Evaluating AI-Driven tools for improving Digital Literacy and Fraud Risk Detection in Indian Public Sector Banks

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Abstract: *The development of Artificial Intelligence (AI) in the banking industry is rapidly expanding new possibilities, both in terms of focusing on the lack of digital literacy in banking staff and managing the increasing risks of fraudulent operations during deals. The present research assesses the effectiveness of AI-based tools and their ability to enhance digital literacy skills and increase the potential of fraud risk detection among the employees of Indian state-owned banking institutions. A mixed-methods research design was adopted, which determined the quantitative data among 312 employees in 14 authorities of the public sectors through a structured questionnaire that was validated by Confirmatory Factor Analysis (CFA). Various statistical methods such as Pearson Correlation, Multiple Regression Analysis, One-Way ANOVA, Paired Sample t-test, Kruskal-Wallis H-test, Chi-Square Analysis and Structural Equation Modelling (SEM) are used to test six hypotheses of the study. Findings indicate that the awareness of AI tools (0.412, $p < 0.001$), frequency of employee training (0.198, $p < 0.001$), and implementation readiness (0.193, $p < 0.001$) are important predictors of digital literacy improvements. The effectiveness of detection of fraud was higher after AI intervention (pre-mean = 61.4, post-mean = 78.9; $t = -18.654$, $p < 0.001$). The proposed theoretical framework was validated because the SSM model fitted adequately (CFI = 0.947; RMSEA = 0.048). The research also adds to the literature by introducing an empirically tested model that provided an association between the adoption of AI tools and the impact on digital competency and fraud risk reduction outcomes in the Indian banking industry.*

Keywords: Artificial Intelligence, Digital Literacy, Fraud Risk Detection, Public Sector Banks, India, Structural Equation Modelling, Financial Technology

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Introduction

Indian banking industry with 12 state-owned banks (PSBs) after the governmentally imposed consolidation of 2019 is still the mainstay of the Indian financial ecosystem. Nevertheless, the industry confronts two problems simultaneously: a chronically low rate of high digital literacy of its huge labor force and an astute increase in the number of complex financial frauds. The (Das et al. 2023) of the Reserve Bank of India states that in FY 2022-23, bank frauds in India reached 30,252 crore and a significant part of them was based on cyber-related weaknesses and inefficiency in the supervision of employees. The phenomenon of Artificial Intelligence has become a disruptive power that is impacting the banking activity worldwide. Artificial intelligence applications such as machine learning (ML)-based anomaly detection, natural language processing (NLP) phishing detection, robotic process automation (RPA) and smart analytics platforms are being implemented to identify fraudulent transactions in real-time, and these systems regularly achieve accuracies of over 95 percent in controlled environments. At the same time, training systems based on AI-driven learning management systems (LMS) and adaptive e-learning platforms are being introduced to employee training systems to build a digital-competency framework in a more technology-focused banking context. Although it is promised, the implementation of the AI-inspired tools in Indian PSBs is not uniform because it is restricted by the inertia of the organization, the infrastructures, the reluctance of the regulators, and the skills gap between the workforce. It is scarce that research should be conducted to establish the empirical connection between AI implementation, digital literacy achievement, and the efficacy of fraud detection in the context of the Indian population in the banking industry. The paper will address that gap by offering a rigorous and data-driven analysis.

1.1 Research Problem

The rate of fraud incidents in the Indian public sector banks remains disproportionately high in comparison with the private sector (Das et al. 2023). One of the main reasons that contribute to such disparity is the low level of digital fluency of frontline workers who must deal with complex AI-integrated systems without any proper training. The current literature is mostly biased towards the technological side of the AI systems, but not the human-capital side- namely how AI tools can be developed and implemented in a way that will allow developing employee competency and preventing fraud more efficiently.

1.2 Significance of the Study

The study has threefold contributions: (i) it offers empirical evidence to support the association of the characteristics of AI tools with measured increases in digital literacy among the employees of the public sector banks; (ii) it quantifies the effect of AI-enhanced digital literacy on the results of fraud detection; and (iii) suggests and validates a structural model, which could be used by policymakers, the bank management, and technology vendors to design effective AI intervention strategies.

Review of Literature

2.1 AI in Banking and Financial Services

The last ten years have seen an exponential increase in the use of AI in the financial services. (Arner, Barberis, and Buckley 2016) present a detailed taxonomy of AI applications in financial services and note that fraud detection, credit scoring, regulatory compliance, and customer service automation are the four main areas of application. Deep learning neural networks, ensemble methods, and support vector machines have furthermore proven to be better at detecting abnormal transaction patterns than the conventional rule-based systems (Ngai et al. 2011). (Bauguess 2017) determined that surveillance infrastructure based on AI used by the U.S. securities and exchange commission has enhanced detection of insider trade and market abuse by 37 percent compared to standard statistical models. Both authors, discovered that in the Indian context, PSBs with an AI-based fraud detection system saved 28.4 percent of losses related to fraud cases in three years, but the results of the study were constrained by a small sample of two banks.

2.2 Banking Workforce Digital Literacy.

Digital literacy has not just been confined to operating a computer but is now a skill that involved critical thinking of digital data, knowledge of data security, using AI tools, and communication technology (Eshet-alkalai 2004; Bawden 2008)). In the banking industry, in particular, define digital literacy as a multi-dimensional concept that encompasses technical skills, cybersecurity knowledge, data interpretation and skills, and the flexibility of AI tools. The (Zahidi 2023) lists as the two leading emerging competencies in the banking and financial services workforce within the five-year period AI collaboration skills and digital fluency. According to studies conducted in the developed economies, the implementation of the targeted AI-driven training programs can help to increase the score of digital literacy among employees by 25-40 percent within six-month implementation periods (Das et al. 2023). Similar evidence in the case of the Indian PSB is scarce.

2.3 Fraud Risk Detection:

Changing Paradigms. Banking frauds are of various types such as identity theft, account takeover, transaction fraud, loan fraud, phishing, and insider fraud. The conventional detection was based on rule-based transaction-level monitoring systems that create high false-positive rates and cannot detect new fraud pattern (Bolton and Hand 2002). The shift to AI-based detection paradigms, in general, unsupervised anomaly detectors, supervised classification systems, and adaptive systems based on reinforcement learning has significantly changed the detection scene.

Author tested AI fraud detection systems in seven Indian state-owned banks and discovered statistically significant gains in the detection rate (68.2% to 84.7%) after the implementation of AI. Nevertheless, their research failed to consider the moderating influence of employee digital competency, which is the subject of this research.

2.4 Theoretical Framework

Three theoretical bases are used in this study. Factors which have an influence on the adoption of AI tools are explained in Technology Acceptance Model (TAM) (Davis 2014). The context of the Technology-Organization-Environment (TOE) framework (Tornatzky 2026) contextualizes organizational and environmental conditions that define the implementation of AI in PSBs. The Human Capital Theory (Becker 1975) forms the basis of association between training investment, skill development, and the performance outcomes in the organizations such as fraud prevention.

Based on the combination of these views, the proposed research is that the properties of AI tools (perceived usefulness, ease of use) modulate with organizational attributes (training frequency, management support, readiness) and human capital (employee competency) to lead to quantifiable results in digital literacy and effectiveness in detecting fraud.

3.1 Research Objectives

Specific objectives of the study are as follows:

2 To evaluate the existing degree of awareness on AI tools and digital literacy among the employees of Indian public sector banks.

2.1 To analyze how AI-based training programs can enhance bank employees on digital literacy skills.

3 To test how AI-based systems are effective in improving the ability of detecting fraud risks within the Indian PSBs.

4 To examine the existence of significant differences in the levels of AI adoption and the results of fraud detection among the various categories of banks in the public sector.

5 To identify the correlation between digital literacy among employees and effectiveness in fraud detection.

6 To test and confirm a structural model of the causal processes through the adoption of AI tools to fraud risk detection outcomes through the mediating role of digital literacy.

3.2 Research Hypotheses

H1: AI tools awareness significantly positively influences digital literacy improvement in the employees of Indian public sector banks.

H2: The levels of digital literacy and effectiveness of fraud detection are positively correlated in Indian PSBs significantly.

H3: AI-based training interventions will result in significant improvement in both digital literacy scores and the rates of fraud detection (pre-post comparison).

H4: There are significant differences in the level of AI tool adoption and the effectiveness of fraud detection in various groups of Indian public sector banks.

H5: Digital literacy category and the level of AI tools adoption are both significantly related to the type of bank and the cadre of employees.

H6: The hypothesized structural equation illustrating the causality between AI tool awareness and digital literacy to the effectiveness of fraud detection has acceptable goodness-of-fit.

Research Methodology

4.1 Research Design

The mixed-methods design chosen in the given study is based on the quantitative orientation with some qualitative insights. The quantitative strand is also a cross-sectional survey design that incorporates a pre-post quasi-experimental component in order to quantify the change of digital literacy and fraud detection in the presence of AI tool intervention. The qualitative strand will entail semi-structured interviews with 18 top banking officials to put quantitative results into perspective.

4.2 Population and Sampling

The target group is the employees of the Indian banks that belong to the public sector, of both operational, supervisory and managerial grades. Stratified random sampling was used so that the sample will have proportional representation of four categories of banks, including: (i) State Bank of India (SBI), (ii) Large Nationalised Banks (Punjab National Bank, Bank of Baroda, Canara Bank, Union Bank), (iii) Medium Nationalised Banks (Bank of India, Indian Bank, Indian Overseas Bank, UCO Bank, Central Bank, Bank of Maharashtra), and (iv) Regional Rural Banks (RRBs) sponsored by PSBs.

The required sample size was calculated using Cochran (1977) formula sample size calculation of finite population with 95 percent level of confidence and 5 percent marginal error which gave minimum sample as 278. To take into consideration any non-response, 380 questionnaires were sent, and 327 of them were returned (86.1% response rate). Following the removal of responses that were not complete, the final analytical sample consisted of N = 312, which is more than the minimum required.

4.3 Data Collection Instrument

The five-question structured questionnaire comprised of five parts; (A) demographic profile; (B) AI tool knowledge and use (6 items); (C) digital literacy (7 items); (D) fraud detection (8 items); and (E) organization, such as training frequency, management support, and readiness (implementation). Measurement of all Likert-scale questions was done based on a five-point scale (1 = Strongly Disagree to 5 = Strongly Agree). Davis (1989) adapted the instrument based on the relevant validated scales and pre-tested it (30 respondents) to confirm that it was clear and face-valid.

4.4 Statistical Methods

Statistic methods that were used include the following: IBM SPSS Statistics 27 and AMOS 24: Frequency distribution, mean, standard deviation of profile of respondents and variable characteristics.

- Reliability Analysis: Cronbach’s Alpha of internal consistency of measurement scales.
- Pearson Correlation Analysis: To study the bivariate relationship of continuous variables (H2).

- Multiple Regression Analysis: To verify predictive effects of AI tool awareness and the associated variables on digital literacy and effectiveness in fraud detection (H1).
- Paired Sample t-test: To assess the changes in pre- and post-levels of digital literacies and fraud rates after AI training intervention (H3).
- One-Way ANOVA with post-hoc Tukey HSD: To establish the difference in means among the bank categories (H4).
- Kruskal-Wallis H-test: Kruskal-Wallis H-test is a non-parametric alternative to ANOVA when it was not met (H4).
- Chi-square-Test of Independence: To test the relationships between categorical variables (H5).
- Structural Equation Modelling (SEM) with AMOS: Confirmatory Factor Analysis and then proceed to path analysis to test proposed structural model (H6).

Results and Discussion

5.1 Descriptive Statistics

The descriptive statistics of all key variables of study are given in Table 1. The moderate-to-high mean score of AI Tool Awareness (M = 3.68, SD = 0.87) and Fraud Detection Effectiveness (M = 3.71, SD = 0.81) indicate that there is an awareness, but there is a significant room of improvement. The standard deviation of Training Frequency would be relatively high due to the uneven distribution of the AI training programs among various categories of banks.

Table 1: Descriptive Statistics of Primary Study Variables (N = 312)

Variable	N	Mean	SD	Min	Max
AI Tool Awareness Score	312	3.68	0.87	1.00	5.00
Digital Literacy Index	312	3.54	0.92	1.00	5.00
Fraud Detection Effectiveness	312	3.71	0.81	1.20	5.00
Employee Competency Level	312	3.45	0.95	1.00	5.00
AI Implementation Readiness	312	3.39	0.98	1.00	5.00
Training Frequency (times/yr)	312	4.21	1.63	1.00	10.00
Fraud Incidents (past 2 yrs)	312	2.84	1.91	0.00	12.00

Note. All Likert-scale variables are measured on a 1–5 scale. Training Frequency and Fraud Incidents are measured on actual numeric scales.

5.2 Reliability Analysis

Table 2 shows that Cronbachs Alpha coefficients of all the constructs are above the recommended 0.70 value (Nunnally and Bernstein 1994) and the overall scale has high reliability (0.923). This ascertains the internal consistency of the measurement instrument.

Table 2: Reliability Statistics — Cronbach's Alpha Coefficients

Construct	Cronbach's Alpha	No. of Items	Interpretation
AI Tool Awareness	0.871	6	Good
Digital Literacy	0.889	7	Good
Fraud Detection Effectiveness	0.902	8	Excellent
Employee Competency	0.856	5	Good
AI Implementation Readiness	0.843	6	Good
Overall Scale	0.923	32	Excellent

Note. Good reliability: $\alpha \geq 0.70$; Excellent reliability: $\alpha \geq 0.90$ (Nunnally & Bernstein, 1994).

5.3 Correlation Analysis (Testing H2)

5.3 Correlation Analysis (Test H2) The Pearson correlation coefficients of important variables of the study are as shown in table 3. At $p < 0.01$, all correlations are positive and statistically significant giving preliminary support to H2. Digital Literacy Index and Fraud Detection Effectiveness ($r = 0.643$, $p < 0.001$) are the strongest correlated variables, which means that the more digital employees are, the more effective they are in detecting fraud. As expected by the theory, AI Tool Awareness shows moderate-to-strong associations with both Digital Literacy ($r = 0.612$) and Fraud Detection Effectiveness ($r = 0.587$).

Table 3: Pearson Correlation Matrix

Variable	1	2	3	4	5
1. AI Tool Awareness	1.000				
2. Digital Literacy Index	0.612**	1.000			
3. Fraud Detection Effectiveness	0.587**	0.643**	1.000		
4. Employee Competency	0.534**	0.601**	0.559**	1.000	
5. AI Implementation Readiness	0.498**	0.523**	0.541**	0.612**	1.000

Note. ** $p < 0.01$ (two-tailed). H2 is supported — significant positive correlations exist between digital literacy and fraud detection effectiveness ($r = 0.643$, $p < 0.001$).

5.4 Multiple Regression Analysis (Testing H1)

5.4.1 Predictors of Digital Literacy Enhancement

Digital Literacy Index was used as the dependent variable and AI Tool Awareness, Training Frequency, Employee Competency, and AI Implementation Readiness were the predictors that were used in multiple linear regression. The total model was found to be significant (F(4, 307) = 76.43, p < 0.001, R 2 = 0.499, Adjusted R 2 = 0.493) to explain about 49.9 percent of the change in digital literacy. The standardized regression coefficients are presented in table 4.

Table 4: Multiple Regression — Predictors of Digital Literacy Enhancement

Predictor	B	SE	β	t	Sig.
(Constant)	0.821	0.213		3.854	0.000
AI Tool Awareness	0.387	0.048	0.412	8.063	0.000
Training Frequency	0.142	0.034	0.198	4.176	0.000
Employee Competency	0.261	0.041	0.287	6.366	0.000
AI Implementation Readiness	0.178	0.039	0.193	4.564	0.000

Note. $R^2 = 0.499$, Adjusted $R^2 = 0.493$, $F(4, 307) = 76.43$, $p < 0.001$. H1 is supported — AI Tool Awareness is the strongest predictor ($\beta = 0.412$, $p < 0.001$).

The strongest predictor is AI Tool Awareness (0.412, t = 8.063, p < 0.001), and then there is Employee Competency (0.287), Training Frequency (0.198), and AI Implementation Readiness (0.193). H1 is thus entirely justified.

5.4.2 Fraud Detection Effectiveness Predictors.

Another regression model with Fraud Detection Effectiveness as the dependent variable produced F(4, 307) = 81.24, p = 0.001, R 2 = 0.514, Adjusted R 2 = 0.508. H2 was further supported by the fact that Digital Literacy Index was the best predictor (= 0.438, p = 0.001).

Table 5: Multiple Regression — Predictors of Fraud Detection Effectiveness

Predictor	B	SE	β	t	Sig.
(Constant)	0.694	0.198		3.505	0.001
Digital Literacy Index	0.421	0.052	0.438	8.096	0.000
AI Tool Awareness	0.312	0.047	0.334	6.638	0.000
Employee Competency	0.198	0.043	0.221	4.605	0.000
Training Frequency	0.087	0.031	0.118	2.806	0.005

Note. $R^2 = 0.514$, Adjusted $R^2 = 0.508$, $F(4, 307) = 81.24$, $p < 0.001$. Digital Literacy is the strongest predictor ($\beta = 0.438$, $p < 0.001$).

5.5 One-Way ANOVA and Kruskal-Wallis H-Test (Testing H4)

ANOVA on a one-way basis was carried out to understand whether there were any differences in Fraud Detection Effectiveness scores assigning to each of four categories of banks. The test of homogeneity of variances ($F = 1.243$, $p = 0.294$) by Levene showed that the variance was homogeneous. The outcome of the ANOVA (Table 6) was very significant ($F(3, 308) = 14.872$, $p < 0.001$) to prove that the effectiveness of fraud detection varies significantly between the types of banks. Post-hoc Tukey HSD tests established that employees of SBI scored much higher than the medium nationalised banks and the RRBs ($p < 0.05$).

Table 6: One-Way ANOVA — Fraud Detection Effectiveness Across Bank Categories

Source	SS	df	MS	F	Sig.
Between Groups	24.361	3	8.120	14.872	0.000
Within Groups	168.234	308	0.546		
Total	192.595	311			

Note. $F(3, 308) = 14.872$, $p < 0.001$. H4 is supported. Post-hoc Tukey HSD confirms SBI > Medium Banks and RRBs ($p < 0.05$).

Since the violation of RRB subsample (Shapiro-Wilk $p = 0.032$) could not be rejected, the non-parametric Kruskal-Wallis H-test was used too and also found the significant differences between the groups (Table 7), which is consistent with the results of the ANOVA.

Table 7: Kruskal-Wallis H-Test — AI Tool Adoption Levels Across Bank Categories

Bank Category	N	Mean Rank	Sig.
State Bank of India (SBI)	78	182.34	
Nationalised Banks (large)	94	156.21	
Nationalised Banks (medium)	87	148.76	
Regional Rural Banks	53	121.45	
$H = 28.43$, $df = 3$			$p < 0.001$

Note. $H(3) = 28.43$, $p < 0.001$. Non-parametric confirmation of H4.

5.6 Paired Sample t-Test (Testing H3)

The paired sample t-test was used to compare pre-intervention and post-intervention results (six months after the deployment of AI training tools) of the 127 respondents who underwent AI training programs during the observation period on five important performance indicators. Findings (Table 8) indicate that all the five measures are statistically significant (all $p < 0.001$), which indicates a strong support of H3.

Table 8: Paired Sample t-Test — Pre and Post AI Intervention Comparison (n = 127)

Measure	Pre-Mean	Post-Mean	t	Sig.
Digital Literacy Score	2.89	3.76	-14.231	0.000
Fraud Detection Rate (%)	61.4	78.9	-18.654	0.000
AI Tool Proficiency	2.71	3.68	-16.823	0.000
Phishing Identification Score	58.3	79.6	-21.043	0.000
Transaction Risk Scoring	55.7	74.3	-17.892	0.000

Note. All comparisons significant at $p < 0.001$. H3 is fully supported. Effect sizes (Cohen's d) ranged from 0.89 to 1.34, indicating large practical significance.

The most significant gain was in the Phishing Identification Score (pre = 58.3, post = 79.6; t = -21.043, p < 0.001), which indicates that AI-based simulated phishing training is the most effective. The effect sizes (Cohens d between 0.89 and 1.34) show large practical importance of all results.

5.7 Chi-Square Test of Independence (Testing H5)

The use of Chi-square tests of independence was used to test the relationships between categorical variables (Table 9). The entire associations were statistically significant ($p < 0.05$), which proved H5. The most significant correlation was between Bank Type and AI Tool Adoption Level ($2(6) = 31.24$, $p < 0.001$, Cramer V = 0.224, medium effect) with the highest level of AI adoption in SBI and large nationalised banks as compared to medium banks and RRBs.

Table 9: Chi-Square Tests of Independence

Association	Chi-Square (χ^2)	df	Sig.
Bank Type × AI Tool Adoption Level	31.24	6	0.000
Employee Grade × Digital Literacy Category	28.67	8	0.000
Training Frequency × Fraud Incident Rate	19.43	4	0.001
AI Readiness × Fraud Detection Outcome	24.89	6	0.000

Note. H5 is supported. All associations significant at $p \leq 0.001$. Cramér's V values indicate moderate effect sizes (0.18–0.27).

5.8 Structural Equation Modelling (Testing H6)

The analysis of SEM through AMOS 24 was done in two phases. Confirmatory Factor Analysis (CFA) was first done to measure the fit of measurement models. The values of AVE were above 0.50 in all constructs (range: 0.54-0.68) which show convergent validity. The inter-construct correlations were squared and greater than the AVE values, thus achieving the discriminant validity. Second, the path relationships between the structural model were estimated. The outstanding direct effects of the results of the SEM were: AI Tool Awareness to Digital literacy (0.421, p.001), Digital literacy to Fraud Detection Effectiveness (0.518, p.001) and AI Tool Awareness to Fraud Detection Effectiveness (0.213, p.01, partially mediated by digital literacy). Model fit indices are as shown in table 10.

Table 10: SEM Goodness-of-Fit Indices

Fit Index	Obtained Value	Acceptable Threshold	Interpretation
χ^2 / df	2.14	< 3.00	Good Fit
CFI	0.947	> 0.90	Good Fit
TLI	0.939	> 0.90	Good Fit
RMSEA	0.048	< 0.08	Good Fit
SRMR	0.052	< 0.08	Good Fit
GFI	0.921	> 0.90	Good Fit
AGFI	0.904	> 0.85	Good Fit

Note. H6 is supported. All fit indices meet recommended thresholds. Bootstrapping (5,000 samples) confirmed partial mediation of Digital Literacy in the AI Awareness → Fraud Detection path (indirect effect = 0.218, 95% CI [0.164, 0.281], $p < 0.001$).

The values of all the fit indices are below the acceptable levels which ensure that the proposed structural model fits the observed data well. H6 is therefore supported. The bootstrapping of 5, 000 samples ensured that digital literacy is a significant mediator of the connection between AI tool awareness and fraud detection efficiency (indirect effect = 0.218, 95 percent CI [0.164, 0.281]).

Discussion

All the results of this research create a subtle image of the Indian public sector banking digital transformation induced by AI. The fact that all the six hypotheses were confirmed shows the strong empirical soundness of the theoretical framework and has important theoretical and practical implications. The high predictive value between the level of awareness of AI tools and digital literacy (+ 0.412) generalizes the Technology Acceptance Model (Davis 2014) to the particular scenario of enhancing the skills of employees working in the banking sector of the state. This result is consistent with as they discovered that the perceived usefulness of AI tools was the most important factor influencing the engagement of employees in digital learning

platforms in Indian PSBs. The present research paper contributes to this line of question by showing a measurable result in terms of the improvement of the level of digital literacy scores, as opposed to the attitudinal adoption. It is notable especially that the rate of fraud detection improved significantly (61.4% to 78.9) after the intervention of AI. This relative increase of 28.5 per cent is similar to the results in the context of developed countries (Bauguess 2017) and indicates that with the appropriate implementation, AI fraud detectors would also be effective in an Indian PSB setting. The significant effect sizes which have been obtained (Cohen d = 0.891.34) are indicative of the fact that these improvements are not purely paper based but rather real.

That digital literacy mediates AI awareness-fraud detection connection partially, as affirmed by bootstrapped SEM, hints at a two-channel mediating pathway, a direct channel in which AI detection algorithms independently detect signs of frauds, and an indirect channel in which employee digital competency facilitates the analysis and action on AI-generated alerts. This result builds upon by explaining the human capital process in which AI tools are converted to the result of fraud risk.

Implications

7.1 Theoretical Implications

The research helps fill the gap in the theoretical literature by (i) developing a single empirical model that integrates TAM, TOE framework, and Human Capital Theory to enable a new theoretical application in the context of AI adoption in public sector banking; (ii) offering quantitative data supporting the mediating role of digital literacy in the technology-outcome relationship that has never been studied empirically, though the relationship between these two factors was postulated long ago; (iii) developing the concept of fraud detection as a quantifiable outcome variable that is associated with the qualities of AI tools and the competency of employees.

7.2 Managerial Implications

The findings are important strategically to the bank management and HR departments, as they stress the benefits of sustained investments into training on AI. The fact that the scores of phishing identification were considerably enhanced after the simulation-based training ($t = -21.043$, $p < 0.001$) indicates that the AI-driven immersive training environments should be prioritized in comparison to the traditional classroom-based training. Banks must embrace a personalized and adaptive learning systems that will be used to evaluate the unique digital competency gaps and provide specific training modules based on the identified gaps.

The research also advises that in the case of RRBs and medium nationalised banks, where AI adoption metrics are even lower than those of other banking institutions, a gradual introduction of the AI-enhanced strategy should be applied: starting with cloud-based AI fraud screening tools that do not necessitate much IT infrastructure, and moving through structured digital literacy training, and, finally, implementing integrated AI detection and reporting systems.

7.3 Policy Implications

In the case of the Reserve Bank of India and the Indian Banking Association (IBA) the inter-bank performance disparity identified in this research case suggests the establishment of a national AI capability development framework regarding the public sector banking. This framework must encompass digitized literacy standards, minimum AI tools implementation policies, collective databases of fraud intelligence available to all PSBs and incentive schemes to promote the use of technology among smaller banks.

Limitations and Future Research

These are a number of limitations that must be considered. To begin with, the primary survey is cross-sectional thus restricting causation, which is partly overcome by the quasi-experimental pre-post aspect. Second, the effectiveness of fraud detection as self-reported is prone to the social desirability bias, and further research ought to be conducted with objective bank-reported fraud data. Third, the paper concentrates solely on the results of employee level; customer-facing fraud detection results and the contribution of AI to the financial literacy of customers should be studied separately. Fourth, the sample, though, though exceeding a sufficient size, is mostly based on urban and semi-urban branches, and the results might not be fully applicable to the banking activities in the countryside.

The direction of future research would be longitudinal research over 3-5 years to monitor the success of AI adoption and fraud, a cross-country comparative study to determine the effectiveness of AI tool in the South Asian system of government-owned financial institutions and qualitative research on the organizational change management challenges of AI implementation within the government-owned financial institution.

Conclusion

This paper is a valuable empirical study in that it presents all the possible reasons to support the idea that AI-driven tools are a strong tool that could be used to improve digital literacy and simultaneously increase the chances of detecting fraud in Indian banks of the public sector. All six hypotheses of the research were proved with the help of a battery of intense statistical tests based on the data of 312 banking employees in 14 PSBs. Digital literacy improvement is greatly predicted by AI tool awareness, digital literacy is a powerful predictor of fraud detection success, full body pre-post improvements by AI training interventions are significant and relevant, inter-bank performance differences are significant and meaningful, and the proposed structural model is well-fit.

The fact that digital literacy partially mediates the relationship between awareness of AI tools and the effectiveness of fraud detection determines the exact mechanism by which AI investments can lead to a lower fraud risk: the process in which the development of human capital and the implementation of technology must be successful. With Indian PSBs operating in a more digital and vulnerable to fraud operating environment, the current research will offer an empirically tested roadmap to AI-based capacity building to have a meaningful impact on financial stability, customer protection, and institutional integrity.

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