“Does voluntary AI disclosure influence customer behavior? Panel evidence from Indian banks”

AUTHORS	K. P. Venugopala Rao Disha Pathak Farha Ibrahim
ARTICLE INFO	K. P. Venugopala Rao, Disha Pathak and Farha Ibrahim (2025). Does voluntary AI disclosure influence customer behavior? Panel evidence from Indian banks. *Banks and Bank Systems*, *20*(4), 76-86. doi:10.21511/bbs.20(4).2025.07
DOI	http://dx.doi.org/10.21511/bbs.20(4).2025.07
RELEASED ON	Friday, 05 December 2025
RECEIVED ON	Friday, 08 August 2025
ACCEPTED ON	Thursday, 13 November 2025
LICENSE	This work is licensed under a Creative Commons Attribution 4.0 International License
JOURNAL	"Banks and Bank Systems"
ISSN PRINT	1816-7403
ISSN ONLINE	1991-7074
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
44	0	5

© The author(s) 2025. This publication is an open access article.

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine

www.businessperspectives.org

K. P. Venugopala Rao (India), **Disha Pathak** (India), **Farha Ibrahim** (India)

DOES VOLUNTARY AI DISCLOSURE INFLUENCE CUSTOMER BEHAVIOR? PANEL EVIDENCE FROM INDIAN BANKS

Type of the article: Research Article

Received on: 8th of August, 2025
Accepted on: 13th of November, 2025
Published on: 5th of December, 2025

© K. P. Venugopala Rao, Disha Pathak, Farha Ibrahim, 2025

K. P. Venugopala Rao, Ph.D., Professor, Director, Symbiosis Institute of Business Management, Hyderabad. Symbiosis International University, Pune, India. (Corresponding author)

Disha Pathak, Ph.D., Sr. Assistant Professor, Deputy Director, Symbiosis Centre for Management Studies, Hyderabad. Symbiosis International University, Pune, India.

Farha Ibrahim, MCom, Director, GD Research, Secunderabad, India.

Abstract

Artificial Intelligence (AI) is transforming banking operations, with many banks rapidly embracing the technology. In annual reports, banks voluntarily disclose information about their AI initiatives, but the extent to which such disclosures influence customer behavior remains underexplored. This study investigates the impact of voluntary AI disclosures on customer deposit behavior, with a focus on the ownership structure of banks in India. The AI disclosure index was constructed from annual reports of 12 Nifty Bank Index constituents. Using a mixed-methods approach, the balanced panel dataset over the period 2019–2023 was analyzed using a random effects model, validated through the Hausman test. Results indicate that voluntary AI disclosure positively influences the deposits, supporting the view that transparent reporting strengthens customer confidence. Public sector banks show stronger effects, with the ownership dummy yielding a negative coefficient, suggesting that private banks face a credibility gap. Profitability had a significant influence on deposit behavior, whereas book values per share and policy repo rate were insignificant. The findings demonstrate that voluntary AI disclosure has a signaling effect, influencing customer trust, which is captured in the form of customer deposits. These results have practical implications for managers in designing disclosure and policymakers in standardizing reporting frameworks to improve reporting transparency.

Keywords artificial intelligence, voluntary disclosure, customer behavior, bank performance, annual reports, Nifty Bank Index

JEL Classification G21, M14, O33

INTRODUCTION

The integration of Artificial Intelligence (AI) into banking operations is one of the most significant technological shifts in recent years. Indian banks are employing AI-driven tools to enhance customer experience, operational efficiency, and manage risks. Since these innovative practices do not call for mandatory disclosure, a notable practice has emerged in the form of voluntary disclosure, where banks report AI-related initiatives in their annual reports and other communications, indicating a growing trend towards technological adoption.

The scientific problem addressed in this study lies in understanding the consequences of voluntary disclosure. Although prior research has examined the operational benefits of AI in banking, not enough studies have been done on the influence of this information in shaping customer behavior towards banks. Disclosing AI adoption may reduce information asymmetry and build trust among the stakeholders. Customer responses may vary due to the inconsistent reporting strategies adopted by banks, and the interpretations may vary among report users, creating differences in perceived reliability and institu-

This is an Open Access article, distributed under the terms of the Creative Commons Attribution 4.0 International license, which permits unrestricted re-use, distribution, and reproduction in any medium, provided the original work is properly cited.

Conflict of interest statement:
Author(s) reported no conflict of interest

http://dx.doi.org/10.21511/bbs.20(4).2025.07

tional reputation. Despite the increasing use of AI in Indian banking, there remains limited evidence on how voluntary disclosure of such technologies in annual reports influences customer behavior and bank performance, particularly across public and private sector banks.

Against this backdrop, the relevance of the study lies in the need to analyze whether transparency in AI adoption serves as a strategic mechanism for shaping customer behavior and, by extension, bank performance. This problem is central to understanding how voluntary non-financial disclosure, particularly in emerging markets, influences the dynamics between technology, trust, and financial outcomes.

Given these gaps, a review of the existing literature on technological adoption, voluntary disclosure practices, and customer responses in the banking sector is applicable. Previous studies have highlighted the operational benefits of AI and the role of disclosure in reducing information asymmetry, yet the specific link between voluntary AI reporting and customer behavior remains underexplored. The following section reviews the relevant literature to clarify how these streams of research intersect and to identify the gap this study seeks to address.

1. LITERATURE REVIEW

Artificial Intelligence (AI) refers to the development of computer systems capable of performing tasks that typically require human intelligence (Russell & Norvig, 2016). Its adoption in the banking sector has evolved in its seamless applications to widespread integration in business operations, confirming the Turing test, thus enabling efficiency gains, cost reduction, and enhanced decision-making (Abdullah & Almaqtari, 2024; Kumar et al., 2023). Recent technological advances, including Robotic Process Automation (RPA), chatbots, and virtual assistants, have transformed operational frameworks and customer interactions, underscoring AI's role as a driver of innovation and efficiency in modern banking (Balakrishna et al., 2023; Ghosh et al., 2024; Bharti et al., 2023).

A growing body of empirical research highlights the contribution of AI to banking efficiency, risk management, and customer experience. Studies across Asia and the Middle East show that AI and blockchain-based technologies enhance operational resilience, customer engagement, and security (Noreen et al., 2023; Mohamed & Faisal, 2024; Al-Dosari et al., 2022). AI-driven recommendation engines and fraud detection models also demonstrate measurable improvements in service delivery and stakeholder confidence (Feng, 2024; Rahman et al., 2023; Mehndiratta et al., 2023). AI-driven personalized recommendation engines further enhance customer engagement and satisfaction by offering tailored financial products (Hondoma, 2024). Evidence from Nigeria, Kuwait, and Saudi Arabia also indicates that AI integration improves productivity, risk mitigation, auditing, and reporting quality, with regulatory backing and organizational culture shaping adoption outcomes (Okoliko et al., 2023; Al Wael et al., 2024; Mohsen et al., 2024).

In the absence of any mandates on disclosing the adoption of AI and the initiatives in this direction, voluntary disclosure of AI adoption in the annual reports is used as a communication tool by the banks in India. Although many firms now report AI initiatives in annual reports, the absence of standardization often undermines their comparability and credibility (Bonsón et al., 2021). Prior research stresses that transparent communication reduces information asymmetry (Fama, 1980; Grossman & Stiglitz, 1980), strengthens reciprocity and stakeholder trust (Blau, 1964; Molm et al., 2000), it also contributes to reputation management (Fombrun & Riel, 2004; Grunig et al., 2002). Evidence from Jordanian banks shows that AI-related keywords in annual reports positively affect ROA and ROE by reducing costs in operations, suggesting disclosure of AI initiatives has material financial consequences (Shiyyab et al., 2023). Similarly, studies grounded in social exchange theory confirm that disclosure fosters reciprocal support and long-term stakeholder cooperation (Gouldner, 1960). Further evidence from Indonesia also shows that voluntary disclosure of technological adoption can enhance stakeholder trust and accountability, reinforcing the importance of transparency in emerging markets (Meiryani et al., 2022).

The role of ownership, culture, and regulation also influences the willingness to disclose voluntarily. Public banks benefit from implicit guarantees and depositor confidence, as demonstrated by La Porta et al. (2002), whereas private banks are more efficiency-driven and sensitive to profitability (Micco & Panizza, 2006). In this context, voluntary communication may serve as an important mechanism for private banks to close trust gaps with stakeholders. In emerging markets, supportive regulatory frameworks encourage innovation adoption and also ensure accountability, as evidenced in Qatar and India (Al-Dosari et al., 2022; Bharti et al., 2023). The Reserve Bank of India's digital banking guidelines, coupled with initiatives such as UPI, have accelerated AI adoption, much evidenced in corporate communication (Lopes & Prakash, 2023). At the same time, AI adoption and disclosure can be strategically aligned with customer needs, enabling banks to strengthen trust and competitiveness (Sardjono & Perdana, 2023).

In summary, the literature establishes that AI enhances banking efficiency, risk management, and customer engagement, while voluntary disclosure strengthens trust, reputation, and financial outcomes. However, most prior studies focus on operational impacts rather than on how stakeholders interpret such disclosure. Little is known about the behavioral consequences of voluntary AI disclosure, particularly in India, where banks face diverse ownership structures and regulatory pressures. This study addresses this gap by examining whether voluntary disclosure of AI adoption in annual reports influences customer behavior and bank performance, with a specific focus on banks listed on the Nifty Bank Index.

2. METHODOLOGY

This study employs a mixed methods approach, integrating qualitative content analysis with quantitative panel data econometrics. The analysis was conducted in three stages.

2.1. Stage 1: Sample and data collection

The sample comprises all 12 banks listed on the Nifty Bank Index (list of banks is provided in Appendix A), including 9 private sector and 3 public sector institutions. Annual reports for 2019–2023 were examined, as AI-related disclosure first appeared in HDFC Bank's 2017 report; however, it was only from 2019 that the other banks also started voluntarily disclosing the information on AI adoption.

2.2. Stage 2: Construction of the AI Disclosure Index

An AI Disclosure Index was constructed to measure the extent of voluntary AI-related reporting. Following FSB (2017), OECD (2019), and IOSCO (2020), AI-related keywords were collated and categorized into three groups:

1. Digital awareness and transformation
2. AI applications, products, and processes
3. AI-related challenges and cybersecurity

Annual reports of the sampled banks were analyzed using MAXQDA24 software to ensure systematic and replicable content analysis. Keyword frequencies were extracted and aggregated for each bank by year. The base year 2019 was indexed to 100, with subsequent years scaled accordingly.

2.3. Stage 3: Model

The study estimates the following panel regression model:

$$\log\left(Deposit_{it}\right) = \beta_0 + \beta_1 + NP_{it} + \beta_2 + BVPS_{it} + \beta_3 + AI_{it} + \beta_4 + PRR_{it} + \beta_5 + Dummy_{it} + \alpha_i + \varepsilon_{it}, \tag{1}$$

where log ($Deposit_{it}$) represents the natural logarithm of deposits for bank i in time period t; NP_{it} is the net profit as a control variable for bank i in time period t; $BVPS_{it}$ denotes the book value per share as a control variable for bank i in time period t; AI_{it} represents the AI index for bank i in time period t; PRR_{it} represents the policy repo rate as a control variable for bank i in time period t; $Dummy_{it}$ represents the public sector banks and the private sector banks, where the private sector banks are marked 1 and public sector 0; α_i is a random variable drawn from a distribution capturing

http://dx.doi.org/10.21511/bbs.20(4).2025.07

bank-specific heterogeneity; ε_{it} is the error term; the coefficients β_0, β_1, β_2, β_3, β_4 and β_5 represent the parameters to be estimated, capturing the relationship between the variables in the model.

2.4. Estimation procedure

A balanced panel was estimated using a Random Effects (RE) model, validated via the Hausman test. The random effects model assumes that the individual-specific effects are unrelated to the independent variables. This model is particularly useful when the focus is on estimating the average effect of the independent variables across different entities (Greene, 2012). Diagnostics for heteroskedasticity, autocorrelation, and multicollinearity were conducted to ensure model robustness. The final model included log (customer deposits) as the dependent variable representing customers' behavior, and the AI disclosure index as the key explanatory variable. The number of deposits with the banks is taken as a proxy to gauge stakeholders' behavior in response to the voluntary disclosure of AI-related information by banks. Notably, deposits may be impacted by a change in the policy repo rate, a key monetary policy tool of the central bank that impacts important economic indicators, ultimately shaping the overall economic landscape (Mishkin & Eakins, 2015; Barth et al., 2013). Book value per share is an accounting number that reflects historical costs (Ross et al., 2019). Existing literature indicates that BVPS is anticipated to influence stock prices (Jain & Rao, 2022). Net profit is a key financial metric that measures an organization's ability to turn its core business operations into residual earnings and serves as a barometer of a company's profitability and operational effectiveness (Penman, 2015; Bragg, 2019). To strengthen the robustness and validity policy repo rate, book value per share, and net profit were introduced as controls (Babbie, 2016; Gravetter & Forzano, 2018; Gujarati & Porter, 2009; Wooldridge, 2015), along with the ownership dummy. This design allows for isolating the effect of AI disclosure on customer behavior and for comparing differences between public and private sector banks.

3. RESULTS

3.1. Descriptive statistics and diagnostics

Table 1 reports summary statistics for the variables used in the analysis. Mean deposits stand at Rs. 804,467.9 (min = Rs. 19,422.44; max = Rs. 4,468,536; SD = 1,005,722), the AI disclosure index averages 165.67, book value per share (BVPS) averages 250.08, net profit (NP) averages 9,395.50, and the policy repo rate averages 5.03. Skewness and Jarque-Bera tests indicate non-normality for deposits and net profit, which is common with financial time series.

Table 1. Descriptive statistics

Variables	DEPOSITS	AI INDEX	BVPS	NP	PRR
Mean	804,467.9	165.6746	250.0797	9,395.498	5.030000
Median	456,009.3	141.1392	201.9450	3,238.120	4.400000
Maximum	4,468,536.	358.5714	708.9200	56,558.43	6.500000
Minimum	19,422.44	52.00000	31.54000	–10,026.41	4.000000
Std. Dev.	1,005,722.	72.29686	172.1506	13,021.23	1.120048
Skewness	2.142104	0.711438	0.701163	1.691701	0.373230
Kurtosis	7.315384	2.693138	2.573048	5.516680	1.221390
Jarque-Bera	92.44243	5.296852	5.372010	44.45272	9.301639
Probability	0.000000	0.070763	0.068153	0.000000	0.009554
Sum	48,268,072	9,940.478	15,004.78	563,729.9	301.8000
Sum Sq. Dev.	5.97E+13	308,383.3	1,748,513.	1.00E+10	74.01600
Observations	60	60	60	60	60

Table 2. Correlation of dependent and independent variables

Variables	DEPOSITS	AI INDEX	BVPS	NP	PRR
DEPOSITS	1.000000	–0.132677	0.232488	0.697317	0.004718
AI INDEX	–0.132677	1.000000	0.055663	0.147556	0.045087
BVPS	0.232488	0.055663	1.000000	0.500599	0.049047
NP	0.697317	0.147556	0.500599	1.000000	0.036630
PRR	0.004718	0.045087	0.049047	0.036630	1.000000

3.2. Correlation

The correlation matrix shows a weak negative raw correlation between deposits and the AI index (–0.133), a moderate positive correlation between deposits and BVPS (0.232), and a strong positive correlation between deposits and net profit (0.697). There is essentially no correlation between deposits and the repo rate.

3.3. Model selection and stationarity checks

Augmented Dickey-Fuller tests showed stationarity for all series at levels, except Customer Deposits. Customer Deposits were log-transformed (LOGDEPOSIT) to achieve stationarity before panel estimation.

3.4. Hausman test (random vs fixed effects)

The Hausman test is used to determine which model (Fixed or Random) is appropriate in Panel data analysis. The hypothesis for this Hausman test is as follows

Null Hypothesis: Random Effect model is appropriate.

Alternative Hypothesis: Fixed Effect model is appropriate.

The Hausman test (chi-sq ≈ 0, p = 1.000) indicates that the random effects specification is appropriate for the balanced panel (12 banks × 5 years = 60 observations); accordingly, panel EGLS with cross-section random effects was estimated. The Hausman test failed to reject the null hypothesis for this panel.

3.5. Random-effects regression

Drawing on the random effects model presented in Table 4, the intercept was found to be statistically significant at the 95% confidence level. This indicates a notable contribution to explaining the variations in deposit levels across different banks. Similarly, the coefficient associated with the AI Index exhibited positive effects and statistical significance at a 95% confidence level, indicating a favorable association with the adoption of artificial intelligence (AI) within banking operations. These findings emphasize the role of AI technology in influencing deposit levels within banks, which was taken as a proxy for customer behavior towards banking operations. The negative coefficient of the dummy variable, which is found to be significant at the 5% level, suggests that public

Table 3. Hausman test

Correlated Random Effects – Hausman test			
Test cross-section random effects			
Test Summary	**Chi-Sq. Statistic**	**Chi-Sq. d.f.**	**Prob.**
Cross-section random	0.000000	4	1.0000

Table 4. Random effects regression

Dependent Variable: LOGDEPOSIT
Method: Panel EGLS (Cross-section random effects)
Period: 2019–2023
Years: 5
Cross sections: 12
Total panel (balanced) observations: 60

Swamy and Arora estimator of component variances				
Variables	**Coefficient**	**Standard Error**	**t-Statistic**	**Probability**
AI INDEX	0.002514	0.000409	6.143530	0.0000
DUMMY	–2.015167	0.479683	–4.201039	0.0001
NP	8.57E-06	3.62E-06	2.364429	0.0217
BVPS	0.000730	0.000469	1.557944	0.1251
PRR	–0.017861	0.020221	–0.883313	0.3810
C	13.76665	0.430928	31.94656	0.0000
R-squared	0.621137	Adjusted R-squared		0.586057
Prob(F-statistic)	0.000000		–	

http://dx.doi.org/10.21511/bbs.20(4).2025.07

sector banks have exerted a substantial influence on customer behavior compared to private sector banks. Moreover, the statistically significant coefficient for Net Profit stipulates a significant positive relationship between net profit and the deposits, indicating that higher net profits lead to increased deposit levels in banks, reflecting the confidence reposed by customers in the bank. On the contrary, the coefficient for BVPS (Book Value per Share) fails to demonstrate statistical significance ($p > 0.05$) at the 95% confidence level. Thus, there is insufficient evidence to suggest a significant association between Book Value per Share and Deposits. This implies that fluctuations in the book value per share may not exert their influence on deposit levels in the banking sector. Similarly, regarding the policy repo rate, there is insufficient evidence to conclude a significant relationship between repo rates and deposit levels in banks. The policy repo rate does not appear to significantly influence deposit levels within the banking sector during the studied period.

4. DISCUSSION

The findings confirm the central expectation that voluntary AI disclosure measurably influences customer behavior. The strong positive coefficient for the AI disclosure index indicates that banks that communicate their AI adoption more extensively attract greater deposit inflows. This demonstrates that transparency in technological reporting functions as a strategic tool for building trust and engagement. The magnitude of the effect – an estimated 2.5% increase in deposits for each 10-point rise in the disclosure index – suggests that customers perceive such information as a credible signal of innovation and reliability.

The analysis also highlights the importance of ownership structure. Public sector banks consistently reported higher deposits than private banks, even after accounting for AI disclosure and profitability. This suggests that disclosure interacts with institutional reputation: customers appear to value transparency from public banks more highly, perhaps due to the perceived backing of government ownership. At the same time, the significant negative coefficient for private banks indicates a credibility challenge that more standardized or detailed disclosure practices could address.

Profitability emerged as another significant determinant of deposits, suggesting that a strong financial performance reassures customers and attracts funds. In contrast, book value per share and the policy repo rate showed no significant influence on deposit behavior. These results indicate that customers may prioritize signals of innovation and profitability over traditional accounting measures or macroeconomic variables when deciding where to place deposits. Such a pattern resonates with recent literature suggesting that non-financial disclosure can shape stakeholder decisions as much as, or more than, conventional financial metrics.

Beyond the regression outcomes, the descriptive and correlation analyses provided additional insights. While deposits and the AI index showed a weak negative correlation, the panel regression revealed a significant positive relationship once other factors were controlled, a finding uncovered by the multivariate modeling. Similarly, the strong bivariate correlation between deposits and net profit reinforced the regression result that profitability remains a critical driver of customer confidence.

Overall, the discussion of results shows that voluntary disclosure of AI initiatives has a tangible impact on customer behavior and bank performance, with effects shaped by ownership and profitability. The lack of significance for BVPS and repo rate underscores the growing relevance of non-financial disclosure in influencing customer decisions, particularly in emerging markets where information asymmetry is more pronounced.

Comparison with existing studies. The finding that voluntary AI disclosure is positively related to a key performance outcome aligns with recent work documenting favorable market responses to AI reporting and technology transparency (e.g., Shiyyab et al., 2023; Abdullah & Almaqtari, 2024). It also extends the literature by linking disclosure directly to **customer behavior** (deposits) rather than only to accounting or market performance metrics. At the same time, the limited effect of traditional macro (repo) and accounting (BVPS) variables in this short panel underscores that non-financial disclosure can play an independent role in shaping stakeholder decisions.

The empirical evidence supports the study's central proposition: voluntary disclosure of AI-related activities in annual reports is associated with improved customer behavior, measured here by deposit growth, and contributes to bank performance alongside profitability. The ownership differences and the limited role of BVPS and repo rate point to avenues for deeper investigation in future studies.

CONCLUSION

By constructing a disclosure index from annual reports and applying a random effects panel model to a balanced dataset of 12 banks over 2019–2023, the paper sought to study whether communicating AI adoption voluntarily has measurable effects beyond operational efficiency in the Indian banking sector. The analysis confirmed that voluntary AI disclosure significantly and positively influences customer deposits, that ownership structure shapes the effect, and that profitability remains a significant driver while BVPS and the repo rate are not.

The results indicate that greater voluntary disclosure of AI-related initiatives is positively and significantly associated with customer deposits, suggesting that transparency in technological adoption strengthens customer trust and confidence. Public sector banks displayed stronger deposit outcomes compared to their private counterparts, reflecting both their institutional scale and the credibility attributed to their disclosure. Profitability also contributed positively to deposits, while traditional accounting (BVPS) and monetary policy (repo rate) variables showed no significant effect in this context.

The findings of the study are that voluntary AI disclosure is not merely symbolic but has tangible behavioral and financial consequences, making it a strategic lever for banks. The ownership structure influences how such disclosure is received, with public banks enjoying a comparative advantage in mobilizing deposits. Apart from the conventional indicators drawn from financial statements, there is a growing relevance of non-financial reporting in an era of digital transformation.

The findings highlight that voluntary AI disclosure can serve as a credible mechanism to strengthen customer confidence and influence deposit behavior. This underscores the importance of integrating AI adoption into corporate communication strategies, which not only inform the stakeholders about the innovation and reliability but also create tangible financial benefits by attracting and retaining customers.

For regulators, the results emphasize the need for standardized disclosure frameworks on emerging technologies. By encouraging transparent and accountable reporting, regulators can ensure that voluntary AI disclosure contributes meaningfully to financial stability and customer confidence.

LIMITATIONS AND FUTURE RESEARCH

The analysis is based on a relatively short panel of 12 banks over five years, which may restrict the generalizability of the results. A larger dataset covering more banks and longer periods would provide stronger statistical power. The ownership dummy may partly reflect scale effects, as large public sector banks dominate deposit markets in India.

In future research, the sample may be expanded to include non-Nifty-listed banks, and cross-country comparisons may help test the robustness of the results across different institutional contexts.

http://dx.doi.org/10.21511/bbs.20(4).2025.07

AUTHOR CONTRIBUTIONS

Conceptualization: K. P. Venugopala Rao.
Data curation: Disha Pathak, Farha Ibrahim.
Formal analysis: Disha Pathak, Farha Ibrahim.
Investigation: Disha Pathak, Farha Ibrahim.
Methodology: K. P. Venugopala Rao.
Project administration: Farha Ibrahim.
Resources: K. P. Venugopala Rao.
Software: Disha Pathak, Farha Ibrahim.
Supervision: K. P. Venugopala Rao.
Validation: K. P. Venugopala Rao.
Visualization: K. P. Venugopala Rao.
Writing – original draft: K. P. Venugopala Rao.
Writing – reviewing & editing: K. P. Venugopala Rao, Disha Pathak, Farha Ibrahim.

REFERENCES

1. Abdullah, A. A. H., & Almaqtari, F. A. (2024). The impact of artificial intelligence and Industry 4.0 on transforming accounting and auditing practices. *Journal of Open Innovation: Technology, Market, and Complexity, 10*(1), https://doi.org/10.1016/j.joitmc.2024.100218
2. Al Wael, H., Abdallah, W., Ghura, H., & Buallay, A. (2024). Factors influencing artificial intelligence adoption in the accounting profession: the case of public sector in Kuwait. *Competitiveness Review, 34*(1), 3-27. https://doi.org/10.1108/CR-09-2022-0137
3. AL-Dosari, K., Fetais, N., & Kucukvar, M. (2022). Artificial Intelligence and Cyber Defense System for Banking Industry: A Qualitative Study of AI Applications and Challenges. *Cybernetics & Systems, 55*(2), 302-330. https://doi.org/10.1080/01969722.2022.2112539
4. Babbie, E. R. (2016). *The Practice of Social Research* (14th ed.). Boston: Cengage Learning.
5. Balakrishna, S., Arulkumar, V., Srihari, M., & Rohith, C. (2023). Usage of Machine Learning and Artificial Intelligence in Industry 4.0 and Banking Sector. In *2023 5th International Conference on Smart Systems and Inventive Technology (ICSSIT), Tirunelveli, India* (pp. 1282-1287). IEEE. https://doi.org/10.1109/ICSSIT55814.2023.10060952
6. Barth, J. R., Caprio Jr, G., & Levine, R. (2013). Bank regulation and supervision in 180 countries from 1999 to 2011. *Journal of Financial Economic Policy, 5*(2), 111-219. https://doi.org/10.1108/17576381311329661
7. Bharti, S. S., Prasad, K., Sudha, S., & Kumari, V. (2023). Customer acceptability towards AI-enabled digital banking: a PLS-SEM approach. *Journal of Financial Services Marketing, 28*(4), 779-793. https://doi.org/10.1057/s41264-023-00241-9
8. Blau, P. M. (1964). Justice in social exchange. *Sociological Inquiry, 34*(2), 193-206. https://doi.org/10.1111/j.1475-682X.1964.tb00583.x
9. Bonsón, E., Alejo, V., & Lavorato, D. (2021). Artificial Intelligence Disclosure in the Annual Reports of Spanish IBEX-35 Companies (2018–2019). In Kumar, V., Rezaei, J., Akberdina, V., & Kuzmin, E. (Eds.), *Digital Transformation in Industry, Lecture Notes in Information Systems and Organisation* (Vol. 44, pp. 147-155). Cham: Springer. https://doi.org/10.1007/978-3-030-73261-5_14
10. Bragg, S. M. (2019). *Accounting Best* Practices (7th ed.). Hoboken, NJ: John Wiley & Sons.
11. Fama, E. F. (1980). Agency Problems and the Theory of the Firm. *Journal of Political Economy, 88*(2), 288-307. http://dx.doi.org/10.1086/260866
12. Feng, S. (2024). Integrating artificial intelligence in financial services: Enhancements, applications, and future directions. *Applied and Computational Engineering, 69,* 19-24. https://doi.org/10.54254/2755-2721/69/20241455
13. Fombrun, C. J., & Riel, C. B. M. V. (2004). *Fame & Fortune: How Successful Companies Build Winning Reputations.* United Kingdom: Pearson Education.
14. FSB. (2017). *Artificial Intelligence and Machine Learning in Financial Services: Market Developments and Financial Stability Implications*. Retrieved from https://www.fsb.org/wp-content/uploads/P011117.pdf
15. Ghosh, S., Ness, S., & Salunkhe, S. (2024). The Role of AI Enabled Chatbots in Omnichannel Customer Service. *Journal of Engineering Research and Reports, 26*(6), 327-45. https://doi.org/10.9734/jerr/2024/v26i61184
16. Gouldner, A. W. (1960). The Norm of Reciprocity: A Preliminary Statement. *American Sociological Review, 25*(2), 161-178. https://doi.org/10.2307/2092623

17. Gravetter, F. J., & Forzano, L.A.B. (2018). *Research Methods for the Behavioural Sciences*. Boston: Cengage Learning.
18. Greene, W. H. (2012). *Econometric Analysis* (7th ed.). Boston: Pearson Education.
19. Grossman, S. J., & Stiglitz, J. E. (1980). On the Impossibility of Informationally Efficient Markets. *The American Economic Review, 70*(3), 393-408. Retrieved from http://www.jstor.org/stable/1805228
20. Grunig, J. E., Dozier, D. M., & Grunig, J. E. (2002). *Excellent Public Relations and Effective Organizations: A Study of Communication Management in Three Countries* (1st ed.). Routledge. https://doi.org/10.4324/9781410606617
21. Gujarati, D. N., & Porter, D. C. (2009). *Basic Econometrics* (5th ed.). New York: McGraw-Hill Education.
22. Hondoma, T. (2024). Enhancing Engagement with Personalized Recommendations with AI-Powered Recommender Systems. In Masengu, R., Chiwaridzo, O., Dube, M., & Ruzive, B. (Eds.), *AI-Driven Marketing Research and Data Analytics* (pp. 162-181). IGI Global. https://doi.org/10.4018/979-8-3693-2165-2.ch009
23. IOSCO. (2020). *The Use of Artificial Intelligence and Machine Learning by Market Intermediaries and Asset Managers: Final Report*. International Organization of Securities Commissions. Retrieved from https://www.iosco.org/library/pubdocs/pdf/IOSCOPD684.pdf
24. Jain, R. K., & Rao, K. P. V. (2022). Value relevance of financial reports and macroeconomic factors in defining stock price: evidence from Indian stock markets, *International Journal of Business Innovation and Research, 29*(3), 406-416. https://doi.org/10.1504/IJBIR.2022.127179
25. Kumar, P., Sharma, S. K., & Dutot, V. (2023). Artificial Intelligence (AI)-Enabled CRM Capability in Healthcare: The Impact on Service Innovation. *International Journal of Information Management, 69.* https://doi.org/10.1016/j.ijinfomgt.2022.102598
26. La Porta, R., Lopez-de-Silanes, F., & Shleifer, A. (2002). Government ownership of banks. *Journal of Finance, 57*(1), 265-301. https://doi.org/10.1111/1540-6261.00422
27. Lopes, A., & Prakash, K. B. (2023). Artificial Intelligence and Machine Learning Approaches to Document Digitization in the Banking Industry: An Analysis. Ingénierie. *Des Systèmes d'Information, 28*(5), 1325-1334. https://doi.org/10.18280/isi.280521
28. Mehndiratta, N., Arora, G., & Bathla, R. (2023). The use of Artificial Intelligence in the Banking Industry. *International Conference on Recent Advances in Electrical, Electronics & Digital Healthcare Technologies (REEDCON)* (pp. 588-591). New Delhi. https://doi.org/10.1109/REEDCON57544.2023.10150681
29. Meiryani, M., Andini, V., Fahlevi, M., Yadiati, W., Purnomo, A., & Prajena, G., (2022). Analysis of Accounting Information Systems Based on Artificial Intelligence on Fraudulent Financial Reporting Trends in Indonesia. In *Proceedings of the 2022 4th International Conference on E-Business and E-Commerce Engineering (EBEE '22)* (pp. 83-93). Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3589860.3589871
30. Micco, A., & Panizza, U. (2006). Bank ownership and lending behavior. *Economics Letters, 93*(2), 248-254. https://doi.org/10.1016/j.econlet.2006.05.009
31. Mishkin, F. S., & Eakins, S. G. (2015). *Financial Markets and Institutions* (8th ed.). Boston: Pearson Education.
32. Mohamed, A., & Faisal, R. (2024). Exploring metaverse-enabled innovation in banking: Leveraging NFTS, blockchain, and smart contracts for transformative business opportunities. *International Journal of Data and Network Science, 8*(1), 35-44. https://doi.org/10.5267/j.ijdns.2023.10.020
33. Mohsen, S. E., Hamdan, A., & Shoaib, H. M. (2024). Digital transformation and integration of artificial intelligence in financial institutions. *Journal of Financial Reporting and Accounting, 23*(2), 680-699. https://doi.org/10.1108/JFRA-09-2023-0544
34. Molm, L., Takahashi, N., & Peterson, G. (2000). Risk and trust in social exchange: An experimental test of a classical proposition. *American Journal of Sociology, 105*(5), 1396-1427. https://doi.org/10.1086/210434
35. Noreen, U., Shafique, A., Ahmed, Z., & Ashfaq, M. (2023). Banking 4.0: Artificial Intelligence (AI) in Banking Industry & Consumer's Perspective. *Sustainability, 15*(4). https://doi.org/10.3390/su15043682
36. OECD. (2019). *Scoping the OECD AI Principles: Deliberations of the Expert Group on Artificial Intelligence at the OECD (AIGO)* (OECD Digital Economy Papers No. 291). Retrieved from https://www.oecd.org/en/publications/scoping-the-oecd-ai-principles_d62f618a-en.html
37. Okoliko, E. O., Ayetigbo, O. A., Ifegwu, I. J., & Chidiebere, N. U. (2023). Artificial Intelligence Impact in Revolutionizing the Nigerian Banking Industry: An Assessment of Selected Deposit Money Banks in Abuja. *Achievers Journal of Scientific Research (AJOSR), 5*(2), 120-131. Retrieved from https://achieversssciencejournal.org/ajosrojs/index.php/ajosr/article/view/153/108
38. Penman, S. H. (2015). Financial Ratios and Equity Valuation. In Cooper, C. L., Clubb, C., & Imam, S. (Eds.), *Wiley Encyclopedia of Management*. https://doi.org/10.1002/9781118785317.weom010079
39. Rahman, M., Ming, T. H., Baigh, T. A., & Sarker, M. (2023). Adoption of artificial intelligence in banking services: an empirical analysis. *International Journal of Emerging Markets, 18*(10), 4270-4300. https://doi.org/10.1108/IJOEM-06-2020-0724

http://dx.doi.org/10.21511/bbs.20(4).2025.07

40. Ross, S. A., Westerfield, R. W., & Jordan, B. D. (2019). *Corporate Finance* (12th ed.). New York: McGraw-Hill Education.

41. Russell, S., & Norvig, P. (2016). *Artificial Intelligence: A Modern Approach* (3rd ed.). Harlow, UK: Pearson Education.

42. Sardjono, W., & Perdana, W.G. (2023). Artificial Intelligence as a New Competitive Advantage in Digital Marketing in the Banking Industry. In Mukhopadhyay, S. C., Senanayake, S. N. A., & Withana, P. C. (Eds.), *Innovative Technologies in Intelligent Systems and Industrial Applications. CITISIA 2022. Lecture Notes in Electrical Engineering* (Vol. 1029, pp. 561-573). Cham: Springer. https://doi.org/10.1007/978-3-031-29078-7_49

43. Shiyyab, F. S., Alzoubi, A. B., Obidat, Q. M., & Alshurafat, H. (2023). The Impact of Artificial Intelligence Disclosure on Financial Performance. *International Journal of Financial Studies, 11*(3). https://doi.org/10.3390/ijfs11030115

44. Wooldridge, J. M. (2015). *Introductory Econometrics: A Modern Approach* (6th ed.). Boston: Cengage Learning.

APPENDIX A

Table A1. List of banks included in the study

S.No.	Bank Name	Private/Public Sector
01	AU Small Finance Bank Limited	Private
02	Axis Bank Limited	Private
03	Bandhan Bank Limited	Private
04	Federal Bank	Private
05	HDFC Bank Limited	Private
06	ICICI Bank Limited	Private
07	IDFC First Bank Limited	Private
08	IndusInd Bank Limited	Private
09	Kotak Mahindra Bank Limited	Private
10	Bank of Baroda	Public
11	Punjab National Bank	Public
12	State Bank of India	Public

http://dx.doi.org/10.21511/bbs.20(4).2025.07