

Artificial Intelligence Adoption and Financial Performance in Indian Banks: A Qualitative Content Analysis

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Abstract

Artificial Intelligence (AI) has emerged as a strategic driver of financial performance in the banking sector by enhancing operational efficiency, improving decision-making, and enabling superior customer service. This research undertakes a qualitative content analysis of four-year report disclosures of four scheduled commercial banks in India between FY2019 and FY2024 comprising 24 documents in the corpus (two public sector banks (State Bank of India and Bank of Baroda) and two private sector banks (HDFC Bank and ICICI Bank). The organized thematic codebook of the study is built around five themes: profitability claims, operational efficiency claims, asset quality claims, disclosed AI applications, narrative tone and specificity. It is based on an interpretivist epistemological stance. The data is analyzed in a two-stage approach that involves a combination of inductive theming to find emergent patterns and deductive coding borrowed from the body of existing literature. Three analytical sub-questions explore the COVID-19 epidemic as a turning point in narratives, the type of AI application with the most often positive or negative results on financial performance, and the disparity in specificity and depth of disclosure between the public and private sector institutions. The findings indicate how AI-related financial success stories have evolved to be aspirational and unclear as of FY2019, more operational and metrics-driven by FY2024. The research adds to the literature by providing a disclosure-based, qualitatively based comprehension of AI adoption as strategically positioned in the banking sector of India that can be used by investors, regulators, and banking executives to determine the accuracy and thoroughness of AI-related corporate messages.

Keywords: Artificial Intelligence, Banking Industry, Financial Results, Corporate Disclosure, Qualitative Content Analysis.

1. Introduction

The accelerating development of Artificial Intelligence (AI), Machine Learning (ML), Big data analytics, and Automation Technologies are leading to a major structural transformation of the banking sector across the world. Core banking functions (such as algorithmic trading, customer relationship management, required regulatory compliance, credit risk assessment, fraud detection, and optimization of operational processes are increasingly being integrated with AI. The rate at which digital transformation is taking place in developing economies such as India is increasing due to the increased competition within the fintech sector, legislative changes, and a significant increase in the adoption of digital technology by consumers and businesses. The focus of the Reserve Bank of India (RBI) on technological modernization as a strategic foundation of financial stability, operational stability and quality of governance has further contributed to the uptake of AI in the Indian banking sector. One of the slow additions by both

Public sector banks (PSBs) and Private sector banks is AI-based customer service systems, such as chatbots, predictive credit rating systems, fraud detection systems, Robotic Process Automation (RPA) to process back-office services and AI-based risk management systems. The COVID-19 pandemic was a pivot that compelled banks to invest additionally in digital infrastructure as the traditional banking channels were disrupted and demand of digital services by the customers increased.

Even though Indian banks are using AI technologies increasingly, not much research has been done on how banks explain and frame the link between using AI and making money in their corporate disclosures. Annual reports are mainly meant by banks to inform regulators, shareholders and the general population of their strategic objectives, technology investments and anticipated financial performance. The Directors Report, the Management Discussion and Analysis (MD&A) and the Letter of the Chairman are the most significant sections of these reports. These filings show how financial companies make and defend their AI investments by using carefully chosen, audited, and intentional stories. This leaves a large gap in research that has not been studied. The financial performance metrics explored in quantitative research include Return on Assets (ROA), Return on Equity (ROE), Net Interest Margin (NIM), Cost-to-Income Ratio, and Non-Performing Asset (NPA) ratios. Nonetheless, no research has broken down the articulation of the relationship between AI disclosures and these financial performance indicators by Indian banks in terms of in their own reporting, the nature of their claims, the specificity or ambiguity of such claims, how the story has changed over time, and how AI financial value is communicated by both the public and the private sector. Therefore, this research would try to answer the question: What do Indian scheduled commercial banks report about the connection between the use of AI and financial performance in their annual report reports, and how has this narrative changed since FY2019 and FY2024?

The present research employs a qualitative content analysis of twenty-four annual report disclosures of four purposely selected Indian banks during FY2019 to FY2024 to provide the answer to this question. The study makes three different contributions to the body of literature. First, it provides the systematic qualitative study of AI-related financial performance reporting stories in Indian bank reporting. Second, it records changes in the disclosure language, urgency, and specificity before, during, and after the COVID-19 epidemic, considering it as a structural point of turn in AI communication. Third, it demonstrates the effect of ownership structure on the definition of financial value of AI by comparing the bank disclosure policies of both public and private market.

The rest of the paper is structured in this manner. The theoretical and empirical literature on AI adoption, bank financial performance, and qualitative content analysis in financial research is reviewed in Section 2. Section 3 provides the research methodology involving the selection of samples, data corpus used, codebook production and analytical strategy. Section 4 presents the thematic findings in the study organized by the theme. Section 5 discusses the findings in context of the existing literature. In the conclusion of Section 6, the theoretical contributions, practical uses and future research goals are discussed.

2. Review of Literature

2.1 AI as a strategic asset in banking

Artificial intelligence is a major organizational instrument in financial institutions such as banks. It transforms how they relate with customers, risk management and how they operate their businesses. The theoretical framework that would be used to analyse the adoption of AI as a driver of bank performance is the Resource-Based View (RBV) of the firm, which was

proposed by Barney (1991). This school of thought assumes that having rare, valuable, unique and non-substitutable resources gives a firm a sustainable competitive advantage. Technological capability, especially analytics and automation based on AI, meets these requirements when appropriately incorporated into organizational systems and functions (Teece et al., 1997). According to this model, banks will perform better than their competitors based on important financial measures as long as they enhance their AI capabilities.

Russell and Norvig (2021) define artificial intelligence (AI) as systems with the capacity to learn rationally, conduct probabilistic reasoning, and make forecasts. These skills closely align with the core banking decision-making processes such as fraud detection, liquidity management, and creditworthiness. In their empirical study of the correlation between AI adoption and bank profitability, Al-Haddad et al. (2023) found statistically significant positive effect on Return on Equity (ROE) and Return on Assets (ROA) which revealed that AI enhances the use of assets and efficiency of management. Nguyen et al. (2022) also argued that the effectiveness of AI is largely mediated by the quality of information and communication technology (ICT) infrastructure and demonstrated that AI investment in isolation is not enough in the absence of a favorable digital ecosystem- a contextual factor that is of high importance in the Indian public sector banking environment.

2.2 AI and Profitability Results

Global banking literature has been keen on the relationship between digital transformation and bank profitability. The direct effect of AI applications on cost-cutting and revenue-optimization plans include intelligent pricing models, automated financial advisor systems, and predictive credit scores, which are key parameters in defining profitability. Banna et al. (2020) conducted a panel data analysis of ASEAN economy banks and concluded that more technologically intensive banks performed better in the metrics of profitability than the less technologically intensive ones proved to have, showing that the adoption of technologies increases the diversification of revenues and ROA. Lee and Shin (2018) argue that AI-based financial innovation enhances client retention and cross-selling effectiveness as well, which indirectly increases ROE by strengthening recurring income streams. These findings show the expected quantitative connection of AI and profitability, which is the criterion of evaluation of the bank disclosure claims in the current research.

2.3 AI Implementation and Workflow productivity.

Operational efficiency is one of the most evident and immediate ways that AI impacts the financial performance of a bank. A major indicator of the efficiency of operations in banking is the Cost-to-Income Ratio, which demonstrates how AI-based automation enhances the workflow optimization, reduces the number of mistakes in transactions, and reduces the human processing time. Fares et al. (2022) report that AI significantly minimizes the cost-to-income ratios by automating rule-based processes and high volumes and simplifying back-office tasks. Such impacts are most evident in loan processing, compliance reporting and customer onboarding. Alsharif et al. (2021) stressed that AI-based fraud detection systems and real-time transaction monitoring tools reduce operational risk management by reducing financial losses associated with fraudulent activity drastically. These proven efficiency results furnish the conceptual foundation of the analysis of how banks report the effects of AI in their annual reports, including relying on general claims of efficiency or on quantifiable, specific improvements.

2.4 A.I. and Asset Quality

A key factor in determining banking stability is asset quality, which is mostly determined by the Non-Performing Asset (NPA) or Non-Performing Loan (NPL) ratio. This is particularly so

in India where the levels of NPA in the public sector banking system have been historical high. One of the most significant uses of AI in banking is credit risk modeling, which has the ability to significantly enhance loan origination choices and post-disbursement oversight. Zhang et al. (2021) assert that credit evaluation through machine learning reduces ex-post default rates significantly, and banks are more capable of detecting high-risk borrowers at the application stage than with traditional statistical models. Bhatore et al. (2020) also reached similar conclusions, concluding that the ensemble machine learning models consistently outperform logistic regression models in loan default prediction-results, which have self-evident implications on NPA management. Li and Wang (2020) also highlight the importance of optimal integration of AI in risk management systems and caution that returns to financial benefits of technological adoption can be negative and prone to strategic coherence of implementation. These findings inform the analysis of the study on the presentation of the contribution of AI to the improvement of the quality of assets in the disclosures of banks.

2.5 Banking, Corporate Disclosure, Narrative Reporting, and Qualitative Analysis

Organizations create, validate, and communicate their strategic priorities to external stakeholders through annual reports, which are an essential corporate communication tool. Beattie (2014) states that the narrative parts of annual reports, such as the MD&A, Directors' Report, and Chairman's Letter, are purposeful, carefully selected texts that reveal how the management frames risk, strategy, and performance of the organization. To shape the perceptions of the stakeholders and create institutional legitimacy, these narratives are rhetorical, but not informative (Merkl-Davies and Brennan, 2007). As Loughran and McDonald (2016) demonstrated, text analysis of corporate disclosure can be used to detect patterns in corporate communication of technological investment and innovation in technology adoption, disclosure specificity and tone of disclosure are indicators of depth of strategic commitment. Cho et al. (2010) also discovered that narrative disclosures are used strategically by organizations to manage legitimacy. It is especially relevant to the Indian banks, which are being scrutinized by regulators and face the pressure of public accountability that might alter the manner in which the adoption of AI is framed.

In the absence of a systematic exploration of how banks themselves discursively construct the AI-financial performance relationship in official disclosures, past qualitative studies in the Indian banking sector have either concentrated on digital banking uptake experiences, client attitudes, or policies and regulations. Malali and Gopalakrishnan (2020) performed a conceptual study of AI uses within Indian banking, but did not examine the financial implications of AI uses and the ways banks communicate them. This study directly fills this gap through a longitudinal analysis of the construction and development of the AI-financial performance narrative of both FY2019 and FY2024 in both a public and a private sector institution by performing structured qualitative content analysis on a longitudinal corpus of Indian bank annual report disclosures.

3. Research Methodology

3.1 Research Design

The approach of this study is interpretive, as it is premised on the notion that meaning is produced socially and that the qualitative and context-sensitive analysis is required to understand how organizations conceptualize and articulate their strategic activities (Creswell and Poth, 2018). This paper dwells upon the meaning making processes of Indian banks in relation to AI adoption and, specifically, how Indian banks articulate the relationship between

AI and financial performance in their official statements. The research design is based on a qualitative content analysis (Krippendorff, 2018), a systematic, reproducible technique of making credible inferences about the contexts of text use. Since content analysis can be used to analyze large volumes of textual data in a systematic, transparent, and repeatable way and still be sensitive to context, tone, and meaning, which the mere quantitative-based text-mining methods merely strip it of, it is particularly suitable to this question. In order to identify emergent patterns that were not foreseen in previous literature, the study blends inductive theming with deductive coding, which is taken from the body of research on AI and financial performance.

3.2 Research Questions

The research has 3 sub-analytical questions and one overarching research question: Central Research Question: In annual report disclosures, how do Indian scheduled commercial banks justify the relationship between the use of AI and financial performance? What is the difference between this story in FY2019 and FY2024?

RQ1: How did the COVID-19 pandemic transform how Indian banks justify the use of AI and its financial consequences?

RQ2: What AI applications are most frequently and accurately related to financial performance results in bank disclosures and how has this association fluctuated throughout the study?

RQ3: How do financial performance reporting and reporting on AI in public and private sector banks differ in terms of specificity, depth and framing?

3.3 Sampling and Reasoning

The four banks were selected using purposive sampling, which is a non-probability sampling method that is appropriate in qualitative research when the sample size is determined by theoretical richness and analytical depth instead of a statistical one (Patton, 2015). Banks were selected to ensure a high level of diversity in two aspects: ownership (both the private and the public sector) and maturity of AI adoption (high and lower AI disclosure intensity). Two banks of the public and the private sector were picked to enable systematic comparison of the ownership categories. The final sample is shown in Table 1.

Table 1: Sample Banks and Selection Rationale

No.	Bank Name	Ownership	Purposive Selection Rationale
1	State Bank of India (SBI)	Public Sector	Largest Indian bank with the most comprehensive AI disclosures and detailed Chairman's letters.
2	Bank of Baroda	Public Sector	One of the most digitally progressive public sector banks with a strong post-merger digital transformation journey.
3	HDFC Bank	Private Sector	Largest private sector bank in India with a well-documented AI adoption and performance story.
4	ICICI Bank	Private Sector	One of the earliest Indian banks to adopt AI, with extensive reporting on AI applications, initiatives, and outcomes.

Note: The sample collectively represents approximately 50% of India's scheduled commercial banking assets. Purposive selection ensures meaningful variation in ownership type and AI disclosure maturity for rich comparative analysis.

3.4 Data Collection

The data comprises annual reports of all four sample banks between FY2019 and FY2024 with 24 documents. In the Indian banking industry, annual reports are the main and most reliable source of official corporate communication. The data structure is shown in Table 2.

Table 2: Data Corpus Structure

Year	Documents	Phase Label
FY2019	4 Annual Reports (1 per bank)	Pre-pandemic baseline – Exploratory AI framing
FY2020	4 Annual Reports (1 per bank)	Pandemic onset – Early crisis-driven digital response
FY2021	4 Annual Reports (1 per bank)	Peak pandemic – Accelerated AI adoption narrative
FY2022	4 Annual Reports (1 per bank)	Recovery – Consolidation of AI gains narrative
FY2023	4 Annual Reports (1 per bank)	Post-pandemic – Embedded AI narrative emerges
FY2024	4 Annual Reports (1 per bank)	Current state – Mature AI framing and greater specificity
Total	24 Annual Reports (6 years × 4 banks)	Full study corpus

Note: Annual reports are downloaded from each bank's official investor relations portal. For PSBs, reports are additionally available through the RBI's publication repository at rbi.org.in.

Each annual report is limited to three sections, namely the Directors' Report, the Letter of the Chairman or Message of the Managing Director and the Management Discussion and Analysis (MD&A). These sections were selected due to their offering the most relevant narrative content to the research questions and are strategically written, forward-looking and performance oriented. Financial schedules, auditor reports and comments to accounts are not included because of their technical and regulatory nature as opposed to the strategic AI narrative.

3.5 Data Analysis

The five dimensions of financial performance (profitability, operational efficiency, asset quality, AI applications, and narrative tone) analyzed in previous empirical studies were strongly correlated with themes in a structured thematic codebook deductively constructed based on the literature analysis. The qualitative data of the study can fit its findings within the body of evidence concerning AI and bank performance due to

its deliberate positioning with the existing quantitative literature. The complete codebook is shown in Table 3.

Table 3: Content Analysis Thematic Codebook

Theme Code	Theme Name	Sub-Code	Sub-Code Definition and Coding Criteria
T1	Profitability Claims	T1a	AI directly linked to improvements in ROA, ROE, revenue growth, or profit increase with specific numerical evidence.
		T1b	AI associated with generating fee income, cross-selling revenue, or creating new income streams.
		T1c	Vague profitability claims where AI is described as "improving returns" or enhancing profitability without measurable evidence.
T2	Operational Efficiency Claims	T2a	AI or automation directly linked to cost reduction or improvement in the cost-to-income ratio.
		T2b	Robotic Process Automation (RPA) or process automation associated with reduced staff costs, faster processing time, or operational savings.
		T2c	Specific efficiency improvements reported (e.g., 40% reduction in turnaround time) versus general statements about efficiency.
T3	Asset Quality Claims	T3a	AI linked to reducing NPAs, improving credit quality, or preventing loan defaults.
		T3b	AI-based early warning systems or credit scoring models claimed to improve loan portfolio quality.
		T3c	AI applied to provisioning accuracy, stress testing, or risk-adjusted performance.

T4	AI Applications Disclosed	T4a	Customer-facing AI, including chatbots, virtual assistants, personalization engines, and AI-enabled mobile banking.
		T4b	Back-office AI, including RPA, workflow automation, document processing, and reconciliation.
		T4c	Risk and fraud AI, including fraud detection, AML systems, KYC automation, and cybersecurity AI.
		T4d	Data and analytics applications, including big data, cloud infrastructure, and predictive analytics.
T5	Narrative Tone and Specificity	T5a	Aspirational or future-oriented language with vague promises and no evidence of deployed AI systems.
		T5b	Specific AI systems deployed with measurable outcomes and concrete implementation details.
		T5c	COVID-19-related narrative where AI adoption or acceleration is explicitly attributed to the pandemic.

Note: Each coded passage is assigned a primary theme code and sub-code. A single passage may receive multiple codes where it addresses more than one theme. The unit of analysis is the paragraph.

3.5 Three-Phase Longitudinal Analysis

The research time is divided into three analytical stages that can be associated with pre-pandemic, pandemic, and post-pandemic time to cover SQ1 on COVID-19 as a narrative turning point. This staged framework makes it possible to analyze the ways the narrative of AI-financial successes is rigorously analyzed within different contextual frames. The phase structure is shown in Table 4.

Table 4: Structure of Longitudinal Analysis at Three Phases

Phase	Years	Label	Analytical Focus
Phase 1	FY2019	Pre-Pandemic	Baseline AI framing – examines how banks introduced and positioned AI prior to the COVID-19 disruption.

Phase 2	FY2020–FY2021	Pandemic Response	Crisis-driven AI acceleration – examines how the COVID-19 pandemic influenced and accelerated AI adoption and reporting.
Phase 3	FY2022–FY2024	Post-Pandemic	Embedded AI – examines the maturation of AI narratives, increased specificity of disclosures, and stronger linkage between AI initiatives and financial performance.

Stage 3 — Deductive Coding

A single or several codes out of the thematic codebook (Table 3) are applied to each flagged paragraph using the specified coding criteria. To maintain cross-sectional and longitudinal context, coding is done methodically year by year and bank by bank. Each coded passage has the original extract, assigned code, page reference, bank and year recorded in a coding log.

Stage 4 — Inductive Theming

Patterns overlooked by the last codebook are searched throughout the corpus of coded texts following deductive coding. Unlike deductively coded themes, emergent themes, i.e. patterns found in the data, not in the literature, **are also noted down and presented as additional findings to the study.**

Stage 5 — Inter-Coder Reliability

A second researcher who is blind to the primary coding independently codes 20% of the coded portions (about 60–80 paragraphs) in order to guarantee coding dependability. Cohen Kappa coefficient is used to estimate inter-coder agreement. In the case of social science content analysis, a Kappa value of 0.70 or higher is considered reasonable (Landis and Koch, 1977). Any disputes are resolved through debate and consensus, and the codebook is made better by the discovery of definitional ambiguity.

Stage 6 - Longitudinal and Comparative Analysis

Coded themes will be mapped on the two ownership groups (PSB vs. private sector) and the three stages of analysis (FY2019-FY2020, FY2021-FY2022, and FY2023-FY2024) to provide answers to the three sub-questions. The depth of the connection of performance is compared with the frequency of theme in an extensive manner. occurrence, and the progression of specificity (aspirational T5a vs. operational T5b language). For each significant conclusion, representative verbatim excerpts from annual reports are chosen as illustrative evidence.

3.7 Trustworthiness and Rigour

Instead of using the reliability and validity standards of quantitative research, trustworthiness in qualitative research is assessed using the criteria of credibility, transferability, dependability, and confirmability, as defined by Lincoln and Guba

(1985). The trustworthiness metrics used in this investigation are shown in Table 5.

Table 5: Trustworthiness Criteria and Measures

Criterion	Source	Measure Adopted in This Study
Credibility	Lincoln and Guba (1985)	All findings are supported with direct verbatim quotations from the annual reports. Themes are cross-checked across multiple documents to ensure consistency and credibility.
Transferability	Lincoln and Guba (1985)	A detailed description of the research context, sample selection, and coding process is provided to enable readers to assess the applicability of the findings to similar settings.
Dependability	Lincoln and Guba (1985)	A comprehensive audit trail is maintained, documenting all coding decisions, revisions, and the rationale behind them throughout the analysis.
Confirmability	Lincoln and Guba (1985)	An inter-coder reliability test is conducted on 20% of the coded passages, and Cohen's Kappa is reported to demonstrate coding consistency and objectivity.
Reflexivity	Morrow (2005)	A researcher positionality statement is included, acknowledging the researcher's interpretive lens and reflecting on its influence throughout the analysis.

3.8 Ethical Considerations

The publicly available statutory documents that are analyzed in this study are the annual reports of listed Indian banks, which are mandated by the Companies Act of 2013, SEBI Listing Obligations and Disclosure Requirements Regulations, and RBI recommendations. No original data involving human participants has been collected. As a result, formal ethical approval is not required. By fully attributing all verbatim passages used as evidence in the findings to the source bank and year, transparency and traceability of all analytical claims are guaranteed.

4. Results & Data Analysis

163 coded paragraph-level disclosures from the annual reports of four Indian banks—State Bank of India, HDFC Housing Development Finance Corporation, ICICI Industrial Credit and Investment Corporation of India, and Bank of Baroda—from FY2019 to FY2024 were examined. Five themes (T1–T5) made up the main thematic coding scheme. The frequency distribution of the main themes throughout the whole dataset is summarized in Table 6.

Figure 1: Theme Frequency Distribution

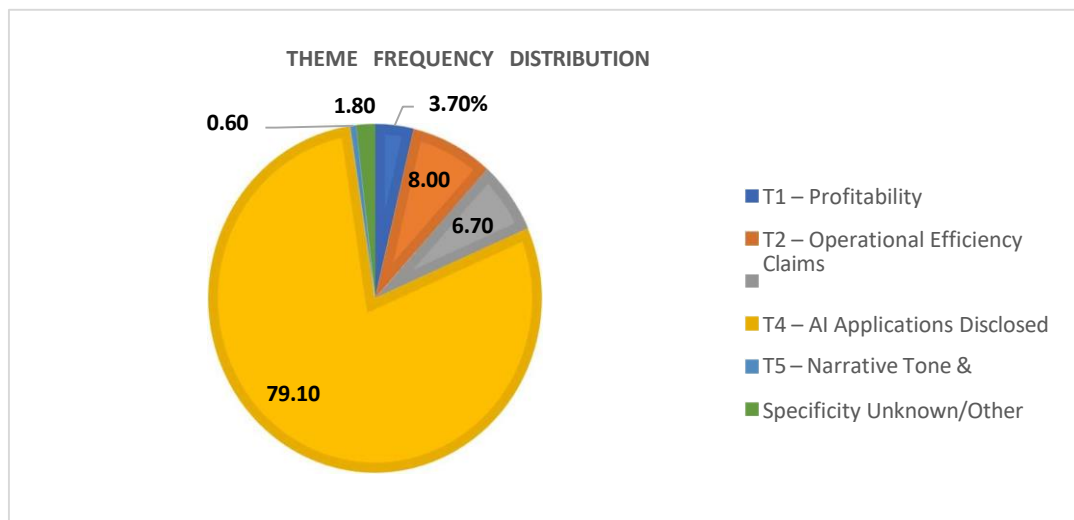


Table 6: Primary Theme Frequency Distribution

Theme	Count	% of Total	Interpretation
T1 – Profitability Claims	6	3.7%	Lowest reported theme: AI was infrequently linked to revenue growth or profitability.
T2 – Operational Efficiency Claims	13	8.0%	Moderate representation: efficiency gains were discussed, often in aspirational rather than measurable terms.
T3 – Asset Quality Claims	11	6.7%	Limited discussion: AI was primarily associated with credit risk management and NPA reduction.
T4 – AI Applications Disclosed	129	79.1%	Dominant theme: most disclosures focused on AI applications and implementation initiatives.
T5 – Narrative Tone & Specificity	1	0.6%	Least represented as a standalone theme; narrative tone was generally embedded within other AI disclosures.
Unknown / Other	3	1.8%	Unspecified or unclear disclosures that could not be classified under the predefined themes.
Total	163	100%	Complete set of AI-related disclosures analysed.

Key Observations

- **T1 (Profitability Claims)** is the least reported theme (n=6, 3.7%), indicating a reluctance on the part of the industry as a whole to directly connect AI to revenue or profit outcomes—possibly because of regulatory prudence and the challenge of attribution.
- **T2 (Operational Efficiency Claims)** is the second most common theme (n=13, 8.0%), indicating that operational efficiency is the favoured framing when banks do make performance-linked AI claims.
- **T3 (Asset Quality Claims)** makes up 6.7% (n=11), suggesting that AI is recognized but not widely discussed in credit risk and NPA management.
- **T4 (AI Applications Disclosed)** With 79.1% of all coded disclosures (n=129), is the most prevalent subject. This demonstrates that the AI-related annual report disclosures made by Indian banks are mostly descriptive of particular applications rather than financial performance correlations.
- **T5 (Narrative Tone and Specificity)** largely serves as a qualitative overlay applied to all disclosures rather than a stand-alone category, hence it only occurs as a stand-alone principal theme in one instance.

4.1. AI Application Analysis

Four subcategories were found within the 129 T4-coded disclosures: T4a (Customer-facing AI), T4b (Back-office Automation), T4c (Risk and Fraud Analytics), and T4d (Data and Analytics Infrastructure). The distribution among banks and subcategories is seen in Table 7.

Table 7: AI Application Sub-Category Distribution (T4)

Theme	Count	% of Total	Interpretation
T1– Profitability Claims	6	3.7%	Lowest reported theme: AI was infrequently linked to revenue growth or profitability.
T2-Operational Efficiency Claims	13	8.0%	Moderate representation: efficiency gains were discussed, often in aspirational rather than measurable terms.
T3- Asset Quality Claims	11	6.7%	Limited discussion: AI was primarily associated with credit risk management and NPA reduction.
T4- AI Applications Disclosed	129	79.1%	Dominant theme: many disclosures focused on AI applications and implementation initiatives.

T5 – Narrative Tone & Specificity	1	0.6%	Least represented as a standalone theme; narrative tone was generally embedded within other AI disclosures.
Unknown / Other	3	1.8%	Unspecified or unclear disclosures that could not be classified under the predefined themes.
Total	163	100%	Complete set of AI-related disclosures analysed.

** Includes some entries coded under multiple sub-themes.*

4.2 Customer-Facing AI (T4a) – 49 Disclosures (38.0%)

AI-based chatbots and voice assistants: The biggest subcategory is client-facing AI, which indicates the focus of the industry on digital customer experience. Significant applications include:

ADI (GenAI chatbot) and ADITI (digital human) of BOB; iPal (13 million+ queries answered) of ICICI; EVA (the first AI chatbot in India) and SIA (multilingual chatbot) of SBI.

Virtual Relationship Management (VRM): HDFC and ICICI deployed AI VRM platforms in the cloud to replicate in-branch banking of relationships through digital channels.

Personalization engines: According to all four banks, AI/ML-based personalization was unveiled to need-based selling, product recommendations, and cross-selling.

Generative AI in customer service: HDFC (FAQ bot with ChatGPT), ICICI (GenAI tools assessment), and BOB (ADI GenAI chatbot) are early applications in the industry of big language models.

The objective of the bank is State Bank of India (2024 Annual Report) "Automation of most processes by real-time integration with both the internal and external systems, introduction of AI/ML driven processes, re-designed UI/UX architecture to enhance customer satisfaction by reducing response times and delivering more personalized experiences to customers".

4.3 Data and Analytics Infrastructure (T4d) - 53 Disclosures (41.1%)

The largest subcategory overall, T4d, shows that Indian banks are making huge investments in data foundations prior to implementing sophisticated AI models. The most important initiatives that have been announced are:

Cloud migration and big data lakes: BOB (ACoE Big Data Lake platform in petabytes), ICICI (enterprise data warehouse) and HDFC (cloud data lake migration).

API banking platforms: The four banks unveiled API banking platforms, which enable fintech partnerships and open banking. ICICI has over 250 APIs.

AI Centers of Excellence (ACOE): BOB (ACOE with AI/ML analytics capacity) and SBI (AI Roadmap in line with Gartner Hype Cycle).

Private cloud infrastructure: A notable disclosure is the private Meghdoot cloud infrastructure of SBI that has efficiency of 95 percent with 5 percent data center footprint.

The State Bank of India (2022 Annual Report) states that Next-Gen Data Warehouse is implemented and enables the growing business data needs and regulatory reporting with the

emphasis on data quality and data integrity.

4.4 Back-Office Automation (T4b) – 15 Disclosures (11.6%)

Robotic Process Automation (RPA) and intelligent document processing are the main topics of back-office automation disclosures:

- ICICI has the most quantified operational AI disclosure in the dataset, with more than 1,500 robotic process automations managing 700 FTE-equivalent tasks.
- HDFC announced ServiceNow to automate IT services and SOAR (Security Orchestration, Automation and Response) to automate IT incidents.
- ICICI is one of the most specialized deployed operational systems that are unveiled. Trade Intelli (AI-ML-OCR) to process trade finance automatically.
- SBI announced AI-based CKYC compliance document scanning and RPA with UiPath that is 2030 times faster than manual testing.
- HDFC (Annual Report 2023) The bank mentions the introduction of Security Orchestration, Automation and Response (SOAR) to minimize the incident response time by integrating security solutions and automating incident lifecycle.
- Risk and Fraud Analytics (T4c) – 13 Disclosures (10.1%)
- Most risk and fraud analytics disclosure is made by SBI and HDFC, and Banks C and D have a minimal contribution:
- SBI: Fraud prone branch identification model; ATM suspicious chargeback detection model; AI/ML to monitor transactions in AML/CFT integrated into AMLOCK platform.
- HDFC: AI/ML cybersecurity operations center that uses SOAR automation, faceless authentication POC that protects against fraud, ML-based AML system, and detection of attack patterns.
- ICICI: Reported AI in portfolio management and credit risk, but did not specifically identify risk/fraud AI as a primary disclosure theme, signifying integrated, but not independent disclosure.
- BOB: EASE 4.0 smart loan analytics are the main source of limited risk AI disclosures.
 - According to the bank, an innovative AI/ML-based technology that can accurately identify attack patterns powers its Cyber Security Operations Centre.

5. Narrative Tone Analysis

Three categories were used to code the narrative tone of AI disclosures: T5a (aspirational/future-oriented language), T5b (operational/specific deployed systems), and T5c (COVID-19 connected AI narrative). The allocation by bank is seen in Table 8.

Table 8: Narrative Tone Distribution by Bank

Bank	T5a (Aspirational)	T5b (Operational)	T5c (COVID)	Total	% Aspirational	% Operational

SBI (Public)	14	21	0	35	40.0%	60.0%
HDFC (Private)	20	35	1	70*	29.4%	51.5%
ICICI (Private)	9	28	0	38*	24.3%	75.7%
BOB (Public)	8	12	0	20	40.0%	60.0%
TOTAL	51	96	1	163	32.3%	60.8%

* Excludes 14 uncategorized entries in HDFC's dataset.

5.1 Operational vs Aspirational: Balance in general

The percentage of disclosures in the whole set of data is operational (T5b) (60.8), and aspirational (T5a) (32.3). This implies that instead of certain vague strategic pronouncements, Indian banks tend to describe specific AI systems or executions, a positive signal that disclosure quality. The percentage of aspirational language is still significant, though. Such statements as AI/ML are being explored, we want to leverage, and plans are underway are all T5a since they typically do not include dates or vendor information or performance metrics.

5.2 Bank-Level Differences

- ICICI (Private) is the most specific in its operations, at 75.7% T5b, which reflects the full disclosures of RPA, chatbots, and trade finance AI with specific system names, scopes of deployment, and measurable outcomes.
- SBI (Public) and BOB (Public) report 60% T5b, which means that banks of the public sector provide less information about total AI projects but perform similarly in terms of specificity in their operations.
- Since several HDFC strategic and ecosystem-level AI disclosures (cloud strategy, API banking vision) use forward-looking terminology, HDFC (Private) reports 51.5% T5b, which is lower than ICICI.

- The AI story (T5c) is unique and related to the work-from-home IT infrastructure and video KYC due to COVID-related conditions. This implies that although COVID boosted the adoption of AI, yearly reports did not use it as the main narrative basis for AI spending.

5.3 Implementations vs Strategic Narratives.

A range of disclosure quality is revealed by the analysis:

- High specificity (T5b): Disclosures which describe the setting of deployment, name the system (e.g., SIA, EVA, SIVA, TradeIntelli), and, in certain cases, approximate impact (e.g., iPal -13M queries; ICICI RPA -1,500 processes; HDFC VRM -300% growth in 18 months).
- Low specificity (T5a): Statements at the board level that do not provide specifics of implementation, such as: AI and ML will revolutionize banking; we are dedicated to using the new technologies. Rather than substantive disclosures, these are strategic signals.

5.4 Public vs Private Comparison

These data include 55 disclosures of two public sector banks (SBI and BOB) and 108 disclosures of two private banks (HDFC and ICICI). The key dimensions are compared in Table 9.

Table 9: Public Sector vs Private Sector Disclosure Comparison

Metric	Public Sector Banks (SBI, BOB)	Private Sector Banks (HDFC, ICICI)
Total Disclosures	55 (33.7%)	108 (66.3%)
% Aspirational (T5a)	40.0%	27.8%
% Operational (T5b)	60.0%	68.5%
Post-COVID Disclosures	34.5%	55.6%
T4a (Customer AI) Share	34.5%	37.0%
T4d (Data Analytics) Share	32.7%	32.4%
Financial Linkages (T1/T2)	14.5%	29.6%
GenAI Disclosures	Moderate (BOB)	High (HDFC, ICICI)
Responsible/Explainable AI	Yes (SBI)	Emerging (HDFC)

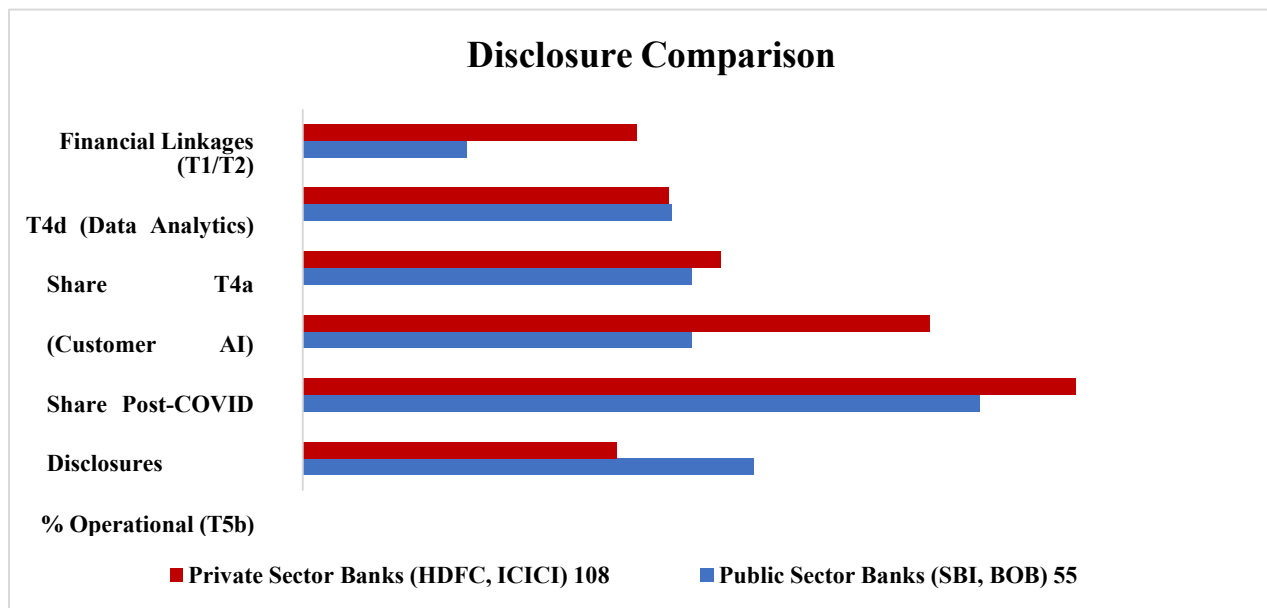


Figure 2: Disclosure Comparison

5.5 Volume and Depth of Disclosures

Although comprising half of the bank sample, the private sector banks comprise 66.3% of all coded disclosures. This difference can be explained by the fact that the number of AI projects in the privately owned banks is greater, as well as they are more likely to release them. 42.9% of the dataset entries come from HDFC alone (n=70).

5.6 Narrative Style Differences

A range of disclosure quality is revealed by the analysis:

Situations that define the deployment environment, name the system (e.g., SIA, EVA, SIVA, TradeIntelli) and in some cases approximate impact (e.g., iPal -13M queries; ICICI RPA -1,500 processes; HDFC VRM -300% growth in 18 months).

- Moderate specificity: Disclosures that describe the application and the kind of technology but exclude vendor, scale and performance data. The typical T4d (data infrastructure) claim that provides a direction, but not evidence, is the statement of We are building a data lake.
- Low specificity (T5a): Declarations by boards that do not specify how the AI is going to be implemented, such as: AI and ML will be the future of banking, we are dedicated to the power of emerging technologies. Rather than being substantive disclosures, these are strategic signals.

6. Phase Analysis: Pre-COVID vs COVID vs Post-COVID

The dataset encompasses three time periods that are associated with the COVID-19 pandemic cycle. The distribution of AI disclosures by phase and bank is shown in Table 5. The dataset encompasses three time periods that are associated with the COVID-19 pandemic cycle. The

distribution of AI disclosures by phase and bank is shown in Table 10.

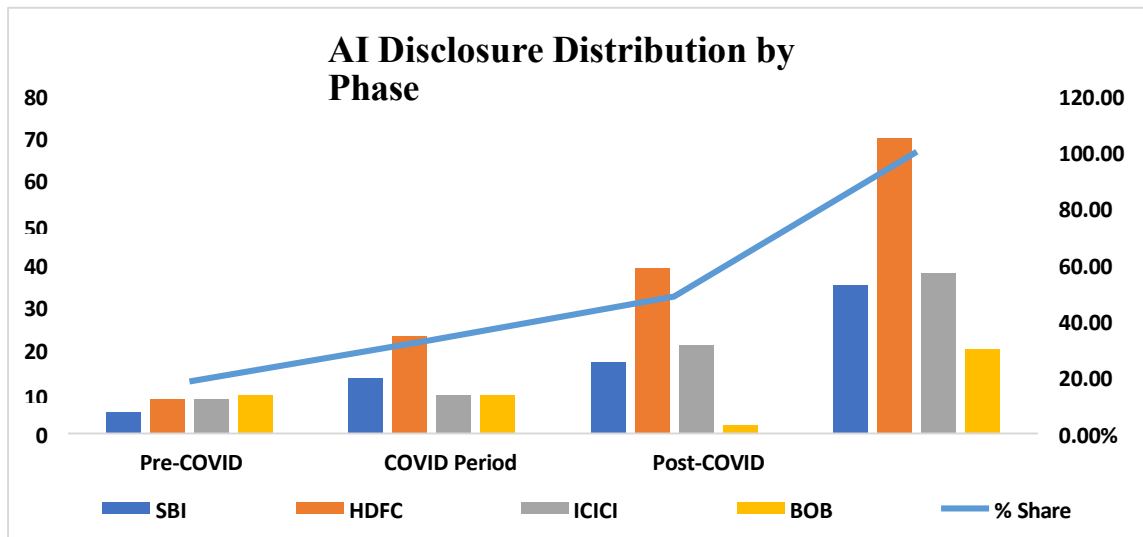


Figure 3: AI Disclosure Distribution by Phase

Table 10: AI Disclosure Distribution by Phase

Bank	Pre-COVID	COVID Period	Post-COVID	Total
SBI (Public)	5	13	17	35
HDFC (Private)	8	23	39	70
ICICI (Private)	8	9	21	38
BOB (Public)	9	9	2	20
TOTAL	30	54	79	163
% Share	18.4%	33.1%	48.5%	100%

6.1 Pre-COVID Phase (n=30, 18.4%)

- Basic AI investments dominate in the pre-COVID filings. Important findings:

SIVA voice assistant, SIA chatbot, ATM fraud models, and RPA deployment are some of the Pre-COVID disclosures SBI made (n=5), meaning that the public sector bank was deploying operational AI technologies prior to FY2020.

- BOB (n=9) has the biggest number of pre-COVID disclosures, mostly on the creation of ACoE, Big Data Lake, and the Baroda Brainy AI robot, indicating that this bank's AI narrative was developing prior to the epidemic.
- HDFC and ICICI show eight Pre-COVID entries, focusing on data analytics infrastructure, RPA adoption, and EVA chatbots.

6.2 COVID Period (n=54, 33.1%)

AI disclosures have significantly increased over the COVID period, especially in:

Digital channel acceleration: HDFC and ICICI specifically reported VRM, Video KYC and digital onboarding AI as COVID-responsive offerings.

- Continuity in operations: AI-assisted remote infrastructure control and work-from-home solutions enabled HDFC to record no IT outages. ICICI expanded its RPA service so that it could continue functioning with fewer physical workers.
- Customer support AI: All banks accelerated the use of chatbots to respond to the growing number of questions during lockdown periods.

6.3 Post-COVID Phase (n=79, 48.5%)

Most disclosures are after COVID, which means the compounding effect of increased use of AI:

HDFC pioneers Post-COVID disclosures (n=39) with its GenAI projects, cloud data lake migration, cybersecurity AI, and customer personalization systems.

With 1,500 RPA implementations, TradeIntelli, iCare omnichannel, and GenAI evaluation, ICICI proves to have a strong post-COVID growth (n=21).

SBI relies on the post-COVID activities through Meghdoot cloud, YONO 2.0, and the Responsible AI framework (n=17).

- BOB has a major decline in Post-COVID disclosures (n=2), which is most likely explained by the fact that its latest annual report in the data was published prior to the post-COVID reporting period, as opposed to a decline in AI activities.

6.4 Effect of COVID-19 on AI Adoption

The analysis of the phases shows that COVID-19 has prompted the use of AI in Indian banks. The shift in pre-COVID 18.4% to 48.5% The shift to the COVID emphasis on digital channels, contact-free services and operational resilience, as well as disclosures in the post-COVID period, show that the pandemic increased investment in AI and disclosure depth across all banks in the public and private sectors in both a significant and profound way.

7. Key Insights

Insight 1: AI Disclosure is Performance-Led, not Application-Led.

The number of disclosures made by T4 (AI Applications) represents 79.1% of all disclosures, which means that the annual reports of Indian banks primarily focus on the implementation of AI systems instead of financial outcomes that such systems produced. Only 3.7% of the disclosures contain explicit profitability correlations (T1) which means that there is a significant lack of contact between AI investment and evidence-based financial success communication.

Insight 2: Data Infrastructure is the Hidden Backbone of AI Strategy

Customer-facing AI (38.0%) is not even as large as T4d (Data and Analytics Infrastructure) the largest subcategory (41.1%). This illustrates the perspective of Indian banks on the implementation of the data-first approach in the implementation of AI, with the investment in cloud migration, data lakes, API platforms, and analytics centers of excellence being made before or alongside customer-facing implementations.

Insight 3: Private Banks dominate in terms of Volume, GenAI, and financial connections

The early adopters of generative AI are private sector banks (ICICI and HDFC) which account for 66.3% of all disclosures and are more operationally specific. And the relationship between AI and financial prosperity is becoming the norm. This is an indication of their greater organizational flexibility, their capability to spend on technology, and the competition pressure to be unique by being innovative.

Insight 4: COVID-19 Was a Structural Inflection Point of AI Adoption

The phase analysis proves the existence of a specific increasing tendency: Pre-COVID (18.4%) → COVID (33.1%) → Post-COVID (48.5%). The pandemic prompted banks to roll out financial solutions that are contactless and AI-driven at scale. This has been accelerating into the post-COVID era of more complex systems (GenAI, cloud AI, AI cybersecurity).

Insight 5: Customer Experience is the Primary AI Battleground

Customer-facing AI (T4a) is the most prominent and distinctive disclosure category across all four banks. A distinct maturity arc in consumer AI across the dataset period can be seen in the evolution from simple FAQ chatbots (HDFC's EVA, SBI's SIA) to transactional AI, VRM platforms, multilingual bots, and digital humans (BOB's ADITI).

Insight 6: AI Governance Leadership/ Operation Lag in Public Banks

Although the number of overall disclosures are less than the number of private banks, SBI (public) is a leader in ethical AI disclosure, as it discloses a Responsible AI governance framework (FEAT). Also, the ratios of aspirational tones of public banks

are higher, which means that it is characterized by a tendency to issue statements on strategic purpose instead of concrete data on deployments.

Insight 7: Quantification is still the Weakest Link in AI Disclosure

Nor do the 163 disclosures that cover ICICI (13M chatbot queries; 1,500 RPA processes; 700 FTE equivalent), HDFC (300% VRM growth; 12% energy reduction), and SBI (RPA 2030% faster than manual) provide quantitative information about AI performance. Due to the lack of standardized AI KPI disclosure frameworks, there are significant differences in disclosure quality and little cross-bank comparability.

8. Research Findings

8.1 Overview

This research analyzed 163 disclosures on AI at the paragraph level in annual reports of four Indian banks, two of which were publicly traded (SBI, BOB) and two of which were privately traded (HDFC, ICICI) over the period of FY2019 to FY2023. The disclosures were coded using a five-theme framework (T1-T5) and analyzed since ownership structure, the time frame of disclosure, the tone of the narrative, and the type of AI application. In accordance with the three main research objectives of the study, the results are shown below.

8.2 RQ1: What is the Disclosure of AI by the Indian Banks in relation to the financial performance?

The findings indicate that there is a wide gap between the financial performance disclosure and AI adoption. Coded disclosures mentioning AI and profitability (T1) and operational efficiency (T2) are only 3.7 and 8.0% respectively, although 79.1 percent of coded disclosures identify specific AI applications (T4). This is indicative of the idea that Indian banks more often than not frame AI as a technological ability narrative, as opposed to a financial performance driver. They tend to be operational in nature when there are monetary links, like cost savings in RPA, efficiency gains in automation, or digital channel scale indicators. Directive language (AI supports efficiency, AI facilitates revenue growth) suggests that there is an appreciation of financial relationships, but not the rigorous evidence necessary to prove the assertion of causation. This is similar to the trend of Clarkson et al. (2008) and Beretta and Bozzolan (2004). The trend is in line with Beretta and Bozzolan (2004) and Clarkson et al. (2008) who observe that the quality of financial disclosure of intangible assets that are hard to attribute is usually poor.

RQ2: Are there any differences in AI Disclosure patterns between Public and Private Sector Banks?

The findings showed that there was a statistically significant difference in SBII disclosures in both the public and the private sectors. Although they comprise half of the sample, private banks have an overrepresented 66.3% of disclosures due to their earlier implementation of cutting-edge AI technologies, including generative AI, and greater operational specificity (avg.). T5b rate of ~68.5% vs. 60% for public banks).

The aspirational tone ratio is higher among the public sector banks (40.0% T5a vs. 27.8% among the private banks), possibly because both of the real differences in the speed of AI implementation and the conservativeness of organizations in strategic communication. Nevertheless, SBI (public) has a superior AI governance disclosure, such as a publicly accessible FEAT Responsible AI framework. This is lacking by far in the case of private banks in this sample.

The post-COVID acceleration was much higher in private banks (55.6% post-COVID disclosures versus 34.5% in public banks), suggesting that the digital imperative of the pandemic was more quickly picked up by the private banks. These findings are in line with previous studies of the different ways in which the financial institutions of the public and private sectors in emerging countries take up innovations (Luo et al., 2021).

RQ3: Which AI Applications are the most widely revealed?

Together, customer-facing AI (T4a: 38.0%) and Data & Analytics Infrastructure (T4d: 41.1%) make up 79.1% of all T4 disclosures, indicating a two-pronged AI approach in Indian banking: investing in data foundations while concurrently implementing customer-experience AI.

The primary disclosers of back-office automation (T4b: 11.6%), are private banks (HDFC, ICICI), with the 1,500+ RPA processes at ICICI being the most operational AI implementation in the dataset. Due to their more sophisticated risk management technology infrastructure, SBI and HDFC have a concentration of risk and fraud analytics (T4c: 10.1%).

The emergence of Generative AI disclosures in Post-COVID reports (HDFC ChatGPT FAQ bot and Branch Co-Pilot; BOB ADI and ADITI digital human; ICICI GenAI evaluation) is a new frontier in the deployment of Indian SBII. The data represents the first phases of this Generative AI shift.

9. Discussion

9.1 AI Adoption and Disclosure Maturity in the Indian Banking

The findings reveal that the application of AI in the banking of India has progressed far beyond the exploratory phase. Regardless of whether they are privately or publicly owned, all four of the banks in the dataset show significant AI implementations in the areas of operations, risk, customer service, and data infrastructure. This is a significant progression, as the literature on AI testing in Indian banking shows beginning to test AI in the banking sector as early as 2016. The breadth, precision and financial basis of AI-related annual report disclosures, known as disclosure maturity, vary widely across institutions. ICICI has the most mature level of disclosure due to the use of accurate names of systems and measurable outcomes. HDFC has the most detailed disclosure of its AI portfolio in each subcategory. SBI is special because of its disclosure of governance and ethics. The disclosure pattern of BOB is the most focused and least diverse, although it is truly innovative (ADITI digital human, Gen AI ADI).

9.2 Aspirational-Operational Disclosure Spectrum

The difference between aspirational and operational AI disclosure is a common topic in this analysis. Although the general operational tone ratio of 60.8% is encouraging, many of the disclosures, particularly AI vision statements in Directors' Reports, have language that communicates an intent but does not provide evidence of how it is achieved. This brings up the issue of AI washing in annual reports, with general statements about AI potentials not backed by a specific, verifiable system disclosure. Standardized AI disclosure frameworks are necessary that will compel banks to differentiate between deployed AI systems, pilot-stage projects, and strategic goals. Regulators and stakeholders can have practical implications. They are similar to ESG reporting standards. The Reserve Bank of India's new guidelines on responsible AI adoption may speed up this standardization.

9.3 COVID-19 as Structural Inflection Point

The COVID-19 pandemic has not just served as an accelerant but also as a main structural

driver of the implementation of AI in Indian banks. The pandemic enabled banks to accelerate AI deployments that would otherwise require additional time planning to deploy because of supply-side forces (such as regulatory forbearance and greater focus on digital investments) and demand-side forces (customers requiring remote services). AI-powered applications like VRM, AI chatbots and digital onboarding have not been removed post COVID indicating permanence of these changes.

9.4 Implication about AI Governance

The disclosure of AI governance is concentrated in SBI (Responsible AI/FEAT framework), which outlines a major gap in the sphere. There is a significant number of annual reports that do not have clear AI governance frameworks, which is concerning as Indian banks turn to using AI to make credit decisions, detect fraud, and target customers in increasing numbers. There are significant implications of these areas on fairness and discrimination. Civil society groups, regulators and investors are urged to request that AI governance be included in the list of standard reporting elements in annual reports of financial institutions.

9.5 Limitations

There are various limitations to this analysis. First, the time-comparability limits since the data is only available on a few annual reports of four banks in a timeframe spanning FY2019 to FY2024. Second, the coding structure is systematic, but it has interpretive judgments that can lead to code bias. Third, the diversity of Indian banking is not adequately reflected in the sample of four banks, excluding small finance banks and regional rural banks. Fourth, annual reports represent edited reports; AI disclosures show what the banks want to present publicly, and this may not be the true picture of the AI implementation.

10. Conclusion

This paper has discussed the disclosures about the connection between financial performance and the adoption of artificial intelligence (AI) by the Indian scheduled commercial banks in their annual reports, the differences between FY2019 and FY2024. It entailed the qualitative content analysis of 163 coded paragraph-level disclosures of four large banks- State Bank of India and Bank of Baroda (public sector banks) and HDFC Bank and ICICI Bank (private sector banks). The patterns of disclosure were examined with a structured thematic codebook comprising of five topics (T1-T5). Categorizations that specifically refer to profitability or financial effect (T1) only constitute 3.7% of all coded disclosures, whereas theme T4 (AI Applications Disclosed) prevails with 79.1%. This comparison implies that banks pay more attention to the discussion of AI implementation and ability building rather than demonstrate the quantifiable financial results. This is consistent with other studies of corporate narrative reporting especially through the attitude of impression management whereby companies focus on strategic strengths rather than actual performance outcomes. Banks adopt a two-structured strategy when reporting AI applications. The first pillar is Investment in Data and Analytics Infrastructure (T4d: 41.1%) which offers the necessary backbone of AI implementation. The second pillar is Customer-Facing AI (T4a: 38.0%), which is the most apparent field of implementation to the end users. The back-office automation (T4b: 11.6) and risk and fraud analytics (T4c: 10.1) do not have a dominant presence but denote the different maturity levels of functional AI applications. In general, the disclosures of private sector banks are more detailed, encompassing wider uses and describing AI uses more explicitly than the disclosures of public sector banks. In the tone analysis, 60.8 percent of disclosures are operational (T5b), and reflect implementations, system descriptions, and occasionally measurable results.

In general, these findings indicate that instead of a measurably and numerically determined determinant of financial performance, the adoption of AI in Indian banking is still mainly characterized as an operational and technological change. The story-focused approach to systems, capabilities and infrastructure as opposed to measured financial performance is an indication that AI disclosure practices are still under development.

These findings suggest that although Indian banks have gone a long way in adopting AI in risk management systems, operational and customer-facing systems, there are missing specific financial performance stories. Hence, in corporate disclosures, AI is framed as efficiency, scalability, and service improvement enabling technology, but is not a measurably definite contributor to profitability.

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