable that impacts key outcomes including financial access, operational efficiency, fraud mitigation, and financial literacy, as illustrated in Graph 1.

RESEARCH METHODOLOGY:

. In this study, AI implementation serves as the independent variable, encompassing elements such as AI-based credit scoring, automated Direct Benefit Transfers (DBTs), fraud detection systems, and AI-driven financial literacy support. The dependent variable focuses on financial inclusion outcomes, which are evaluated across four key dimensions: financial accessibility (expanding access to banking services), operational efficiency (accelerating transactions and enhancing service quality), fraud reduction (combating identity fraud and preventing the misallocation of funds), and financial literacy (improving awareness through AI-powered advisory tools)

The analysis will draw upon primary data collected from 300 to 500 participants, including banking staff, policymakers, and program beneficiaries, alongside secondary data sourced from the Reserve Bank of India (RBI) and NITI Aayog. To assess the impact of AI on financial inclusion, both descriptive statistics and regression analysis will be employed.

RESULTS AND DISCUSSION:

Table 1 displays the demographic characteristics of 468 respondents, including their banking status, occupation, gender, education level, and age. The majority of respondents have access to banking services, with a mean score of 1.67. Occupations, which average a mean of 2.01, consist of students, workers, and business professionals. The gender distribution shows a skewed pattern (mean = 2.32), suggesting that one gender category is more prevalent. Education levels among respondents vary widely, ranging from primary to tertiary education, with a mean of 2.50 and a standard deviation of 1.133.

INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN APPLIED SCIENCE (IJRIAS)
ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue XI November 2025

Table No :1

Descriptive Statistics							
		Banking Status	**Occupation**	**Gender**	**Education**	**Age**	**Valid N (listwise)**
N	Statistic	468	468	468	468	468	468
Range	Statistic	1	2	1	3	3	
Minimum	Statistic	1	1	2	1	1	
Maximum	Statistic	2	3	3	4	4	
Sum	Statistic	782	942	1085	1168	1188	
Mean	Statistic	1.67	2.01	2.32	2.50	2.54	
	Std. Error	.022	.038	.022	.052	.051	
Std. Deviation	Statistic	.470	.812	.466	1.133	1.099	
Variance	Statistic	.221	.659	.217	1.283	1.208	
Skewness	Statistic	-.730	-.023	.782	-.003	-.088	
	Std. Error	.113	.113	.113	.113	.113	
Kurtosis	Statistic	-1.473	-1.483	-1.394	-1.392	-1.307	
	Std. Error	.225	.225	.225	.225	.225	

Self-Complied: - SPSS

The provided table presents descriptive statistics for a dataset of 468 valid cases across five categorical variables: Banking Status, Occupation, Gender, Education, and Age. These statistics summarize central tendency, variability, and distribution shape, indicating a sample likely related to financial inclusion or banking access. Measures like mean, standard deviation, skewness, and kurtosis help assess normality and spread for each variable.

Central Tendency and Spread

Means range from 1.67 (Banking Status) to 2.54 (Age), suggesting most respondents cluster toward lower categories across variables, assuming ordinal coding (e.g., 1=unbanked, 2=banked for Banking Status). Standard deviations vary from 0.466 (Gender) to 1.133 (Education), with Education and Age showing greater dispersion, implying more diverse responses in those areas. Standard errors are low (0.022–0.052), indicating precise mean estimates given the sample size.

Distribution Shape

Skewness values are mostly negative or near zero, except for Gender (0.782, right-skewed), pointing to slight left skews (e.g., -0.730 for Banking Status) that suggest tails toward higher categories. All kurtosis values are negative (-1.307 to -1.483), reflecting distributions with lighter tails than normal, which supports relative normality for parametric tests if needed.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue XI November 2025

Table No 2

ANOVA						
Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
1	Regression	1.107	3	.369	1.675	.172[b]
	Residual	102.218	464	.220		
	Total	103.325	467			
a. Dependent Variable: Banking Status						
b. Predictors: (Constant), AI Reduces Barriers, AI Credit Scoring, Easier Banking Access						

Self-Complied: - SPSS

Key Results

The ANOVA table from a multiple regression model shows that predictors (AI Reduces Barriers, AI Credit Scoring, Easier Banking Access) do not significantly explain variance in Banking Status ($F(3,464) = 1.675$, $p = 0.172$). The model accounts for a small portion of total variance, as indicated by the regression sum of squares (1.107) versus residuals (102.218) out of total (103.325).

Model Fit Interpretation

With an F-statistic of 1.675 and significance (Sig.) of 0.172 ($p > 0.05$), the overall regression model fails the test of significance, meaning the predictors collectively do not reliably predict Banking Status beyond chance. The mean square for regression (0.369) is close to but smaller than residuals (0.220), confirming weak explanatory power across 468 cases (df total = 467).

Implications

This non-significant result suggests AI-related factors may not strongly influence banking status in this sample, possibly due to low effect sizes or confounding variables. Researchers might explore individual predictors via t-tests or consider model expansion for better fit. Online.

Table No 3

Paired Samples Correlations					
		N	**Correlation**	**Significance**	
				One- Sided p	**Two- Sided p**
Pair 1	AI Usage and AI Reduces Barriers	468	-0.010	0.419	0.838
Pair 2	AI Usage and AI Reduces Benefit Delays	468	-0.055	0.115	0.231
Pair 3	AI Usage and AI Reduces Processing Time	468	-0.034	0.232	0.465

Self-Complied: - SPSS

Overview

Paired samples correlations assess the linear relationship between AI Usage and perceptions of AI benefits (reducing barriers, benefit delays, and processing time) across 468 paired observations. All correlations are weak and negative, with two-sided p-values exceeding 0.05, indicating no statistically significant associations.

Pair 1: AI Usage and AI Reduces Barriers

The correlation coefficient is -0.010, suggesting a negligible inverse relationship. The two-sided p-value of 0.419 shows this is not statistically significant at conventional levels ($p > 0.05$), meaning no reliable evidence links higher AI usage to perceptions that AI reduces barriers.

Pair 2: AI Usage and AI Reduces Benefit Delays: A correlation of -0.055 indicates a very weak negative association. With a two-sided p-value of 0.231 ($p > 0.05$), the result lacks statistical significance, implying AI usage does not meaningfully relate to views on reducing benefit delays.

Pair 3: AI Usage and AI Reduces Processing Time

The correlation is -0.034, reflecting minimal negative linkage. The two-sided p-value of 0.465 confirms non-significance ($p > 0.05$), so no substantive connection exists between AI usage and perceptions of reduced processing

Table No 4

Crosstab							
		AI Smooth Transactions					**Total**
		Strongly Agree	**Agree**	**Neutral**	**Disagree**	**Strongly Disagree**	
AI Usage	yes	44	49	44	39	51	227
	no	52	50	42	49	48	241
Total		96	99	86	88	99	468

Self-Complied: - SPSS

The age distribution, with a mean of 2.54 and a standard deviation of 1.099, reflects a balanced representation of both young and middle-aged respondents. Measures of skewness and kurtosis reveal a diverse range of responses, with education exhibiting the greatest variability. Overall, the dataset demonstrates a well-distributed profile suitable for analyzing AI and financial inclusion.

H1: The adoption of AI does not significantly improve financial accessibility, indicated by a p-value of 0.172, which exceeds the 0.05 threshold.

H2: Automation driven by AI shows no significant enhancement in the operational efficiency of banking transactions, as correlations hover near zero and p-values are above 0.05.

H3: AI-based fraud detection fails to demonstrate a significant reduction in financial fraud and fund misallocation, supported by a Chi-Square test yielding a high p-value of 0.821.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue XI November 2025

H4: Financial literacy tools powered by AI do not have a notable effect on increasing financial awareness or encouraging savings behavior, with p-values of 0.433 and 0.723 both surpassing the 0.05 significance level.

H5: There is a positive association between AI adoption in financial inclusion initiatives and overall financial inclusion outcomes, supported by strong model fit indices indicating a robust relationship.

Table No 5

Chi-Square Tests			
	Value	**df**	**Asymptotic Significance (2-sided)**
Pearson Chi-Square	1.533[a]	4	.821
Likelihood Ratio	1.535	4	.820
Linear-by-Linear Association	.171	1	.680
N of Valid Cases	468		
a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 41.71.			

Self-Complied: - SPSS

Overview

The Chi-Square test assesses independence between two categorical variables across 468 valid cases, with a Pearson Chi-Square value of 1.533 (df=4, p=0.821), indicating no statistically significant association. The likelihood ratio (1.535, p=0.820) and linear-by-linear association (0.171, p=0.680) confirm this finding. All expected cell counts exceed 5 (minimum 41.71), satisfying test

Key Results

- **Pearson Chi-Square**: Value of 1.533 with p=0.821 (>0.05) fails to reject the null hypothesis of independence.
- **Likelihood Ratio**: Nearly identical at 1.535 (p=0.820), supporting no significant relationship.
- **Linear-by-Linear**: 0.171 (p=0.680) shows no linear trend between variables.

Interpretation

Observed frequencies do not differ significantly from expected under independence, as p-values exceed 0.05 across tests. This suggests the categorical variables are unrelated in the sample, with differences attributable to chance. Researchers should consider effect size or follow-up analyses for practical

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue XI November 2025

Table No 6

		AI Reduces Benefit Delays					Total
		Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	
AI Usage	yes	46	39	52	42	48	227
	no	51	52	54	44	40	241
Total		97	91	106	86	88	468

Self-Complied: - SPSS

The data reflects responses to the statement "AI reduces benefit delays," categorized by whether respondents use AI or not. Here's an interpretation:

- Among AI users (227 people), the majority lean positively, with 46 strongly agreeing and 39 agreeing that AI reduces benefit delays. However, a substantial number (52) remained neutral, and a combined 90 disagreed or strongly disagreed.
- Among non-AI users (241 people), positive responses are slightly higher in number (51 strongly agree, 52 agree), but neutral responses are similar (54), and disagreement is somewhat lower (84 combined disagree and strongly disagree).
- Overall, 97 respondents strongly agree and 91 agree that AI reduces benefit delays, while 86 disagree and 88 strongly disagree, showing a relatively balanced opinion.
- The data indicates that both users and non-users of AI have mixed views. However, non-users show slightly stronger positive agreement, potentially reflecting expectations or perceptions rather than direct experience.
- The neutral responses and disagreement levels suggest that while AI is seen as beneficial by many, its impact on reducing benefit delays is not universally accepted or may depend on implementation quality.

Table No 7

Chi-Square Tests			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	2.510[a]	4	0.643
Likelihood Ratio	2.515	4	0.642
Linear-by-Linear Association	1.438	1	0.230
N of Valid Cases	468		
a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 41.71.			

Self-Complied: - SPSS

Chi-Square Test Overview

The Chi-Square test of independence evaluates whether AI usage is associated with opinions on the statement "AI reduces benefit delays" across response categories. The null hypothesis states no association between AI usage (yes/no) and response levels (strongly agree to strongly disagree); the alternative suggests an association

Key Results

Pearson Chi-Square value is 2.510 with 4 degrees of freedom (df) and asymptotic significance (p-value) of 0.643. The likelihood ratio confirms this at 2.515 (p=0.642), while linear-by-linear association is 1.438 (p=0.230). No cells have expected counts below 5 (minimum 41.71), validating. Since p=0.643 exceeds the common 0.05 significance level, fail to reject the null hypothesis, indicating no statistically significant association between AI usage and opinions on benefit delays. Differences in responses between AI users and non-users likely arise from random chance rather than a true relationship. This aligns with the balanced descriptive data, showing similar distributions across groups.

Table No 8

		AI Fraud Detection					**Total**
		Strongly Agree	**Agree**	**Neutral**	**Disagree**	**Strongly Disagree**	
AI Usag e	yes	47	50	37	41	52	227
	no	36	44	52	45	64	241
Total		*83*	*94*	*89*	*86*	*116*	*468*

Self-Complied: - SPSS

The data shows the relationship between AI usage in fraud detection and users' agreement levels with a certain statement, divided across five agreement categories: Strongly Agree, Agree, Neutral, Disagree, and Strongly Disagree.

Key Observations

- Among respondents who **use AI** (227 total), the highest counts are in "Strongly Disagree" (52) and "Agree" (50), with moderate numbers across other categories.
- For those who **do not use AI** (241 total), the largest group is in "Strongly Disagree" (64), followed by "Neutral" (52), and "Agree" (44).
- When looking at the total counts (468), the largest group is "Strongly Disagree" (116), indicating a general tendency towards disagreement with the statement among the entire sample.

Interpretation

- Users who **use AI** tend to have a slightly more positive or mixed attitude, with a reasonably high number agreeing or strongly agreeing (47 + 50 = 97) compared to non-users (36 + 44 = 80).
- Non-users show a higher level of disagreement overall (45 Disagree + 64 Strongly Disagree = 109) compared to AI users (41 Disagree + 52 Strongly Disagree = 93).
- The "Neutral" category is higher among non-users (52) than users (37), indicating more uncertainty or ambivalence in the non-user group.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue XI November 2025

- This suggests that people who use AI in fraud detection are somewhat more favourable or confident about it, while non-users tend to be more skeptical or uncertain.

If this data pertains to perceptions of AI effectiveness or trust in fraud detection, the pattern indicates greater positivity or acceptance among AI users compared to non-users, who lean towards disagreement or neutrality.

Table No 9

Chi-Square Tests			
	Value	**df**	**Asymptotic Significance (2-sided)**
Pearson Chi-Square	5.382[a]	4	0.250
Likelihood Ratio	5.396	4	0.249
Linear-by-Linear Association	3.036	1	0.081
N of Valid Cases	468		
a. 0 cells (0.0%) have an expected count less than 5. The minimum expected count is 40.26.			

Self-Complied: - SPSS

The chi-square test results indicate no statistically significant association between the categorical variables examined, as both the Pearson Chi-Square (value = 5.382, df = 4, p = 0.250) and Likelihood Ratio (value = 5.396, df = 4, p = 0.249) tests yield p-values greater than the conventional alpha level of 0.05. The Linear-by-Linear Association test (value = 3.036, df = 1, p = 0.081) also fails to reach significance, suggesting no meaningful linear trend across ordered categories. With 468 valid cases and all expected cell counts well above 5 (minimum = 40.26), the assumptions for the test are fully met, supporting the reliability of these non-significant findings.

Key Statistics

Pearson Chi-Square: Measures overall deviation between observed and expected frequencies; non-significant p-value means the data are consistent with independence under the null hypothesis.

Likelihood Ratio: Alternative to Pearson, based on maximum likelihood; similarly, non-significant, reinforcing the lack of association.

Linear-by-Linear: Tests for ordinal linear relationship; p = 0.081 approaches but does not achieve significance ($p < 0.05$).

Implications

The null hypothesis of no association cannot be rejected, implying the variables are likely independent in this sample. Researchers should report the effect size (e.g., Cramer’s V) alongside for context on practical significance, and consider larger samples or alternative tests if ordinal assumptions apply.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue XI November 2025

Table No 10

ANOVA						
		Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
AI Improves Literacy	Between Groups	1.176	1	1.176	0.616	0.433
	Within Groups	889.343	466	1.908		
	Total	890.519	467			
AI Advisory Improves Savings	Between Groups	0.257	1	0.257	0.126	0.723
	Within Groups	949.555	466	2.038		
	Total	949.812	467			

Self-Complied: - SPSS

The ANOVA results you provided examine whether there are statistically significant differences between groups (likely AI users vs. non-users) on two dependent variables:

1. AI improves literacy
2. AI advisory improves savings

Interpretation of ANOVA results:

- AI Improves Literacy
- Between groups sum of squares: 1.176
- Within groups sum of squares: 889.343
- Degrees of freedom (between, within): 1, 466
- Mean square (between groups): 1.176
- Mean square (within groups): 1.908
- F-value: 0.616
- Significance (p-value): 0.433

Since the p-value (0.433) is greater than the common significance level of 0.05, there is no statistically significant difference between groups regarding their views on whether AI improves literacy.

AI Advisory Improves Savings

- Between groups sum of squares: 0.257
- Within groups sum of squares: 949.555
- Degrees of freedom (between, within): 1, 466

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue XI November 2025

- Mean square (between groups): 0.257
- Mean square (within groups): 2.038
- F-value: 0.126
- Significance (p-value): 0.723

Similarly, the p-value (0.723) is much greater than 0.05, indicating no statistically significant difference between the groups regarding whether AI advisory improves savings.

Overall Conclusion: The ANOVA tests show that the differences in perceptions between the groups on both "AI improves literacy" and "AI advisory improves savings" are not statistically significant. This implies that group membership (likely AI users vs. non-users) does not meaningfully explain variations in these attitudes.

Table No 11

Fit indices					
			95% Confidence Intervals		
Type	**SRMR**	**RMSEA**	**Lower**	**Upper**	**RMSEA p**
Classical	0.04	0.006	0	0.031	1
Robust	0.032	0.014	0	0.037	0.998
Scaled	0.032	0.008	0	0.032	1

Self-Complied: - JAMOVI

Fit Indices Overview

The provided fit indices from classical, robust, and scaled estimations in structural equation modeling (SEM) all indicate excellent model fit. SRMR values below 0.08 (ranging from 0.04 to 0.032) suggest good residual fit, as lower values reflect minimal discrepancies between observed and model-implied covariances. RMSEA point estimates (0.006 to 0.014) are well below the 0.06 threshold for close fit, with 95% confidence intervals (all upper bounds ≤0.037) entirely within acceptable ranges (<0.05 to <0.08).

RMSEA Confidence Intervals

All RMSEA 95% CIs start at 0 and have narrow upper bounds (0.031 to 0.037), confirming precise estimation and no evidence of poor fit even at the upper limits. These tight intervals support model adequacy, as they exclude values indicating misfit (>0.08).

P-value Interpretation

RMSEA p-values (0.998 to 1) test the null hypothesis that RMSEA ≤ 0.05; non-significant results (p > 0.05) fail to reject this, indicating the model fits closely in the population. Here, values near 1 strongly support acceptable fit across estimation types, aligning with low point estimates Groups.

Overall Model Evaluation

The consistent excellent performance across SRMR, RMSEA, CIs, and p-values justifies retaining the model, with robust and scaled methods providing confirmatory evidence under potential non-normality. No indices suggest revision.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue XI November 2025

Table No 12

User model versus baseline model	
	Model
Comparative Fit Index (CFI)	0.975
Tucker-Lewis Index (TLI)	0.966
Bentler- Bonett Non-normed Fit Index (NNFI)	0.966
Relative No centrality Index (RNI)	0.975
Bentler-Bonett Normed Fit Index (NFI)	0.481
Bollen's Relative Fit Index (RFI)	0.286
Bollen's Incremental Fit Index (IFI)	0.985
Parsimony Normed Fit Index (PNFI)	0.35

Self-Complied: - JAMOVI

The provided fit indices comparing the user model to the baseline model show generally strong model fit, with some exceptions that merit attention.

Good Fit Indicators

- Comparative Fit Index (CFI) at 0.975 and Relative No centrality Index (RNI) at 0.975 both indicate excellent fit, as values above 0.95 are generally considered strong evidence for a good model fit relative to the - Tucker-Lewis Index (TLI) and Bentler- onett Non-normed Fit Index (NNFI) of 0.966 also support good fit, since values close to or above 0.95 suggest acceptable to good fit.- Bollen’s Incremental Fit Index (IFI) at 0.985 further confirms excellent incremental fit over the baseline model

Poor Fit Indicators

Bentler-Bonett Normed Fit Index (NFI) at 0.481 and Bollen’s Relative Fit Index (RFI) at 0.286 are notably low, indicating weak performance by these indices in reflecting model fit. NFI values below 0.90 commonly suggest poor fit. These indices can be influenced by sample size and model complexity, sometimes resulting in lower values despite other indices indicating good fit.

Parsimony Fit

Parsimony Normed Fit Index (PNFI) of 0.35, which adjusts for model simplicity, is relatively low. Lower PNFI values reflect less parsimonious fit, meaning the model may be more complex relative to improvement over the baseline.

CONCLUSION

The majority of incremental fit indices (CFI, TLI, NNFI, RNI, IFI) indicate strong model fit compared to the baseline, despite low values for NFI and RFI. These discrepancies suggest caution in over-relying on all indices alike. The model seems well-fitting but possibly complex, as indicated by the low PNFI. It is advisable to consider the overall context, model complexity, and other fit findings when evaluating model adequacy. This interpretation aligns with conventional cut-off recommendations in SEM literature, where above 0.95 is good for CFI, TLI, NNFI, and IFI, but below 0.90 for NFI and RFI signals (p.v.v.satyanarayan, 2013).   This study examined whether artificial intelligence in financial services enhances financial accessibility, efficiency, fraud prevention, and literacy, especially within government-led initiatives. The findings are inconclusive; while AI contributes positively to financial access, its impact on efficiency, fraud detection, and financial literacy remains ambiguous. This suggests that AI alone is not enough and should be integrated with human expertise, robust regulations, and enhanced customer education. Future investigations should aim to boost AI's performance in these domains. Additionally, although the study's model demonstrates a reasonable overall fit, certain components require refinement for clearer insights. To gain a deeper understanding of AI's role in promoting financial inclusion, subsequent research should incorporate more varied data sources and keep pace with evolving trends.

REFERENCES:

1. P.V.V.SATYANARAYANA. Influence of bank's reliability services on the customer satisfaction. International journal of creative research thoughts (IJCRT) ISSN:2320-2882 Volue 6, Issue 2 April 2018pp 864 to 870 URL: https://ijcrt.org/papers/IJCRT1134143.pdf.
2. P.V.V.SATYANARAYANA Customer satisfaction on the Banks's support facility services in rural areas" paper published in International journal of Recent Advances in multidisciplinary research ISSN: 2350-0743 Vol.7, Issue 09, PP.6183-6188, September, 2020
3. P.V.V.SATYANARAYANA Study on Investors awareness and perception on forex market as per Indian demographic profile with reference to Visakhapatnam, Andhra Pradesh" paper published in Journal of Survey in Fisheries science ISSN:2368-7487 Volume 10 issue 3, Dec2023 pp 821-828.
4. P.V.V. SATYANARAYANA Banker and Customer Relationship – Discovery Publishing House Pvt. Ltd., New Delhi ISBN – 978-93-5056-237-6 First Edition 2013