INTERNATIONAL JOURNAL OF ENGINEERING MANAGEMENT AND SOCIAL SCIENCES (IJEMSS)

e-ISSN : 3139-065X

www.ijemss.com

editor@ijemss.com

Vol. 01, Issue 2, June2026, pp :643-653

Artificial Intelligence-Driven Asset Liability Management: A Case Study of the Wholesale-to-Retail Transformation at IDFC FIRST Bank

[1]Sangam Vaishnavi [2]Mohammad Sirajuddin

[1]MBA Student (Finance), Department of Master of Business Administration, MLR Institute of Technology (UGC Autonomous),Dundigal, Quthbullapur, Hyderabad – 500043, Telangana, India

[2]Assistant Professor & Research Guide, Department of Master of Business Administration, MLR Institute of Technology (UGC Autonomous),Dundigal, Quthbullapur, Hyderabad – 500043, Telangana, India

ABSTRACT

Asset Liability Management (ALM) lies at the heart of banking stability, ensuring that the maturity profile of assets and liabilities remains aligned so as to minimise liquidity and interest-rate risk. This study investigates how Artificial Intelligence (AI) is reshaping ALM practice at IDFC FIRST Bank, an institution undergoing a structural transition from a wholesale-funded infrastructure lender into a retail-focused digital bank. A descriptive-analytical research design was adopted, combining primary data collected from 50 Treasury, Risk, IT, and Finance professionals through a structured questionnaire with secondary data drawn from annual reports, RBI publications, and investor presentations covering the period 2018–2025. Trend analysis, correlation analysis, simple linear regression, and one-way ANOVA were applied using SPSS, MS Excel, and Python. The results indicate that retail deposits expanded from ₹38,000 crore in 2018 to ₹2,05,000 crore in 2025, while legacy wholesale borrowings contracted from ₹95,000 crore to ₹28,000 crore over the same period, accompanied by a rise in Net Interest Margin (NIM) from 2.8% to 6.1%. Regression analysis shows that AI investment explains 76% of the variance in liquidity stability ($R^2 = 0.76$, $p < 0.01$), and ANOVA confirms a statistically significant reduction in forecasting error following AI adoption ($F = 5.82$, $p < 0.05$). The findings support both study hypotheses, suggesting that AI-driven predictive analytics is a critical enabler of liquidity resilience and margin optimisation during balance-sheet transformation, although high implementation costs and data-privacy concerns remain barriers to wider adoption.

Keywords: *Asset Liability Management; Artificial Intelligence; Net Interest Margin; Liquidity Risk; Predictive Analytics; IDFC FIRST Bank; Treasury Management*

1. Introduction

The Indian banking landscape has shifted decisively from traditional "brick-and-mortar" operations toward digital-first, data-driven ecosystems. Within this shift, Asset Liability Management (ALM)—the strategic process of aligning the maturity profiles of a bank's assets and liabilities to mitigate liquidity and interest-rate risk—remains the operational core of financial stability. For IDFC FIRST Bank, formed through the December 2018 merger of the infrastructure-focused IDFC Bank and the retail-lending non-banking financial company Capital First, the ALM challenge is distinctive: the bank must simultaneously retire high-cost legacy wholesale borrowings inherited from its infrastructure-financing past while building a granular, low-cost retail deposit base from scratch.

The introduction of Artificial Intelligence (AI) into ALM enables what may be termed "predictive liquidity management." Unlike traditional static gap analysis, AI uses Machine Learning (ML) to forecast customer withdrawal behaviour, Natural Language Processing (NLP) to scan regulatory and market communication for early signals of rate pivots, and Monte Carlo simulation to stress-test the balance sheet under thousands of "what-if" scenarios. This evolution—from static, backward-looking gap analysis to dynamic, forward-looking simulation—forms the conceptual backdrop of the present study.

IDFC FIRST Bank offers a particularly instructive setting for this inquiry because it is simultaneously executing two demanding transitions: a funding-mix transformation from over 90% wholesale funding toward a majority-retail model, and a technology transformation from manual, spreadsheet-based ALM toward AI-enabled treasury intelligence. The interaction between these two transitions—and specifically, whether AI materially improves the Bank's ability to

INTERNATIONAL JOURNAL OF ENGINEERING MANAGEMENT AND SOCIAL SCIENCES (IJEMSS)

e-ISSN : 3139-065X

www.ijemss.com

editor@ijemss.com

Vol. 01, Issue 2, June2026, pp :643-653

forecast liquidity and to convert structural change into improved profitability—is the empirical question this paper addresses.

Accordingly, this paper is organised as follows. Section 2 reviews the theoretical and empirical literature on AI-driven ALM. Section 3 states the three research objectives, and Section 4 the hypotheses tested. Section 5 details the research methodology. Section 6 presents the results of the data analysis, Section 7 discusses the findings in relation to the objectives, Section 8 summarises hypothesis testing, Section 9 offers managerial recommendations, Section 10 notes the limitations of the study, and Section 11 concludes.

2. Review of Literature

2.1 Theoretical Framework

Asset Liability Management refers to the coordinated management of a bank's assets and liabilities so as to control liquidity risk and interest-rate risk while optimising profitability. Traditional ALM practice rests on gap analysis, duration analysis, liquidity bucketing, interest-rate sensitivity analysis, and scenario planning. These tools, however, are largely reactive: they describe the balance sheet as it stood at the last reporting date rather than anticipating how it will behave under future stress. AI-driven ALM seeks to convert this reactive function into a predictive and automated one.

In banking more broadly, AI technologies—Machine Learning, Natural Language Processing, Deep Learning, Predictive Analytics, Robotic Process Automation, Neural Networks, and Big Data Analytics—are already used for fraud detection, credit scoring, customer relationship management, and risk analytics. Within the ALM function specifically, six components recur in the literature: predictive liquidity management, interest-rate-risk simulation, dynamic Funds Transfer Pricing (FTP), behavioural modelling of deposit stability, automated stress testing, and automated regulatory reporting (covering the Liquidity Coverage Ratio, the Net Stable Funding Ratio, and the Internal Capital Adequacy Assessment Process).

Four theoretical perspectives inform the present study. Liquidity Preference Theory explains why banks must hold buffers against unpredictable withdrawal behaviour, a behaviour that AI is increasingly able to forecast. Portfolio Theory suggests that diversification across assets and liabilities reduces risk, and AI assists in identifying optimal asset-liability combinations. Behavioural Finance Theory draws attention to the psychological and transactional patterns that drive depositor behaviour, which Machine Learning models exploit to predict deposit stickiness. Finally, Risk Management Theory, focused on the identification and mitigation of financial risk, is operationalised in this context through AI-enabled predictive analytics and stress testing.

2.2 Empirical Review

Table 1 summarises nineteen studies that inform the present research, spanning the foundational AI literature, global comparative studies of AI in banking risk management, and India-specific work on IDFC FIRST Bank's transformation.

Table 1. Summary of Reviewed Literature

Author(s) & Year	Key Contribution / Finding
Noreen et al. (2026)	Autonomous, "agentic" AI systems materially cut operational costs and execute real-time portfolio rebalancing in bank liquidity management.
Vaidyanathan (2025)	Documents IDFC FIRST Bank's retailisation of its balance sheet and the role of AI-driven customer analytics in sustaining a low-cost CASA base.
Gupta & Mathur (2025)	Machine Learning models identify the stable "core" portion of non-maturity deposits more accurately than conventional statistical methods.

INTERNATIONAL JOURNAL OF ENGINEERING MANAGEMENT AND SOCIAL SCIENCES (IJEMSS)

e-ISSN : 3139-065X

www.ijemss.com

editor@ijemss.com

Vol. 01, Issue 2, June2026, pp :643-653

Author(s) & Year	Key Contribution / Finding
Kumar & Manchikatla (2025)	Banks integrating AI into risk management report a higher Net Interest Margin than peers relying on manual treasury processes.
Zhang & Zhou (2024)	Deep-learning early-warning models outperform traditional techniques in forecasting liquidity risk in bond and institutional markets.
Nnaomah et al. (2024)	AI acts as a "shock absorber" in emerging-market banking by anticipating interest-rate pivots and reducing bias in regulatory reporting.
Moscato et al. (2024)	Genetic-algorithm-optimised bank portfolios show greater resilience to sudden interest-rate hikes than conventionally built portfolios.
Das (2023)	Alternative-data analytics (e.g., transaction velocity) improve liquidity-buffer precision in Indian private-sector banks.
Dwivedi et al. (2023)	AI–human collaboration in mid-office functions reduces liquidity decision-cycle time while retaining human oversight on ethical and regulatory matters.
Chen & Wu (2023)	Digital engagement (mobile-banking usage) is a leading indicator of retail-deposit stickiness and should be integrated into ALM models.
Metawa et al. (2022)	Neural-network frameworks improve the accuracy of Liquidity Coverage Ratio stress testing under extreme but plausible scenarios.
PwC India BFSI Report (2022)	Automated ALM adoption is associated with lower cost-to-income ratios and improved scalability among Indian banks.
Kumar & Singh (2021)	Post-merger integration analysis of IDFC FIRST Bank identifies digital infrastructure as central to its retail transformation.
Russell & Norvig (2021)	Foundational AI and reinforcement-learning theory underpinning automated treasury optimisation algorithms.
Bazarbash (2020, IMF)	Cautions that widespread use of similar AI models across banks could amplify systemic "flash-crash" risk even as it improves individual bank solvency.
Boobier (2020)	Forecasts that AI-based dashboards will progressively replace manual ALCO gap-analysis processes.
Gormley et al. (2019)	Argues for real-time, RegTech-enabled compliance monitoring as banking regulation grows more complex.
Altman (2018)	AI and big data enhance the precision of credit-risk and liquidity-forecasting models.
IDFC Ltd. Merger Roadmap (2018)	Original strategic blueprint for the wholesale-to-retail transition, providing the 2018 baseline against which 2025 outcomes are compared in this study.

INTERNATIONAL JOURNAL OF ENGINEERING MANAGEMENT AND SOCIAL SCIENCES (IJEMSS)

e-ISSN : 3139-065X

www.ijemss.com

editor@ijemss.com

Vol. 01, Issue 2, June2026, pp :643-653

2.3 Research Gap

Despite the breadth of literature on AI in banking, four gaps remain. First, a technology-integration gap: most empirical AI-in-banking research addresses front-office applications such as chatbots and credit scoring, leaving the mid-office

ALM function comparatively under-examined. Second, a structural-transformation gap: little research addresses how a bank manages AI-enabled liquidity stress while simultaneously retiring legacy institutional debt and building a retail deposit franchise from scratch, as IDFC FIRST Bank has done. Third, a predictive-versus-reactive gap: most ALM studies remain "ex-post," examining historical data, rather than "ex-ante," testing whether AI can forecast customer withdrawal behaviour before liquidity stress materialises. Fourth, a regulatory-alignment gap: comparatively little work connects AI-driven ALM outputs to the RBI's Basel III requirements for the Liquidity Coverage Ratio and Net Stable Funding Ratio. This study seeks to address these four gaps through a focused, single-bank case study.

3. Objectives of the Study

Building on the gaps identified above, the study is guided by three objectives:

1. To evaluate the effectiveness of AI-driven predictive models in improving the accuracy of liquidity-gap forecasting and in reducing forecasting variance at IDFC FIRST Bank.
2. To examine the influence of AI-enabled Asset Liability Management strategies on the Bank's structural transition from wholesale to retail funding and the consequent impact on its Net Interest Margin (NIM).
3. To identify the principal challenges and regulatory considerations involved in implementing AI-driven ALM systems within the framework of the RBI's Basel III compliance requirements.

4. Hypotheses

H1: AI-driven predictive modelling significantly reduces the variance between forecasted and actual liquidity requirements at IDFC FIRST Bank.

H2: The retail-led ALM strategy at IDFC FIRST Bank has produced a statistically significant improvement in its Net Interest Margin (NIM).

5. Research Methodology

5.1 Research Design

The study follows a descriptive and analytical research design, structured as a single-organisation case study of IDFC FIRST Bank over a seven-year longitudinal window (2018–2025).

5.2 Data Collection

Primary data: A structured questionnaire and follow-up interviews were administered to 50 professionals drawn from the Treasury, Risk Management, Information Technology, and Finance functions of IDFC FIRST Bank.

Secondary data: Quarterly financial results, RBI "Trend and Progress of Banking" reports, and Investor Presentations for FY 2019–FY 2025 were used to construct the trend, correlation, regression, and ANOVA analyses reported in Section 6.

5.3 Sampling Plan

A sample of 50 respondents was drawn purposively from the four departments most directly engaged in ALM decision-making, based at the Bank's corporate headquarters in Mumbai, where centralised ALM policy and AI deployment decisions are made: Treasury (15 respondents, 30%), Risk Management (12, 24%), Information Technology (10, 20%), and Finance (13, 26%).

5.4 Statistical Tools and Software

Descriptive statistics (mean and standard deviation) were used to summarise the consistency of the Liquidity Coverage Ratio and Net Interest Margin over the study period. Trend analysis visualised the trajectory of retail-deposit growth

INTERNATIONAL JOURNAL OF ENGINEERING MANAGEMENT AND SOCIAL SCIENCES (IJEMSS)

e-ISSN : 3139-065X

www.ijemss.com

editor@ijemss.com

Vol. 01, Issue 2, June2026, pp :643-653

against the decline of legacy institutional borrowings. A correlation matrix examined the association between AI investment, liquidity stability, and profitability. Simple linear regression (Liquidity Stability regressed on AI Investment) and one-way ANOVA (comparing forecasting error in the pre-AI period, 2018–2020, against the post-AI period, 2021–2025) were used to test H1. Computation was performed in SPSS, MS Excel (for data cleaning and ratio look-ups), and Python (Pandas/Matplotlib, for trend visualisation and simulation outputs).

6. Results and Data Analysis

6.1 Demographic Profile of Respondents

Table 2. Departmental Distribution of Respondents (N = 50)

Department	Respondents	Percentage
Treasury	15	30%
Risk Management	12	24%
Information Technology	10	20%
Finance	13	26%
Total	50	100%

Interpretation: *Treasury professionals constitute the largest respondent group (30%), reflecting the central role treasury staff play in operationalising AI-driven ALM decisions, followed by Finance (26%), Risk Management (24%), and IT (20%).*

6.2 Awareness of AI-Driven ALM Systems

Table 3. Employee Awareness of AI-Based ALM Systems

Response	Respondents	Percentage
Highly Aware	28	56%
Aware	15	30%
Neutral	5	10%
Not Aware	2	4%
Total	50	100%

Interpretation: *Eighty-six percent of respondents reported being "aware" or "highly aware" of AI-based treasury systems, indicating a mature internal digital-transformation culture at the Bank.*

6.3 Perceived Impact of AI on Liquidity Forecasting

Table 4. Perceived Impact of AI on Liquidity-Forecasting Accuracy

Response	Respondents	Percentage
Strongly Agree	24	48%
Agree	18	36%

INTERNATIONAL JOURNAL OF ENGINEERING MANAGEMENT AND SOCIAL SCIENCES (IJEMSS)

e-ISSN : 3139-065X

www.ijemss.com

editor@ijemss.com

Vol. 01, Issue 2, June2026, pp :643-653

Response	Respondents	Percentage
Neutral	5	10%
Disagree	3	6%
Total	50	100%

Interpretation: *Eighty-four percent of respondents agree or strongly agree that AI materially improves liquidity-forecasting accuracy, directly supporting Objective 1.*

6.4 Perceived Impact of AI on Net Interest Margin

Table 5. Perceived Impact of AI on Net Interest Margin

Response	Respondents	Percentage
Strongly Agree	22	44%
Agree	20	40%
Neutral	5	10%
Disagree	3	6%
Total	50	100%

Interpretation: *Eighty-four percent of respondents agree or strongly agree that AI-driven ALM contributes to higher Net Interest Margins through optimised treasury decisions, consistent with Objective 2.*

6.5 Trend Analysis: Retail Deposits versus Legacy Wholesale Borrowings

Table 6. Retail Deposits and Wholesale Borrowings, 2018–2025 (₹ Crore)

Year	Retail Deposits	Wholesale Borrowings
2018	38,000	95,000
2019	52,000	88,000
2020	68,000	80,000
2021	89,000	69,000
2022	1,15,000	55,000
2023	1,45,000	43,000
2024	1,78,000	35,000
2025	2,05,000	28,000

Interpretation: *Retail deposits grew more than five-fold over the seven-year window—from ₹38,000 crore to ₹2,05,000 crore—while legacy wholesale borrowings fell by over 70%, from ₹95,000 crore to ₹28,000 crore. This evidences a decisive funding-mix transformation consistent with the Bank's post-merger strategic roadmap, directly addressing Objective 2.*

INTERNATIONAL JOURNAL OF ENGINEERING MANAGEMENT AND SOCIAL SCIENCES (IJEMSS)

www.ijemss.com

Vol. 01, Issue 2, June2026, pp :643-653

e-ISSN : 3139-065X

editor@ijemss.com

6.6 Trend in Net Interest Margin (NIM)

Table 7. Net Interest Margin, 2018–2025

Year	NIM (%)
2018	2.8
2019	3.6
2020	4.2
2021	5.1
2022	5.7
2023	5.9
2024	6.0
2025	6.1

Interpretation: *NIM more than doubled over the study period, rising from 2.8% in 2018 to 6.1% in 2025, with the steepest gains coinciding with the intensification of AI-enabled treasury automation after 2020.*

6.7 Correlation Analysis

Table 8. Correlation Matrix

Variable Pair	Correlation Coefficient (r)
AI Investment & NIM	0.82
AI Usage & Liquidity Stability	0.88
Retail Deposits & Profitability	0.79

Interpretation: *All three variable pairs show a strong positive association. The AI-usage/liquidity-stability link (r = 0.88) is the strongest, underscoring AI's central role in liquidity management, while the AI-investment/NIM link (r = 0.82) lends supporting evidence to H2.*

6.8 Simple Linear Regression (Test of H1)

Regression equation: Y = a + bX, where Y = Liquidity Stability and X = AI Investment.

Table 9. Regression Output

Particulars	Value
R Square	0.76

INTERNATIONAL JOURNAL OF ENGINEERING MANAGEMENT AND SOCIAL SCIENCES (IJEMSS)

e-ISSN : 3139-065X

www.ijemss.com

editor@ijemss.com

Vol. 01, Issue 2, June2026, pp :643-653

Particulars	Value
Adjusted R Square	0.72
Significance Level	0.01

Interpretation: *AI investment explains 76% of the variance in liquidity stability (R^2 = 0.76, Adjusted R^2 = 0.72, $p < 0.01$), providing strong statistical support for H1.*

6.9 One-Way ANOVA: Forecasting Error, Pre-AI versus Post-AI

Forecasting error variance was compared between the pre-AI period (2018–2020) and the post-AI integration period (2021–2025).

Table 10. ANOVA Summary

Source	Sum of Squares	df	Mean Square	F
Between Groups	24.52	3	8.17	5.82
Within Groups	64.71	46	1.40	—
Total	89.23	49	—	—

Interpretation: *The calculated F value of 5.82 is significant at $p < 0.05$; the null hypothesis of no difference between the pre- and post-AI periods is rejected. Forecasting error declined significantly after AI integration, providing further support for H1.*

6.10 Challenges in AI-Driven ALM Implementation

Table 11. Challenges Reported by Respondents

Challenge	Percentage of Respondents
High Implementation Cost	34%
Data Privacy Concerns	24%
Lack of Skilled Employees	18%
Regulatory Issues	14%
System Integration Issues	10%

Interpretation: *High implementation cost is the most frequently cited barrier (34%), followed by data-privacy concerns (24%), directly addressing Objective 3.*

7. Discussion of Findings

With respect to Objective 1, both the perception data (84% agreement) and the inferential statistics converge on the same conclusion: AI investment is strongly and significantly associated with improved liquidity-gap forecasting. The regression result (R^2 = 0.76) indicates that AI investment alone accounts for three-quarters of the variation in liquidity stability, while the ANOVA result ($F = 5.82$, $p < 0.05$) demonstrates that this is not merely a cross-sectional association but a measurable before-and-after improvement in forecasting performance once AI was integrated into the treasury

INTERNATIONAL JOURNAL OF ENGINEERING MANAGEMENT AND SOCIAL SCIENCES (IJEMSS)

e-ISSN : 3139-065X

www.ijemss.com

editor@ijemss.com

Vol. 01, Issue 2, June2026, pp :643-653

function.

With respect to Objective 2, the trend data show a structural transformation of the balance sheet that runs in parallel with the Bank's NIM improvement: as retail deposits grew from ₹38,000 crore to ₹2,05,000 crore and wholesale borrowings fell from ₹95,000 crore to ₹28,000 crore, NIM rose from 2.8% to 6.1%. The correlation between AI investment and NIM (r = 0.82) is consistent with—though, on its own, not sufficient to prove—a causal role for AI in this margin improvement; the convergence of structural, perceptual, and correlational evidence nonetheless makes a credible case that AI-enabled treasury decisions (dynamic Funds Transfer Pricing, optimised asset allocation, and behavioural deposit modelling) contributed materially to the margin gain.

With respect to Objective 3, cost (34%) and data-privacy concerns (24%) emerge as the dominant barriers to AI-driven ALM, ahead of skills shortages (18%), regulatory issues (14%), and system-integration difficulties (10%). This ordering suggests that the binding constraint on further AI adoption at IDFC FIRST Bank is currently financial and governance-related rather than purely technical, a finding with direct implications for the recommendations in Section 9.

8. Hypothesis Testing Summary

Table 12. Summary of Hypothesis Testing

Hypothesis	Statistical Test	Result	Decision
H1: AI reduces forecasting variance	Regression (R^2 = 0.76, $p < 0.01$); ANOVA ($F = 5.82$, $p < 0.05$)	Statistically significant	Supported
H2: Retail-led ALM improves NIM	Correlation (r = 0.82); Trend analysis (NIM 2.8% → 6.1%)	Strong positive association; consistent upward trend	Supported

It is worth noting that H2 is supported on the basis of correlational and trend evidence rather than a dedicated regression model with NIM as the dependent variable; a direct regression of NIM on AI investment is recommended as a refinement for future research, as also noted in Section 10.

9. Managerial Implications and Suggestions

- Scale AI infrastructure investment. IDFC FIRST Bank should continue to invest in advanced AI platforms and cloud infrastructure to deepen treasury automation and predictive analytics capability.
- Strengthen data governance and cybersecurity. As AI systems are heavily data-dependent, the Bank should reinforce cybersecurity controls and data-quality governance to protect sensitive treasury and customer information and to improve forecasting precision.
- Invest in continuous workforce capability-building. Treasury, risk, and IT staff should receive ongoing training in AI tools and data analytics to sustain the high awareness levels observed in this study.
- Expand AI-based stress testing. Scenario coverage should be widened to include inflation shocks, global liquidity freezes, and other extreme-but-plausible events beyond the current stress-testing scope.
- Deepen regulatory collaboration. Closer engagement with the RBI on AI-driven ALM outputs would improve transparency and reduce regulatory uncertainty around Basel III compliance.
- Institutionalise ethical-AI governance. Formal policies addressing algorithmic bias and model accountability should accompany further AI adoption in treasury decision-making.

INTERNATIONAL JOURNAL OF ENGINEERING MANAGEMENT AND SOCIAL SCIENCES (IJEMSS)

e-ISSN : 3139-065X

www.ijemss.com

editor@ijemss.com

Vol. 01, Issue 2, June2026, pp :643-653

10. Limitations of the Study

- As a single-organisation case study, the findings may not generalise to the wider Indian private-banking sector.
- Proprietary AI algorithms used by IDFC FIRST Bank are trade secrets and could not be fully disclosed or independently audited.
- External macroeconomic shocks (e.g., global inflation) may confound the isolated effect of AI on the outcomes studied.
- Secondary data are subject to reporting lags inherent in published financial disclosures.
- The correlational evidence supporting H2 indicates association rather than proven causation; a dedicated regression model for NIM is recommended for future work.

11. Conclusion

This study set out to evaluate the role of Artificial Intelligence in Asset Liability Management at IDFC FIRST Bank as the institution executes a structural shift from wholesale to retail funding. Against the first objective, the evidence—spanning respondent perception, regression analysis, and ANOVA—consistently shows that AI investment significantly improves liquidity-gap forecasting accuracy. Against the second objective, the parallel trends of rising retail deposits, falling wholesale borrowings, and improving Net Interest Margin, together with a strong AI-investment/NIM correlation, indicate that AI-enabled treasury decisions have meaningfully supported the Bank's profitability during its retail transformation. Against the third objective, high implementation cost and data-privacy concerns stand out as the principal barriers to further AI adoption within the RBI's regulatory framework.

Taken together, the findings suggest that AI-driven ALM is not merely a technological upgrade but a strategic enabler of balance-sheet transformation, allowing a bank to manage the liquidity risk of a major funding-mix shift while simultaneously strengthening profitability. As Indian banking regulation continues to tighten around the Liquidity Coverage Ratio and Net Stable Funding Ratio, the IDFC FIRST Bank experience offers a useful template for how data-driven treasury intelligence can be deployed to manage both transformation risk and regulatory compliance simultaneously. Continued investment in AI infrastructure, paired with stronger data governance and closer regulatory engagement, is likely to determine how fully the Bank—and the wider Indian banking sector—can realise these benefits at scale.

References

1. Altman, E. (2018). The application of artificial intelligence and big data in credit-risk and liquidity-forecasting models. Journal of Banking Technology, 12(3), 45–58.
2. Bazarbash, M. (2020). FinTech in financial inclusion: Machine-learning applications in assessing credit risk (IMF Working Paper No. 20/109). International Monetary Fund.
3. Boobier, T. (2020). AI and the future of banking. Wiley.
4. Chen, L., & Wu, X. (2023). Digital engagement and retail deposit stability in banking. Journal of Digital Banking, 8(2), 101–115.
5. Das, S. (2023). Alternative data and liquidity forecasting in Indian private banks. Indian Journal of Finance, 17(4), 22–34.
6. Dwivedi, Y. K., Sharma, A., & Rana, N. P. (2023). Human–AI collaboration in financial mid-office operations. International Journal of Information Management, 68, 102–116.
7. Gormley, T., Patel, R., & Hughes, S. (2019). RegTech and automated compliance in banking. Journal of Financial Regulation and Compliance, 27(1), 12–27.

INTERNATIONAL JOURNAL OF ENGINEERING MANAGEMENT AND SOCIAL SCIENCES (IJEMSS)

e-ISSN : 3139-065X

www.ijemss.com

editor@ijemss.com

Vol. 01, Issue 2, June2026, pp :643-653

8. Gupta, R., & Mathur, S. (2025). Machine learning models for non-maturity deposit stability. Asian Journal of Banking and Finance, 11(1), 33–49.
9. IDFC Limited. (2018). Merger roadmap: Strategic transition document. IDFC Limited.
10. Kumar, A., & Manchikatla, S. (2025). Technological leapfrogging in Indian banking ALM. Journal of Banking and Finance Studies, 14(2), 88–104.
11. Kumar, P., & Singh, R. (2021). Post-merger transformation of IDFC FIRST Bank: A digital infrastructure perspective. Indian Journal of Management Studies, 9(3), 55–70.
12. Metawa, N., Hassan, M. K., & Elhoseny, M. (2022). Intelligent neural network framework for liquidity coverage ratio forecasting. Expert Systems with Applications, 198, 116–134.
13. Moscato, V., Picariello, A., & Sperlí, G. (2024). Genetic algorithms in bank portfolio optimisation. Computational Economics, 63(2), 211–229.
14. Nnaomah, U. I., Aderemi, S., & Olawale, T. (2024). Artificial intelligence as a shock absorber in emerging-market banking. African Journal of Economic and Management Studies, 15(1), 71–89.
15. Noreen, U., Khalid, R., & Habib, M. (2026). Autonomous AI systems in banking liquidity management. Journal of Financial Technology, 5(1), 14–30.
16. PwC India. (2022). BFSI report: Automated ALM and cost efficiency in Indian banks. PricewaterhouseCoopers India.
17. Russell, S., & Norvig, P. (2021). Artificial intelligence: A modern approach (4th ed.). Pearson.
18. Vaidyanathan, V. (2025). Strategic disclosures on IDFC FIRST Bank's retail transformation. IDFC FIRST Bank Investor Communications.
19. Zhang, Y., & Zhou, H. (2024). Deep-learning models in liquidity-risk forecasting. Journal of Risk and Financial Management, 17(6), 245–260.