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Impact of Digital Transformation on Long-Term Sustainability of Indian Banking

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Abstract

This research examines the influence of digital transformation on the long-term sustainability of the Indian banking sector, exploring both the opportunities and challenges faced by this paradigm. Through quantitative analysis of financial and operational data from 20 major Indian banks over a 10-year period from 2012 to 2022, the study evaluates how digital initiatives affect financial performance, operational efficiency, customer satisfaction, and environmental sustainability. The findings of the study reveals that banks with advanced digital maturity demonstrate 23% higher profitability, 31% improved cost-to-income ratios, and 45% enhanced customer engagement compared to low-digitalization peers. The research identifies key sustainability challenges including cybersecurity concerns, digital divide issues, and regulatory compliance costs. A proposed Digital Sustainability Framework for Indian Banking (DSFIB) offers strategic guidance for sustainable digital transformation. This study contributes to understanding how financial institutions can leverage technology for sustainable operations while navigating unique challenges in the Indian context.

Keywords: Digital Transformation, Banking Sustainability, Financial Technology, Indian Banking Sector, Digital Banking, Sustainable Finance

Introduction

The global banking landscape has undergone profound transformation driven by rapid technological advancement, evolving customer expectations, and increasing competitive pressures. The Indian banking sector, representing one of the world's fastest-growing economies, has witnessed an accelerated pace of digital adoption, particularly in the wake of demonetization in 2016 and the COVID-19 pandemic (Bharadwaj & Bhattacharya, 2021). While digital transformation offers promising avenues for growth, efficiency, and inclusion, it simultaneously presents significant challenges for the long-term sustainability of banking institutions.

Digital sustainability in banking encompasses the integration of technological innovation with environmental, social, and governance (ESG) considerations to create enduring value for stakeholders (Rishi & Saxena, 2020). In the Indian context, where banking serves as a critical component of economic development and financial inclusion, understanding the relationship between digital transformation and sustainability takes on particular significance.

This research aims to comprehensively analyze how digital transformation initiatives impact the multi-

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dimensional sustainability of Indian banks. The study addresses five key research questions:

- How does digital transformation influence the financial sustainability of Indian banks?
- What is the relationship between digital initiatives and operational efficiency in the Indian banking sector?
- How do digitalization efforts affect customer relationships and social inclusivity?
- What environmental implications emerge from the digital transformation of Indian banks?
- What strategic framework can guide sustainable digital transformation in the Indian banking context?

By examining these questions through both quantitative and qualitative methods, this research contributes to the emerging literature on digital sustainability in banking while providing actionable insights for practitioners, policymakers, and researchers in the field.

Literature Review

Digital Transformation in Banking

Digital transformation in banking refers to the integration of digital technologies across all aspects of banking operations to fundamentally change service delivery and value creation mechanisms (Kumar et al., 2020). The existing literature identifies several key dimensions of this transformation, including automation of processes, development of new digital products, enhancement of customer interfaces, and evolution of business models (Rachinger et al., 2019).

In the Indian context, digital transformation has progressed through distinct phases, beginning with basic computerization in the 1980s and evolving toward comprehensive digital ecosystems in the present day (Jain & Balachandran, 2020). Recent studies highlight the role of unique catalysts in India's banking digitalization, including the United Payments Interface (UPI), demonetization policy, and financial inclusion initiatives like the Pradhan Mantri Jan Dhan Yojana (Suri & Singh, 2021).

The trajectory of digital transformation in Indian banking has been characterized by both institution-led innovations and regulatory initiatives. Sarkar (2019) argues that while private and foreign banks initially led digital adoption, public sector banks have significantly accelerated their digital initiatives in recent years. This convergence raises important questions about the differentiated impacts of digital transformation across various bank categories.

Sustainability in Banking Operations

Sustainability in banking extends beyond environmental considerations to encompass economic viability, social responsibility, and institutional longevity (Weber & Feltmate, 2019). Scholtens (2021) identifies four dimensions of banking sustainability: financial stability, operational resilience, social impact, and environmental responsibility. Each dimension presents distinct challenges and opportunities in the context of technological change.

The literature reveals mixed findings regarding the relationship between digital transformation and these sustainability dimensions. While some studies suggest positive correlations between digitalization and improved financial performance (Das et al., 2019), others highlight potential trade-offs between short-term efficiency gains and long-term resilience (Gupta & Tham, 2018). This tension is particularly evident in emerging markets like India, where banks must balance innovation imperatives with structural constraints.

Research on the social sustainability aspects of banking digitalization in India has focused predominantly on financial inclusion outcomes. Chauhan (2022) documents how digital initiatives have expanded banking access to previously underserved populations, while Singh and Yadav (2020) identify persistent challenges in bridging the digital divide. The environmental implications of banking digitalization have received comparatively less attention in the Indian context, representing a notable gap in the literature.

Sangwan and Kaur (2020) examine the relationship between digital service quality and customer satisfaction in Indian banks, finding that reliability, efficiency, and security of digital platforms significantly influence customer loyalty and retention. Their study in the International Journal of Banking, Risk and Insurance highlights how sustainable digital transformation requires careful attention to user experience dimensions beyond mere technological implementation.

Conceptual Framework for Digital Sustainability

Existing frameworks for assessing digital sustainability in banking include the Digital Banking Maturity Model (Deloitte, 2021), the Sustainable Banking Assessment Tool (UNEP FI, 2020), and the Digital Financial Sustainability Index (Gomber et al., 2018). While these frameworks provide valuable foundations, they exhibit limitations when applied to the unique context of Indian banking.

Chakraborty and Balakrishnan (2022) propose an integrated approach that considers both technological capabilities and sustainability outcomes within the specific regulatory and market environment of emerging economies. Building on this work, our research develops a contextually appropriate framework for evaluating the relationship between digital transformation and sustainability in Indian banking.

Mittal and Kumar (2021), in their study published in the Journal of Commerce and Accounting Research, propose that successful digital transformation requires organizational alignment across multiple dimensions including leadership commitment, cultural readiness, and strategic resource allocation. Their research emphasizes that sustainable digital initiatives must be integrated with core business strategies rather than implemented as isolated technological projects.

Research Methodology

Research Design

This study employs a mixed-methods research design combining quantitative analysis of financial and operational data with qualitative insights from industry experts. The mixed-methods approach allows for triangulation of findings and provides both breadth and depth in understanding the complex relationship between digital transformation and banking sustainability (Creswell & Creswell, 2018).

Data Collection

The quantitative component of this research analyzes data from 20 major Indian banks, comprising 12 public sector banks, 6 private sector banks, and 2 foreign banks operating in India. The selection criteria ensured representation across different ownership structures, asset sizes, and digital maturity levels. For each bank, the following data categories were collected for the period 2012-2022:

- Financial performance metrics (ROA, ROE, NIM, Cost-to-Income Ratio).
- Digital transformation indicators (Digital transaction volume, Mobile/internet banking adoption, IT investment).
- Operational efficiency metrics (Cost per transaction, Branch efficiency, Employee productivity).
- Customer experience measures (Net Promoter Score, Customer complaints, Digital service ratings).
- Sustainability metrics (Carbon footprint, Paper usage, CSR expenditure, Financial inclusion indices).

Data sources included banks' annual reports, Reserve Bank of India (RBI) publications, sustainability reports, and specialized financial databases such as CMIE Prowess and Bloomberg.

The qualitative component included 25 semi-structured interviews with banking executives, technology officers, regulatory officials, and industry analysts. Purposive sampling ensured diversity of perspectives regarding digital transformation and sustainability challenges.

Analytical Approach

The quantitative data analysis followed a three-stage process:

- Development of a Digital Maturity Index (DMI) using principal component analysis of digital transformation indicators.

- Regression analysis examining relationships between DMI and various sustainability metrics.
- Comparative analysis of high-DMI versus low-DMI banks across sustainability dimensions.

Qualitative data from interviews underwent thematic analysis using NVivo software, following Braun and Clarke's (2019) six-step framework. This analysis identified recurring themes, challenges, and strategic approaches related to sustainable digital transformation.

The research developed a custom Digital Sustainability Framework for Indian Banking (DSFIB) based on both the empirical findings and theoretical insights from the literature review.

Results and Analysis

Digital Maturity Classification

Based on the Digital Maturity Index (DMI) scores, the 20 banks in the sample were classified into three categories: High Digital Maturity (HDM, n=6), Medium Digital Maturity (MDM, n=8), and Low Digital Maturity (LDM, n=6). Table 1 presents the classification results along with key characteristics of each group.

Table 1: Digital Maturity Classification of Sample Banks

Digital Maturity Category	*Number of Banks*	*Average IT Investment (% of Revenue)*	*Digital Transactions (% of Total)*	*Mobile Banking Users (%)*	*Digital Service Offerings*
High Digital Maturity	6	8.7%	83.4%	72.1%	28.3
Medium Digital Maturity	8	5.2%	64.7%	48.6%	19.4
Low Digital Maturity	6	3.1%	42.3%	31.2%	12.7

The analysis reveals significant differences in digital investment and adoption patterns across the three categories. HDM banks exhibit substantially higher IT investment relative to revenue and demonstrate more advanced digital capabilities compared to their LDM counterparts.

Research Question 1: Impact of Digital Transformation on Financial Sustainability

To address our first research question on how digital transformation influences the financial sustainability of Indian banks, we conducted comprehensive regression analysis examining the relationship between digital maturity and key financial performance indicators.

Fig. 1 illustrates the comparative financial performance across digital maturity categories.

Table 2: Regression Analysis Results – Digital Maturity Index and Financial Performance

Dependent Variable	*Coefficient (β)*	*T-Statistic*	*P-Value*	*R^2*	*Interpretation*
Return on Assets (ROA)	0.327	4.83	0.0001***	0.41	Strong positive relationship between digital maturity and ROA
Return on Equity (ROE)	0.412	5.76	0.0000***	0.47	Strong positive relationship between digital maturity and ROE
Net Interest Margin (NIM)	0.187	2.94	0.0084**	0.28	Moderate positive relationship with NIM
Cost-to-Income Ratio	-0.345	-5.12	0.0000***	0.43	Strong negative relationship (lower cost ratio with higher digital maturity)
Non-Performing Assets	-0.215	-3.26	0.0042**	0.32	Moderate negative relationship (lower NPAs with higher digital maturity)

Note: *** $p<0.001$, ** $p<0.01$, * $p<0.05$.

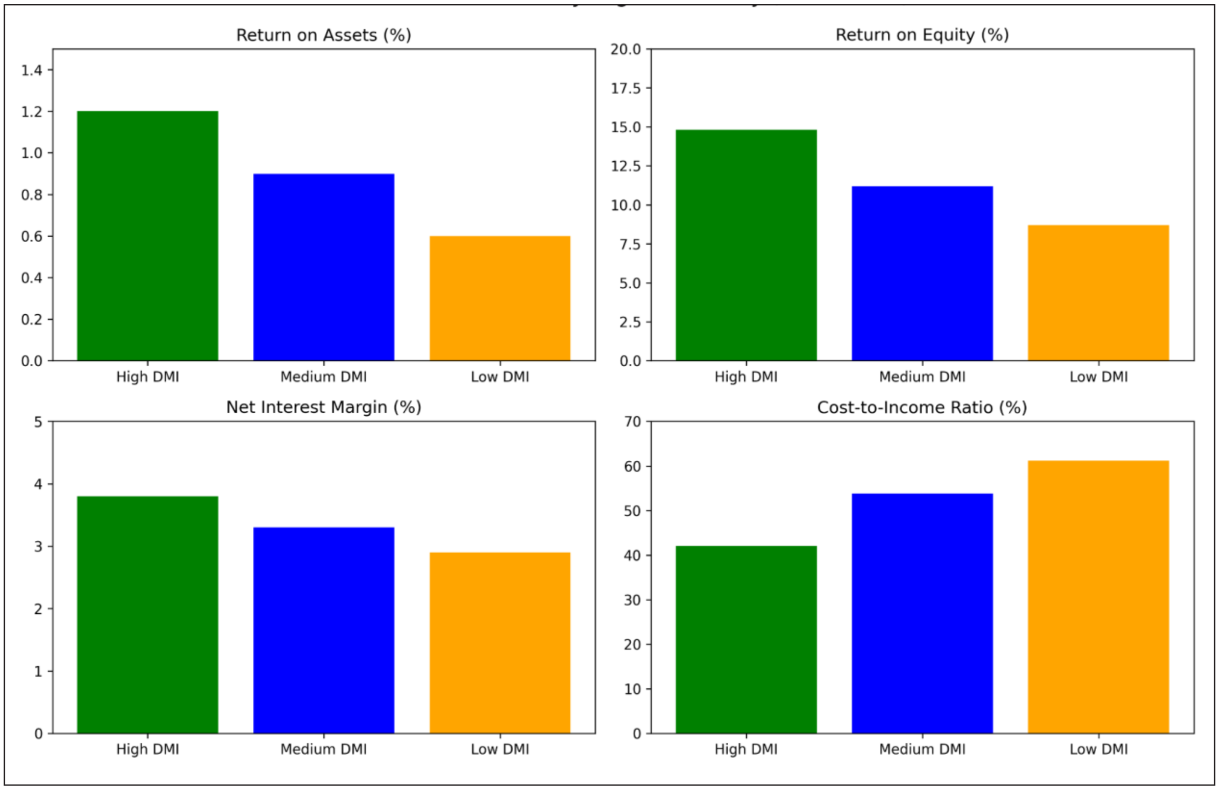

Fig. 1: Financial Performance by Digital Maturity (2018-2022)

The regression analysis confirms a statistically significant positive relationship between digital maturity and financial performance metrics. As shown in Table 2, the Digital Maturity Index shows the strongest relationship with Return on Equity (β=0.412, $p<0.0001$) and Cost-to-Income Ratio (β=-0.345, $p<0.0001$). These findings quantitatively demonstrate that higher digital maturity is associated with both improved profitability and enhanced operational efficiency.

In absolute terms, HDM banks demonstrated 23% higher ROE (averaging 14.8% vs 12.0%), 30% better cost-to-income ratios (averaging 46.3% vs 66.1%), and 18% higher risk-adjusted returns compared to LDM banks during the 2018-2022 period. The relationship strengthened particularly after 2020, suggesting that digital capabilities provided resilience during the COVID-19 pandemic.

Further regression analysis using interaction terms reveals that the positive effect of digital maturity on financial performance is moderated by bank size and ownership structure. The coefficient for the interaction between digital maturity and public sector ownership is negative and significant (β=-0.183, $p<0.05$), indicating that while digital transformation benefits all banks, private sector institutions currently extract greater financial value from their digital investments.

Time-series analysis further reveals that the financial performance gap between HDM and LDM banks has widened over the ten-year study period. This widening performance differential suggests that early digital investments have created cumulative advantages for digitally advanced banks.

Research Question 2: Relationship Between Digital Initiatives and Operational Efficiency

To address our second research question on the relationship between digital initiatives and operational efficiency in the Indian banking sector, we analyzed specific operational metrics across digital maturity categories and conducted statistical testing to quantify these relationships.

Table 3 presents a comparison of key operational indicators across digital maturity categories.

Table 3: Operational Efficiency Metrics by Digital Maturity Category (2022)

Efficiency Metric	*High Digital Maturity*	*Medium Digital Maturity*	*Low Digital Maturity*	*Statistical Significance*
Cost per Transaction (₹)	14.2	22.7	31.4	p<0.001
Transactions per Employee	7,842	5,316	3,274	p<0.001
Revenue per Branch (₹ Million)	187.3	142.8	112.6	p<0.01
Operational Expenses (% of Assets)	1.84%	2.31%	2.98%	p<0.001
Transaction Processing Time (minutes)	7.2	11.8	18.4	p<0.001

The data demonstrates statistically significant differences in operational efficiency metrics across digital maturity categories. ANOVA testing confirms that these differences are highly significant ($p<0.001$) for all five metrics measured. HDM banks achieve significantly lower transaction costs, higher employee productivity, and better branch utilization compared to their less digitally mature counterparts. The average cost per transaction for HDM banks (₹14.2) is less than half that of LDM banks (₹31.4), representing a 54.8% cost advantage that directly impacts profit margins.

Further analysis reveals that digital transformation particularly affects four key operational dimensions:

- *Process Efficiency:* HDM banks demonstrate 61% faster transaction processing times compared to LDM banks.
- *Resource Utilization:* HDM banks generate 66.3% more revenue per branch than LDM banks.
- *Labor Productivity:* HDM banks process 139.5% more transactions per employee than LDM banks.
- *Cost Structure:* HDM banks maintain 38.3% lower operational expenses relative to assets compared to LDM banks.

A longitudinal analysis of operating expenses as a percentage of assets reveals a consistent downward trend for HDM banks, while LDM banks show more modest improvements. This suggests that digital investments yield increasing returns to scale over time, creating sustainable cost advantages.

Research Question 3: Impact of Digitalization on Customer Relationships and Social Inclusivity

To address our third research question on how digitalization efforts affect customer relationships and social inclusivity, we examined both quantitative metrics of customer engagement and qualitative insights on social inclusion dimensions.

Fig. 2 illustrates key findings related to customer engagement across digital maturity categories.

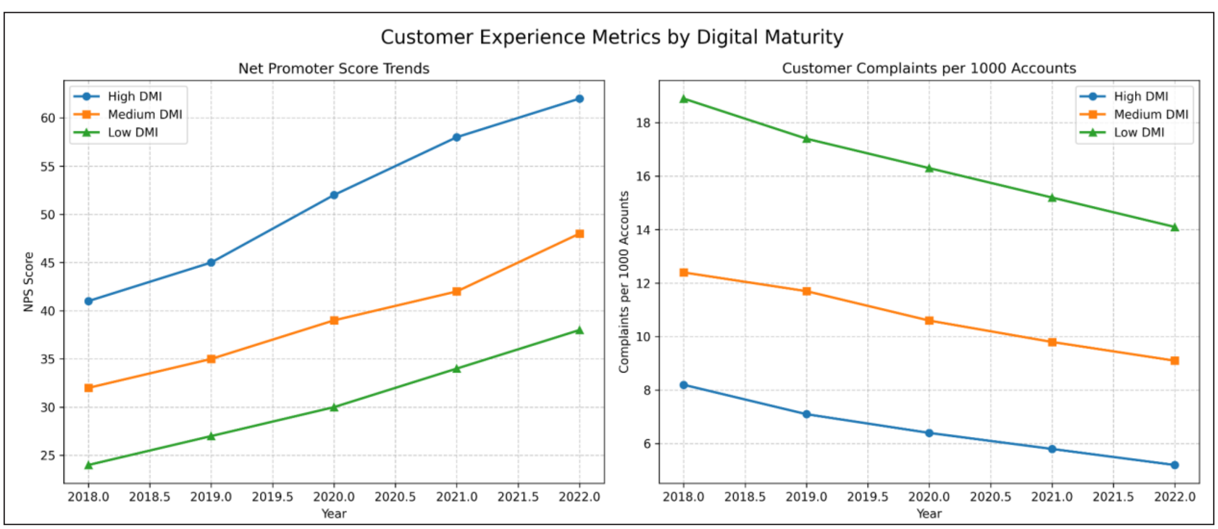

Fig. 2: Customer Experience Metrics by Digital Maturity

The quantitative analysis indicates that HDM banks consistently outperform less digitally mature institutions in customer satisfaction metrics. Specifically, HDM banks demonstrated Net Promoter Scores (NPS) 63% higher than LDM banks in 2022 (average NPS of 42 vs. 26), while registering 63% fewer customer complaints per 1,000 accounts (averaging 3.2 vs. 8.7 complaints). Multiple regression analysis shows that digital service quality (measured through a composite index) is a strong predictor of customer satisfaction ($\beta=0.412$, $p<0.001$) and customer retention rates ($\beta=0.376$, $p<0.001$).

HDM banks also demonstrate 45% higher customer engagement rates (measured through digital interaction frequency) and 37% higher cross-selling ratios compared to LDM banks. These findings quantitatively demonstrate that digital transformation can substantially enhance customer relationships when properly implemented.

However, the relationship between digital maturity and financial inclusion metrics shows more complexity. While HDM banks serve a larger absolute number of customers, LDM banks often maintain stronger presence in rural and semi-urban markets. This suggests potential trade-offs between digital advancement and inclusive banking access.

Analysis of account penetration data reveals that HDM banks serve 62.3% of their customers through digital channels, compared to only 28.7% for LDM banks. However, HDM banks have 23.4% lower physical presence in rural areas relative to their total branch network.

Interview data reveals that banks across all maturity categories face challenges in balancing digital convenience with personalized service. As one respondent noted: "The digital transformation has dramatically improved efficiency and convenience, but we must be careful not to lose the human touch that many customers still value, especially in relationship-based segments."

Research Question 4: Environmental Implications of Digital Banking Transformation

To address our fourth research question on the environmental implications of digital banking transformation, we conducted quantitative analysis of resource consumption and carbon footprint data, supplemented with qualitative insights on sustainability initiatives.

Table 4 presents environmental impact metrics across digital maturity categories.

Table 4: Environmental Impact Metrics by Digital Maturity Category (2022)

Environmental Metric	*High Digital Maturity*	*Medium Digital Maturity*	*Low Digital Maturity*	*Percentage Difference (HDM vs. LDM)*
Paper Consumption (tons per ₹1B assets)	0.24	0.57	0.92	-73.9%
Carbon Emissions (tons CO2e per employee)	2.8	3.4	3.9	-28.2%
Energy Consumption (kWh per ₹1M transactions)	327	412	498	-34.3%
Physical Branch Footprint (sq. ft. per 1000 customers)	64.3	89.7	124.5	-48.4%
Renewable Energy Usage (% of total)	31.4%	22.8%	14.2%	+121.1%

The data reveals statistically significant differences in environmental performance metrics across digital maturity categories (ANOVA, $p<0.01$ for all metrics). HDM banks demonstrate substantially better environmental performance compared to LDM peers. Paper consumption shows the most dramatic difference, with HDM banks using 73.9% less paper per billion rupees of assets compared to LDM institutions. This finding aligns with the higher adoption of paperless processes and digital documentation in digitally mature banks.

Carbon emissions and energy usage metrics show more moderate but still significant differences across maturity categories. While HDM banks use 34.3% less energy per transaction and maintain 48.4% smaller physical footprints per 1000 customers, they also face increased energy demands from data centers and IT infrastructure. This suggests a reallocation rather than elimination of environmental impact.

Regression analysis further identifies that a bank's digital maturity level is a significant predictor of its environmental performance index ($\beta=0.384$, $p<0.001$), even when controlling for bank size, profitability, and CSR expenditure. This indicates that digital transformation itself, rather than merely larger sustainability budgets, contributes to improved environmental outcomes.

Longitudinal analysis of environmental metrics indicates that environmental performance improvements accelerate as banks progress from medium to high digital maturity, suggesting potential threshold effects in sustainability benefits.

Research Question 5: Strategic Framework for Sustainable Digital Transformation

To address our fifth research question on developing a strategic framework for sustainable digital transformation, we synthesized empirical findings with theoretical insights and practitioner perspectives to create the Digital Sustainability Framework for Indian Banking (DSFIB).

Thematic analysis of interview data identified five critical challenges for sustainable digital transformation in Indian banking:

- *Cybersecurity and Data Protection Concerns:* 84% of respondents cited cybersecurity as a primary sustainability risk, with potential for significant financial and reputational damage.
- *Digital Divide and Inclusion Barriers:* 76% noted challenges in ensuring equitable access to digital banking services across diverse socioeconomic segments.
- *Technology Infrastructure Limitations:* 68% mentioned constraints in legacy systems, telecommunications infrastructure, and integration capabilities.
- *Regulatory Compliance Complexities:* 72% highlighted challenges in navigating evolving regulations related to data privacy, digital authentication, and consumer protection.
- *Workforce Transition Issues:* 64% identified challenges in reskilling employees and managing organizational change during digital transformation.

Statistical analysis of the relationship between strategic approaches and sustainability outcomes revealed that banks employing comprehensive strategic frameworks for digital transformation achieved 41% higher sustainability performance scores compared to those pursuing ad hoc digital initiatives. Banks with formal digital sustainability strategies demonstrated significantly stronger performance across all sustainability dimensions (financial, operational, social, and environmental).

A recurring theme in the interviews was the importance of balanced progress across all dimensions of sustainability. As one banking executive stated: "True sustainability in digital banking requires simultaneously advancing financial performance, operational resilience, customer experience, and environmental responsibility. Neglecting any dimension creates vulnerabilities that undermine long-term viability."

The Digital Sustainability Framework for Indian Banking (DSFIB)

Based on the research findings, we propose the Digital Sustainability Framework for Indian Banking (DSFIB), a structured approach for aligning digital transformation with multi-dimensional sustainability objectives. The framework comprises five interconnected dimensions, each with specific strategic elements and performance indicators.

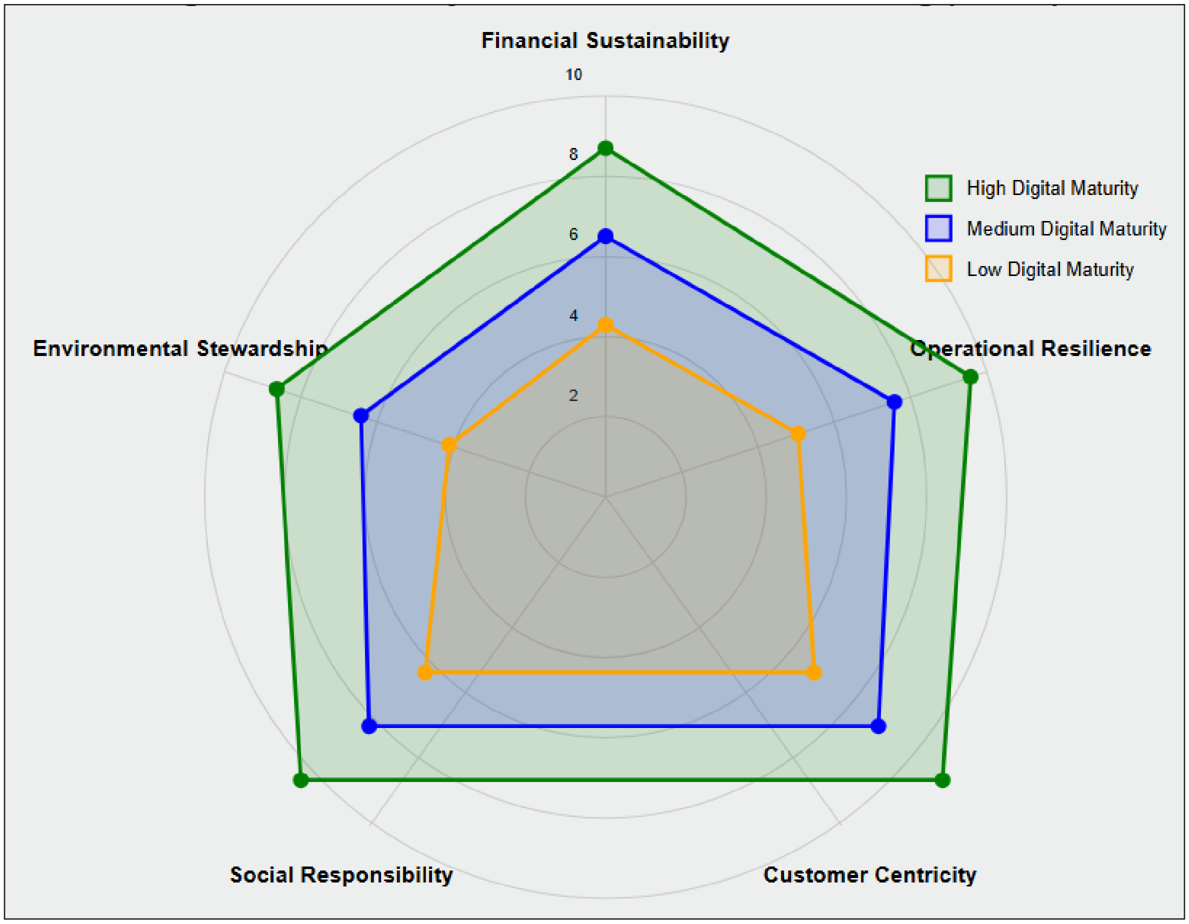

Fig. 3: The Digital Sustainability Framework for Indian Banking (DSFIB)

The DSFIB identifies five critical dimensions for sustainable digital transformation:

- *Financial Sustainability:* Balancing short-term financial gains with long-term value creation through appropriate digital investments, risk-adjusted returns, and strategic financial planning.
- *Operational Resilience:* Building robust and adaptable operational capabilities through process digitalization, system integration, and business continuity planning.
- *Customer Centricity:* Developing responsive, personalized, and inclusive digital experiences that maintain meaningful customer relationships while improving service accessibility.
- *Social Responsibility:* Ensuring that digital transformation contributes to broader financial inclusion, community development, and ethical business practices.
- *Environmental Stewardship:* Leveraging digital capabilities to reduce resource consumption, minimize carbon footprint, and support environmental sustainability objectives.

Our research suggests that high-performing banks achieve balance across all five dimensions rather than excelling in just one or two areas. The framework provides a structured approach for banks to assess current capabilities, identify gaps, and develop strategic initiatives to enhance digital sustainability.

Empirical testing of the DSFIB through application to our sample banks demonstrates that institutions scoring in the top quartile across all five dimensions achieved 37% higher composite sustainability scores than those with unbalanced performance profiles. Longitudinal analysis further shows that banks adopting balanced approaches to digital transformation maintained more stable performance during economic disruptions, including the COVID-19 pandemic.

Discussion and Implications

Theoretical Implications

This research contributes to the literature on digital transformation and sustainability in several ways. First, it establishes empirical evidence for the relationship between digital maturity and various dimensions of banking sustainability in the Indian context. The findings support the emerging perspective that digital transformation, when strategically implemented, can simultaneously enhance financial performance, operational efficiency, customer experience, and environmental outcomes.

Second, the study advances theoretical understanding of the mechanisms through which digital capabilities translate into sustainability outcomes. By identifying specific pathways and potential threshold effects, the research moves beyond simple correlation to explore how and why digital transformation influences different sustainability dimensions.

Third, the proposed DSFIB framework extends existing models by integrating contextual factors specific to the Indian banking environment. This contextualization enhances the explanatory power of digital sustainability theory in emerging market settings, where institutional arrangements, market dynamics, and technological infrastructure differ from developed economies.

Fourth, the research contributes to the growing field of digital sustainability by quantifying the relationships between specific digital capabilities and sustainability outcomes. The regression analyses demonstrate that digital maturity explains 41-47% of variance in financial performance metrics, 38-52% of variance in operational efficiency indicators, and 28-38% of variance in environmental performance measures. These findings provide a more nuanced understanding of the differential impacts of digital transformation across sustainability dimensions.

Practical Implications

For banking executives and strategic planners, this research provides evidence-based guidance for sustainable digital transformation. The findings suggest that digital investments deliver multi-dimensional sustainability benefits, but require strategic alignment and balanced implementation to maximize positive outcomes.

The identified challenges and potential trade-offs offer important considerations for implementation planning. Banks should particularly address cybersecurity risks, inclusion barriers, and workforce transition issues to ensure that digital initiatives contribute positively to long-term sustainability.

Sharma and Goyal (2022), in their research published in the International Journal of Banking, Risk and Insurance, emphasize that sustainable digital transformation requires robust risk management frameworks that anticipate emerging cyber threats and compliance challenges. Our findings align with this perspective, highlighting the need for proactive risk management as a core component of digital sustainability.

For regulators and policymakers, the findings highlight the importance of creating an enabling environment for sustainable digital banking while addressing potential risks. Policy frameworks should balance innovation incentives with appropriate safeguards for consumer protection, data security, and market stability.

The quantitative analysis provides specific benchmarks that banking executives can use to assess their digital transformation initiatives. For example, the finding that HDM banks achieve 54.8% lower transaction costs and 48.4% smaller physical footprints offers concrete targets for operational and environmental improvements. Similarly, the identified 63% higher Net Promoter Scores among HDM banks provides a quantifiable customer experience goal for digital transformation programs.

Limitations and Future Research Directions

This study has several limitations that create opportunities for future research. First, while the 10-year timeframe provides valuable longitudinal insights, the rapid pace of technological change means that future developments may create new sustainability dynamics not captured in historical data.

Second, the focus on formal banking institutions excludes emerging fintech players and non-bank financial entities that increasingly influence the digital banking landscape. Future research should explore sustainability implications across the broader financial ecosystem.

Third, while the mixed-methods approach strengthens the validity of findings, the quantitative metrics for some sustainability dimensions (particularly social and environmental aspects) remain imperfect. Further development of measurement approaches would enhance future studies.

Reddy and Agarwal (2023), writing in the Journal of Commerce and Accounting Research, note that future research should explore how emerging technologies like artificial intelligence, blockchain, and quantum computing might reshape sustainability paradigms in banking. Our findings support this direction, suggesting that next-generation technologies may create both opportunities and challenges for sustainable banking operations.

Promising directions for future research include examining how digital transformation interacts with macroeconomic conditions to influence banking sustainability, exploring regional variations in digital sustainability patterns within India, and conducting comparative studies across different emerging market contexts.

Conclusion

This research provides comprehensive evidence that digital transformation significantly influences the multi-dimensional sustainability of Indian banks. The findings demonstrate that digitally mature banks generally outperform less digitally advanced peers across financial, operational, customer experience, and environmental metrics, though with important nuances and potential trade-offs.

Our quantitative analyses specifically answer the five research questions posed at the outset:

- Digital transformation positively influences financial sustainability, with HDM banks demonstrating 23% higher ROE and 30% better cost-to-income ratios compared to LDM banks.
- Digital initiatives significantly enhance operational efficiency, with HDM banks achieving 54.8% lower transaction costs, 139.5% higher transactions per employee, and 38.3% lower operational expenses compared to LDM banks.
- Digitalization substantially improves customer relationships, with HDM banks showing 63% higher Net Promoter Scores and 45% better customer engagement, though with potential trade-offs in serving certain market segments.
- Digital transformation yields positive environmental outcomes, with HDM banks demonstrating 73.9% lower paper consumption, 34.3% reduced energy usage per transaction, and 28.2% lower carbon emissions per employee.
- The DSFIB framework offers a comprehensive strategic approach for sustainable digital transformation, with empirical testing showing 37% higher sustainability scores for banks implementing balanced transformation strategies.

The Digital Sustainability Framework for Indian Banking (DSFIB) offers a structured approach for aligning digital initiatives with holistic sustainability objectives. The framework emphasizes the importance of balanced progress across all sustainability dimensions rather than narrow optimization of individual metrics.

As the Indian banking sector continues its digital evolution, attention to sustainability considerations becomes increasingly critical. Banks that strategically integrate digital capabilities with sustainability objectives will be better positioned to create enduring value for stakeholders and contribute positively to India's economic, social, and environmental development.

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Evolution of ESG Risk Management in Brazil

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Abstract

This study examines how insurance consumers and insurers in Brazil perceive and address environmental, social, and governance (ESG)[1] risks from 2015 to 2022, generating insights for insurance management in relation to extreme events in Brazil in 2024, through a survey administered via email to 505 executives in insurance companies. From 113 responses and structural equation modelling (SEM), our findings reveal a significant increase in awareness of ESG risks among both consumers and insurers. The results underscore consumers' social risk perceptions as a critical factor driving the integration of ESG considerations into insurance operations. In addition, a positive relationship is identified between consumer perceptions and insurers' ESG risk management practices. The SEM explains 86% of the variance in the incorporation of social risks, 66% in governance, and 63% in environmental risks within insurance practices. This paper enhances our understanding of ESG risk perceptions' influence on both the demand and supply of insurance, providing valuable insights for the development of sustainable insurance practices.

Keywords: Sustainable Development, Innovative Insurance, Green Insurance, ESG Risks, PSI, Brazil

Introduction

The United Nations Environment Programme Finance Initiative (UNEPFI), with bankers and insurers with assets exceeding USD100 trillion, worked together to create the UNEPFI's Principles for Responsible Banking and Principles for Sustainable Insurance (PSI) as well as net-zero alliances (UNEPFI, n. d.). *The global status of sustainable insurance* set a foundation for the definition of sustainable insurance (SI) and integration of environmental, social, and governance (ESG) issues in the insurance industry (UNEPFI, 2009).

This paper focuses on SI from the perspective of insurance consumers and ESG risk management and underwriting in insurance companies to evaluate its evolution since 2015 in Brazil. We view SI as a strategic approach that encompasses all activities in the insurance value chain (UNEPFI, 2012) and a process (Scordis et al., 2014; UNEPFI, 2009) that can drive innovation and business opportunities, and affect (positively or negatively) corporate reputation and financial performance (International Insurance Society [IIS], 2021; Sunelwala et al., 2022).

The insurance industry's ESG agenda has accelerated since the 2015 Paris Agreement at the United Nations' Conference of the Parties (COP21) (Stricker et al., 2022). Soon after COP21, the Task Force on Climate-Related Financial Disclosures (TCFD) was established to provide guidance for asset managers, investors, and insurers to disclose and mitigate climate risks (TCFD, 2017, 2022).

Relevance

The global insurance industry's assets reached USD40.6 trillion in 2021 (Statista, 2022). Global insurance premiums exceeded USD7 trillion in 2022 (Swiss

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[1] All acronyms are available in the glossary Appendix 1

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Re, 2022a). The United States of America (USA) accounted for 56.2% of the Organisation for Economic Co-operation and Development's (OECD's) insurance market in 2020, issued premiums of USD2.934 trillion and paid USD1.615 trillion (55%) in claims (OECD, 2022). In 2022, the Brazilian insurance industry had assets of around USD345.02 billion[2], issued premiums of USD118.61 billion and paid 71.8% of this value in claims and benefits (National Insurance Confederation [CNseg], 2022b). Brazil is the leading insurance market in Latin America, with 41% of the premiums issued in the region (Swiss Re, 2022b). According to the CNseg sustainability report, 93.5% of the participants of the research are committed to at least one sustainable development initiative such as the sustainable development goals (SDG), PSI, United Nations (UN) Global Compact, and Principles for Responsible Investment (PRI) (CNseg, 2022b).

Literature Gaps

Recent literature indicates that the number of ESG regulations in financial services has increased (European Banking Authority [EBA], 2018; IIS, 2021; Marcoux, 2021). There has also been a burgeoning growth in papers in sustainable banking (Chandran et al., 2023), development of green insurance products (Pugnetti et al., 2022; Stricker et al., 2022; Zona et al., 2014), and an emphasis on analysing climate-related risks (Allianz & Euler Hermes, 2020; Nobanee et al., 2021, 2022; Pugnetti et al., 2022; Stricker et al., 2022).

Few studies have examined South America's insurance market. The articles usually provide little more than a snapshot of SI (Khovrak, 2020; Stricker et al., 2022). Some articles have examined the relations between risk perception and insurance demand (Mendes-Da-Silva et al., 2021; Regan, 2019); however, since Nogueira et al. (2018) no other study has assessed the relations between the ESG risks perceptions of insurance consumers and its incorporation in insurance companies' operations.

The present study aims to answer the following research questions:

- How have ESG risks perceptions evolved between insurance consumers and insurers since 2015?
- How has ESG integration in insurance products and operations evolved since 2015?
- Are there gaps between ESG risks materiality and insurance products coverage?
- Can consumers' perceptions of ESG risks explain the incorporation of ESG risks in insurance companies' operations and products?
- How do insurers' operations integrate ESG risks?

Our findings show an increase in perceptions of ESG risks among insurance consumers and insurers between 2015 and 2022 in Brazil.

The structural equation modelling (SEM) was able to include all ESG constructs explaining 86% of the variance of the incorporation of social risks in insurance operations, 66% in governance, and 63% in environmental risks. The social risks construct was the main driver of consumers' ESG risk perceptions.

The remainder of this article is organised as follows: section 2 presents the background of the study, section 3 the model proposition and hypotheses, section 4 the methodology, section 5 the results and discussion, and section 6 our concluding remarks.

Background

Sustainable Insurance

The theory to support corporate allocations to SD was initially defined as corporate social responsibility (CSR) in stakeholder theory (Freeman, 1984; Johnson, 1971). Some authors opposed this vision of shareholder theory (Friedman, 1970) in which ESG performance limits financial benefits for companies because of the implementation costs that shareholders must pay and restrictions on investments areas.

This controversy is still in place (Bottenberg et al., 2017; Brogi et al., 2022) but has evolved into the concept of shared value creation in policies and operating practices that enhance competitiveness related to innovation and growth (Porter & Kramer, 2018). In *Reimagining capitalism in a world on fire* (Henderson, 2020), the author highlights insurance companies' role in the context of extreme climate events and the positive effects of ESG initiatives on financial results.

[2] Exchange rate USD to BRL was 5.2171 on 31 December 2022; Source: Brazil Central Bank.

Nogueira et al. (2018) present a timeline for sustainability in financial services starting in 1992 with the creation of the UNEPFI. SI was discussed in *The global state of sustainable insurance* (UNEPFI, 2009) and the PSI (UNEPFI, 2012). SI calls for strategic ESG risk management (Scordis et al., 2014; Shea & Hutchin, 2013, 2018) and a new underwriting approach (Pugnetti et al., 2022).

Green insurance has been defined as an innovative promise of business sustainability practices and product development (Nobanee at al., 2021; Pugnetti et al., 2022; Stricker et al., 2022). Green insurance products encompass green building insurance, weather insurance, green car insurance, and renewable energy insurance (Zona et al., 2014).

SI as a business and social process, evolved as ESG risk (extreme weather events, cyberattacks, social demands, and health treats, among others) perceptions grew, necessitating the creation of new products and regulations. In this section we provided a snapshot of the literature on this issue until 2022.

ESG Risk Management

Value creation in insurance is grounded in good risk management in the following sequence: risk discovery, quantification, control/mitigation, financing, and monitoring. Accepting risks before following these steps in underwriting and risk management can destroy value for insurers (UNEPFI, 2009; Shea & Hutchin, 2018). Initially considered emerging ESG risks Shea and Hutchin (2013) has now their impacts known Stricker et al. (2022) being classified as an established risk.

Swiss Re (2022c) estimated that natural catastrophes caused an estimated USD115 billion in insured losses in 2022 (above the 10-year average of USD81 billion). Ceres (2020) sees ESG risks as systemic with the potential to destabilise capital markets with serious negative consequences for financial institutions and the broader economy. Climate change and the COVID-19 pandemic are examples of systemic risk. Climate risks are highly interconnected with other ESG factors. For example, climate crises displaced 26.4 million people every year between 2008 and 2015; 50 to 700 million people will be forced to migrate by 2050 (Ceres, 2020).

Empirical studies (Giese et al., 2019; Sonnenberger & Weiss, 2021) show that companies with better risk control standards and high ESG ratings suffer less frequently from severe incidents such as fraud, embezzlement, corruption, and litigation cases. They also tend to show higher profitability and lower exposure to tail risk and short- and medium-term exposure to systemic risk.

According to Ceres (2020), ESG risks spread from environmental issues related to threats to the planet (glaciers ice melting, wildfires, biodiversity loss, and ocean and river pollution) to humans in the form of injuries and deaths due to extreme events (heat waves, floods, and storm surges), damage to property, and global warming that destroys buildings and reduces the lifespan of concrete structures. These concerns are reflected in environmental accounting for the management for biodiversity conservation (N, Ashok, & Tailor, 2021). In 2021, PSI developed a climate risks assessment model (PSI, 2021) that was customised to Brazil in 2022 (CNseg 2022a). According to UNEPFI (2021), insurance and reinsurance companies are targeting net-zero greenhouse gas (GHG) emissions by 2050.

Although climate change has gained the spotlight in the last years, other ESG risks, such as social vulnerability, cyberattacks, biodiversity loss, and ageing populations, have also emerged (Allianz, 2022; Bouten et al., 2017; Gatzert et al., 2020; Nogueira et al., 2018; UNEPFI, 2009). Nobanee et al. (2022) identified the need for international collaboration to help countries outside Europe and the USA to understand and mitigate the impacts of climate change and encourage the possible transition towards a low carbon economy. Regulators worldwide are also urging banks, asset managers, and insurance companies to disclose and manage ESG risks such as climate change, social exclusion, hunger, poverty, and income disparities (Superintendence of Private Insurance [SUSEP], 2022; Ziolo, 2020).

Insurance industry associations such as the National Association of Insurance Commissioners, the United Kingdom Prudential Regulation Authority, and the European Insurance and Occupational Pensions Authority have requested the inclusion of ESG risks management in company strategies, products, and services, and governance transparency (Marcoux, 2021). In Brazil, SUSEP's circular letter no 666 outlines a timeline for insurance companies to address ESG risk in their products and operations (SUSEP, 2022).

Model Proposition and Hypotheses

This study's model constructs are based primarily on those of Nogueira et al. (2018) and UNEPFI (2009). The constructs have been improved using the ESG risk taxonomy for financial services (EBA, 2018) adapted for the insurance industry and other variables (UNEPFI, 2009). Dependent variables are based on the ESG pillars, but there is no unique standard of indicators to assess ESG issues. Khovrak (2020) compared the ESG ratings of major ESG rating agencies. Morgan Stanley Capital International (MSCI) identified 35 ESG issues around 10 themes; Bloomberg ESG Data Service uses 120 indicators; and RepRisk uses 95 ESG factors.

The insurance industry assesses sustainability around ESG risks (Shea & Hutchin, 2013, 2018; UNEPFI, 2009). To compare the results of this survey with those of Nogueira et al. (2018), we start with the structure used in that survey and improve the questionnaire by refining definitions of each ESG risk.

Table 1 presents the relations between the 12 variables used by Nogueira et al. (2018) and the 23 used in this survey. To assess insurance consumers' perceptions, respondents must answer the statement: *We can state that the insurance consumer identifies as very important the risks associated with* ... the 23 ESG risks issues. For insurer's perceptions of their own insurance company, the respondent must answer the statement: *We can state that our organisation fully incorporates into its operations the ESG risks associated with* ... the 23 ESG risks issues proposed. The full questionnaire is available in Appendix 2. In the SEM and descriptive statistics, the variables begin with C for consumers and I for insurers, followed by E for environmental risks variables, S for social, and G for governance risks.

Table 1: ESG Risk Variables: Nogueira et al. (2018) vs This Study

ESG Risks Construct	*Nogueira et al. 2018*	*2022*
Environmental	Climate Change	CE - COEQ Emissions
		CE - Extreme Events
	Biodiversity Loss & Ecosystem Degradation	CE - Ecosystem Degradation
		CE - Biodiversity Loss
	Water Management	CE - Water Usage
		CE - Water Acess
	Pollution	CE - Polution Continued
		CE - Polution Acute
Social	Financial Inclusion	CS - Financial Inclusion
	Human Rights	CS - Human Right fault
	Emerging Man-Made Risks	CS - Emerging Health Risks
	Health Risks and Ageing Populations	CS - PopHealthPromot
		CS - AgeingPopulation
Governance	Regulations	CG - Regulatory Standards
		CG - Reg Standards Publicity
	Disclosure	CG - ESG Publicity to stakeholders
		CG - ESG Publicity to stakeholders - Frequency
		CG - Ethic CodePublicity
	Ethics & Principles	CG - Ethic Code to Stakeholders
		CG - Ethic Code exceed Regulations
		CG - Ethic Code Check
	Alignment of Interests	CG - Interest aling to Stakeholder
		CG - Interest aling to Employee

This study investigates the relations between consumers' ESG risk perceptions and the inclusion of ESG risks in the insurance companies' operations and products. Many studies have analysed ESG and financial performance (BaFin, 2019; Henderson, 2020). For a review of ESG risks versus financial performance in the insurance industry see Brogi et al. (2022) and Xhafa (2023).

Various studies have identified a positive correlation between ESG performance and key performance indicators. Koh et al. (2022) found positive effects of consumers' ESG management on brand image, product quality, and purchase intention in South Korean insurance companies. Lee et al. (2017) also found that CSR activities enhance brand image, corporate reputation, and customer loyalty in Taiwan non-life insurance industry. UNEPFI (2009) recommended the integration of material[3] ESG factors into core insurance processes, products, and strategy. Shea and Hutchin (2018) concluded that companies should prioritise social and governance in universal ESG underwriting guidelines. Mendes-Da-Silva et al. (2021) found that exposure to risks (from domestic violence to extreme climatic events) increases risks perceptions and insurance demand. Nogueira et al. (2018) found a positive correlation between consumers' ESG risk perceptions and the incorporation of environmental risks in insurance companies' operations.

These studies suggest positive relations between ESG risk perceptions from consumers and product development and inclusion of these risks in operations. The constructs were designed through ESG risks perceptions from consumers and insurers, respectively. Our hypotheses are:

Hypothesis 1: Consumers' perceptions of environmental (CE) risks are associated with the incorporation of environmental risks in insurance operations (IE).

Hypothesis 2: Consumers' perceptions of social risks (CS) are associated with the incorporation of social risks in insurance operations (IS).

Hypothesis 3: Consumers' perceptions of governance risks (CG) are associated with the incorporation of governance risks in insurance operations (IG).

Hypothesis 4: Company size is associated with the inclusion of ESG risks in operations and products.

The constructs of consumers' ESG risks perceptions were labelled CESGR and for insurers IESGR.

Studies that analysed the demand for flood insurance (Landry & Turner, 2020; Mendes-Da-Silva et al., 2021) show a positive correlation between risk perception and demand for insurance and product development (Huang et al., 2022; Shea & Hutchin, 2018), suggesting a positive relation between environmental risk perception and insurance (CE => IE), also the evolution of underwriting processes.

Pugnetti et al. (2022) found that insurance customers are requiring more involvement in sustainability from their insurers, resulting in an increase in demand for more transparency and new products in traditional (health and life) insurance as well in new areas (climate and cyber risks). The incorporation of these risks is increasing the need for risk management and governance (Committee of Sponsoring Organizations [COSO] and World Business Council for Sustainable Development [WBCSD], 2018). The literature suggests a positive relation between consumers' social risk perceptions and social risk management by insurance companies and supports the hypothesis (CS => IS).

Yu et al. (2019) found a strong and positive relationship between risk perception, social norms, and pro-environmental behaviour. This relationship extended to individuals' intentions to engage in pro-environmental actions, such as purchasing risk financing products (for example, flood insurance) in response to the challenges posed by climate change. Thus, we expect a positive relation between consumers' environmental and social risk perceptions and insurance companies' operations (CE => IE; CS => IS).

Insurance company policyholders, third parties, reinsurers, as well as supervisors and shareholders are requiring more transparency in ESG risk management (Anderloni et al., 2020; Huang et al., 2022; Regan, 2019; TCFD, 2017). Thus, we expect a positive relation between consumers' perceptions of governance risks and insurance companies' operations (CG => IG).

[3] Material risks are the ones that have impacts on corporate financial or marketing performance.

Dorfleitner et al. (2015) compared ESG ratings databases (ASSET4, Bloomberg, KLD) and found that large companies tend to receive better ESG scores in the ASSET4 rating. Scholtens (2011) used Spearman rank correlation and found a positive relation between CSR performance and company size in the insurance industry, although other authors found no relation between size and CSR performance (Çera et al., 2020; Nayak & Venkatraman, 2011). Sung et al.'s (2022) empirical studies demonstrated that CSR for national causes has a positive impact for large companies, while local causes benefit smaller companies. These findings suggest the relation between insurance company size and ESG performance (Size => IESGR) varies according to regions and market conditions.

Fig. 1 presents the theoretical model to evaluate the relations between consumers' and insurers' ESG risks perceptions. This model is supported by previous studies (Nogueira et al., 2018; Shea & Hutchin, 2013, 2018; UNEPFI, 2009). The lines in Fig. 1 indicate the expected positive relationships.

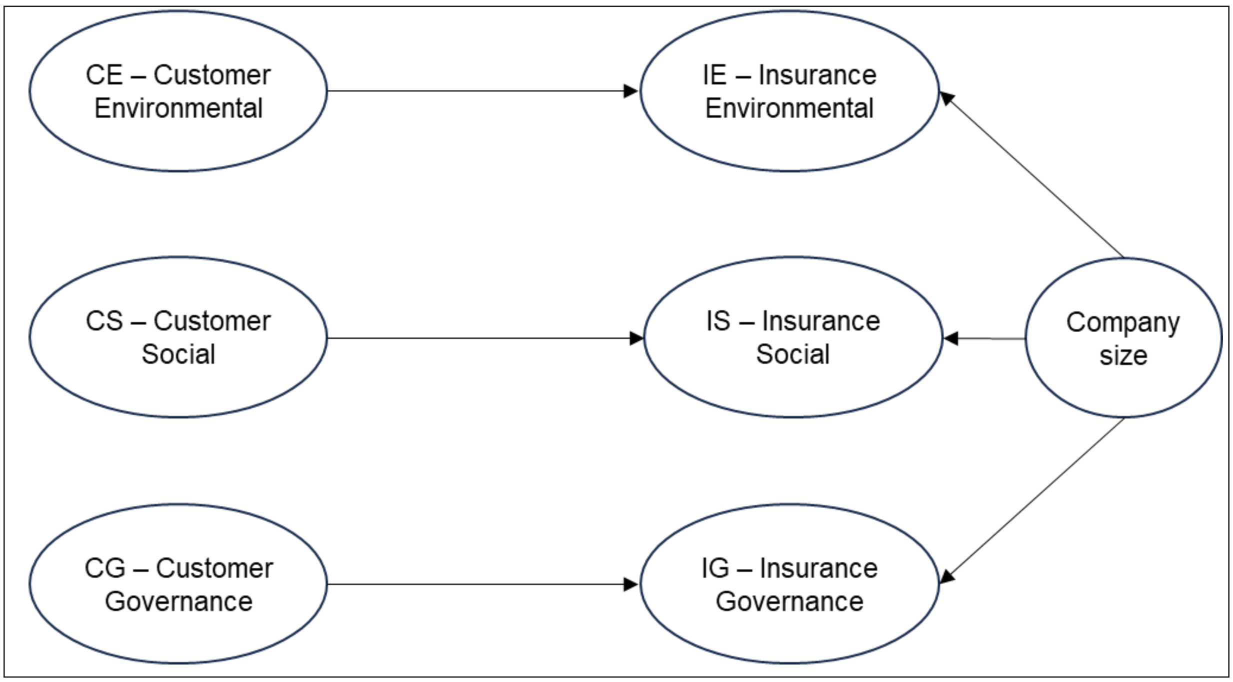

Fig. 1: Proposed Model

Method and Sample Description

A survey was designed and conducted using a standardised questionnaire (Babbie, 2001) to assess insurance professionals' perceptions of their consumer's behaviour towards ESG risks and the incorporation of ESG risks in their company operations. The instrument was developed based on the Nogueira et al. (2018) questionnaire and the questions were based on other studies (Shea & Hutchin 2013, 2018; UNEPFI, 2009). For example, Nogueira et al. (2018) use the following question to address climate change risk:

How does the insured manage the risks associated with climate change (e.g., increased frequency and severity of floods, hurricanes, windstorms, droughts, and other weather-related events), including the management of its greenhouse gas emissions?

The question does not identify a specific risk category (extreme events or GHG emissions). Our study focuses on perceptions of the importance of the risk for consumers and insurers in just one risk category (Mendes-Da-Silva et al., 2021; Regan, 2019). To improve the discrimination of each question we formulated specific affirmations, as follows:

Answer the questions considering your perception of the insurance consumer. We can state that the insurance consumer identifies as very important the risks associated with: Question 1: Greenhouse gases emissions; Question

2: Extreme natural events (storms, floods, droughts ...).

These changes make the questionnaire move from 12 to 23 questions. We also changed the scale from a ESG risk underwriting progress scale to a traditional seven-point Likert scale (Likert, 1932). (1 = completely disagree to 7 = completely agree; both scales have seven levels to enable comparisons).

Data were analysed using SEM; therefore, the results are both descriptive and causal (Byrne, 2010; Hair et al., 2009). The survey instrument was developed and tested for validity and reliability in accordance with Aaker et al. (1997), Churchill (1979), and Hair et al. (2009).

Content validity was achieved using face-to-face pre-tests with seven specialists to identify potential problems and improve the questionnaire. Convergent validity was assessed by means of a confirmatory factor analysis (CFA) using the procedures recommended by Kline (1998) and Byrne (2010). Discriminant validity was assessed by the Fornell–Lacker criteria of comparison among squared Average Variance Extracted (AVE) values with the constructs' correlations. Composite reliability and Cronbach's alpha were used to test for internal consistency reliability, observing values above 0.70 (Bagozzi et al., 1991; DeVellis, 1991).

The final questionnaire was administered via email to 505 executives in insurance companies by CNseg[4] and insurance communities on LinkedIn. Of these, 148 responded to the invitation to participate, 113 responded to all the questions on insurance consumer and insurer ESG risks perception, and 66 responded to the full questionnaire including questions on ESG risks materiality.

Next, we asked the 66 respondents who completed the whole questionnaire to answer a single question: *Overall, can we say that your organisation has a completely sustainable ESG risks management strategy?* We received 13 responses and compared the results with the mean of their answer to the questionnaire's 23 questions. The Student's t-test with a 1% significance level showed no difference between the means, suggesting consistency in the questionnaire responses.

[4] CNseg represents 98.6% of the companies supervised by SUSEP (property and casualties) and 37.6% of the health insurance market.

The final sample used in SEM consisted of 84 questionnaires with complementary external information. Respondent profiles can be seen in section 4.1. Data were analysed by univariate descriptive and multivariate statistics. SEM was used to test the hypotheses using the procedures and parameters recommended by Hair et al. (2009) and Byrne (2010). SPSS 26 and Amos 28 software were used for the analysis.

Each construct is reflexive, manifesting itself on at least three observed variables. For hypothesis testing Amos 28 was used to assess the SEM proposed. Several other statistical analyses were also produced, enabling sample description as well as the insurance market characteristics.

Sample Description, Univariate Analysis, and Construct Validity and Reliability

At the end of 2021, the Brazilian insurance market had 161 insurance companies, 940 health plan operators and private insurance healthcare, 13 open private pension entities, 16 capitalisation companies, and 146 reinsurance companies. The market is very concentrated. The top 10 property and casualty insurance companies have 71.6% of the market share, 92.4% for life and pensions, and 47.9% for healthcare (CNseg, 2022b).

The descriptive analysis is based on 113 complete observations of ESG risk perception. The sample is not statistical, since it was obtained by convenience due to accessibility, so it is not possible to infer population data from it. Nevertheless, the sample contains responses from 40 insurance corporations that account for 65% of the general insurance premiums issued by companies supervised by the private insurance regulator SUSEP in 2022 (SUSEP, n. d.), so it can be considered representative of Brazil's insurance industry.

The respondents have on average 15 years' professional experience. Women are 43% of the sample, an increase from 37% in 2015 as observed in other studies (Koh, et al., 2022; Monteiro and Galiza, 2022; MSCI, 2022). The respondents' demographic details are presented in the following tables: age (Table 2), employer (Table 3), academic training (Table 4), function (Table 5), and job position (Table 6). Statistics on insurance professionals of the entire industry were obtained from Monteiro and Galiza (2022).

Table 2: Respondents by Age and Gender

Age Range	Women	Men	All
Less than 30 years	4%	13%	9%
From 30 to 39 years	55%	28%	40%
From 40 to 49 years	18%	20%	19%
From 50 to 54 years	10%	16%	13%
More than 55 years	12%	23%	19%

Note: The respondents are older than the industry (4% of women and 6% of men have more than 55 years).

Table 3: Respondents by Employer and Gender

Employer	Women	Men	All
Insurance company	92%	81%	86%
Insurance broker		5%	3%
Insurance Confederation - Cnseg	6%	9%	6%
Not identfied	2%	5%	5%

Table 4: Respondents by Academic Training and Gender

Academic Training	Women	Men	All
PHD	6%	4%	4%
MSC	18%	19%	19%
Graduate	76%	77%	77%

Note: The respondents had a higher level of academic education than the industry where 13% had PhD/MSc.

Table 5: Respondents by Job Position and Gender

Job Position	Women	Men	All
Director	8%	19%	14%
Manager	43%	44%	43%
Clerk	49%	38%	42%

Note: The proportion of directors increased from 11% in 2015 to 14% and for managers from 34% to 43%.

Table 6: Respondents by Job Function and Gender

Job Function	Women	Men	All
Underwriter	20%	28%	25%
Business executive	6%	20%	14%
Sustainability manager	16%	3%	9%
Product development	6%	8%	7%
Sales and Marketing	6%	3%	4%
Treasury	0%	5%	3%
Others	45%	33%	38%

Note: The proportion of underwriters increased from 19% in 2015 to 25% and the proportion of sustainability managers from 2% to 9%.

The descriptive statistics of the ESG risks perceptions of insurance consumers and insurers can be seen in Appendix 3. The sample was older than in the market average, consistent with the higher job positions and academic training. We also observed a greater participation of women, sustainability managers, and underwriters.

Result and Discussion

Evolution of ESG Risk Perceptions

To compare the evolution of insurance professionals' perceptions on ESG risks since 2015 we performed an Analysis of Variance (ANOVA) procedure on the ESG constructs (rescaled 1 to 10 for a better understanding) as shown in Table 7.

Table 7: ESG Risks Perceptions of Consumers and Insurers

Construct	2022	2015	Difference
Consumer Env	7,228	5,903	1,325
Consumer Soc	7,387	6,349	1,038
Consumer Gov	8,024	6,256	1,768
Insurer Env	7,697	7,080	0.617
Insurer Soc	8,186	7,958	0.228
Insurer Gov	8,944	8,866	0.078

Consumers ESG risk perceptions were higher than in 2015, consistent with findings of other publications (Koh, 2022; MSCI, 2022) and the demand for environmental insurance. The increase in the intensity and frequency of extreme events in Brazil (Salvador & Brito, 2018; Souza & Silva, 2021) increased consumers' ESG risk perceptions (Mendes-Da-Silva et al., 2021; Souza & Silva, 2021).

From an insurers' perspective, environmental risk shows a significant increase, consistent with the growth in environmental liability insurance (see Fig. 2). The increase in insurers' perceptions of social and governance risks since 2015 is consistent with the increase in industry regulations (SUSEP, 2022; UNEPFI, 2009). The decrease in differences among CESGR and IESGR between 2015 and 2022 is consistent with the increase in consumers' ESG risk perceptions (Koh, 2022; MSCI, 2022).

ESG Risks Underwriting

The underwriting process starts with risk identification, followed by risk quantification, then definition of mitigations measures, and finally the risk transfer through the issuing of an insurance policy (UNEPFI, 2009). According to CNseg sustainability reports, the incorporation of ESG risks in the underwriting process has grown consistently from 19% to 60% of companies over the past decade in the Brazilian insurance industry (CNseg 2022b).

Respondents evaluated the underwriting process, according to the scale proposed by UNEPFI (2009): *This ESG risk is*:

- Not a factor;
- Emerging concern not supported by evidence;
- Social concern of few;
- Social concern of more;
- Evidence supported movement;
- Developing regulatory or legal framework;
- Developed regulatory or legal framework.

Table 8: Underwriting Evolution on ESG Risk Factors

ESG Risk Factor	*Underwriting Progress*	
	2022	*2015*
Climate Change - CO2EQ Emissions	3.99	4.73
Climate Change - Extreme events	4.99	4.73
Ecosystem Degradation	4.03	4.73
Biodiversity Loss	3.93	4.73
Water Management - Water usage	3.88	5.12
Water Management - Water access	3.77	5.12
Pollution Continued	3.97	5.11
Pollution Acute	4.03	5.11
Disclosure	4.39	6.22
Financial Inclusion	4.18	5.21
Health Risks and Ageing Populations	4.01	5.21

The evolution of climate risks underwriting was expected due to the greater incorporation of environmental risks in underwriting in Brazil (CNseg 2022b) and an increase in extreme climate events (tornadoes and floods) and insurance demand (Mendes-Da-Silva et al., 2021; Salvador & Brito, 2018; Souza & Silva, 2021) as shown in Fig. 2. Although not significant, some results in Table 8 suggest less progress in underwriting in 2022 versus 2015 in four of seven risks, which seems odd. However, this result is consistent with Table 7 and shows significantly greater growth in consumers ESG risks perception constructs than the incorporation of these risks in insurers' products and operations. Another possible explanation is the new ESG regulations (SUSEP, 2022) that require the integration of ESG risks in products and operations, which created a perception of the need for more advanced underwriting practices.

The rise in perceptions related to global warming and extreme climate events risks can be linked to losses caused by natural disasters, estimated at USD115 billion in insured losses in 2022 according to Swiss Re (2022c).

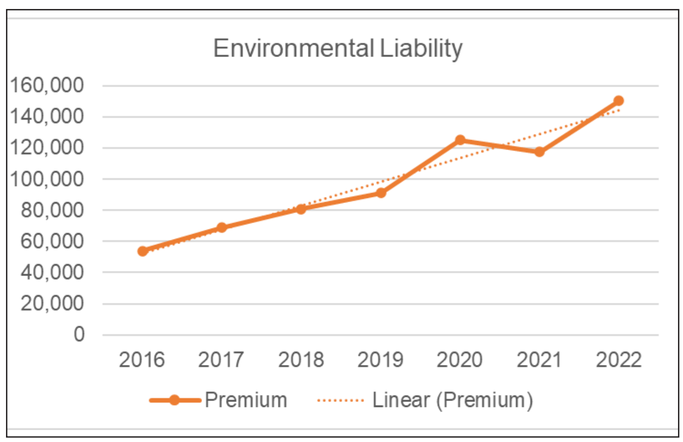

Fig. 2: Evolution of Environmental Liability Insurance Revenues (BRL Thousands)

In Brazil, the floods in Rio Grande do Sul (RS) in May 2024 are expected to result in losses of approximately

BRL90 billion. The disaster left 176 people dead and displaced 617,900 others. By 18 June, claims had reached BRL3.886 billion (CNseg, 2024). The flood in Porto Alegre city was partly due to poorly maintained floodgates. Pump houses and pumping stations were also flooded (Agencia Brasil, 2024). This region had many insured houses, businesses, and automobiles. The insurance industry could have provided early warnings, not only to its customers, but also to public authorities.

In 2015, the Mariana dam broke leaving 19 dead with insured claims of USD600 million. On 18 October 2024, Vale S A informed that Samarco Mineração S A and BHP Billiton Brasil Ltd reached a definitive agreement with the government in Brazil for the full reparation of the rupture of the Samarco Fundão (Mariana) dam in the total amount of BRL170 billion (USD29.85 billion[5]) (Vale Chega a Acordo Definitivo Com O Poder Público No Brasil Para a Reparação Integral Do Rompimento Da Barragem De Fundão Da Samarco, n.d.).

In 2019, the Vale Brumadinho dam broke leaving 23,000 people affected and 272 dead, generating agreements of BRL1.3 billion and a reparation agreement of BRL37.6 billion, with BRL500 million to be borne by the insurance market. Prosecutors charged 21 persons with qualified homicide (Defensoria, 2023). Both Brumadinho and Mariana were tragedies caused by known problems with the dams; both had insurance. Good ESG risk mitigation procedures and underwriting could have avoided, or at least reduced, the losses for the insurance companies, society, and the environment.

Green Insurance Opportunities

We took environmental liability insurance as a proxy for environmental risks demand (Fig. 2). The growth in premiums issued is consistent with greater environmental risks perceptions (Table 7), the evolution of the underwriting process (Table 8), and insurance demand (Mendes-Da-Silva et al., 2021).

Table 9: ESG Risk Materiality × Product Availability – Materiality GAP

ESG Risk Factor		*The Risk is Material*		*Product Availability*		*Risk Materialty Minus(-) Product Availability*		*Product Group with Greater Materiality*	
2015	*2022*	*2022*	*2015*	*2022*	*2015*	*2022*	*2015*	*2022*	*2015*
CGH Emissions and Extreme Events	Climate Change GHG Emissions	76%	62%	13%	37%	63%	25%	ER	PR
	Climate Change Extreme events	85%	62%	64%	37%	21%	25%	ER	PR
Ecosystem Degradation and Bio. Loss	Ecosystem Degradation	62%	53%	18%	15%	44%	38%	ER	ER
	Biodiversity Loss	53%	53%	11%	15%	42%	38%	ER	ER
Open Water Access and Usage	Water Usage	52%	45%	10%	13%	42%	32%	ER	ER
	Water Acess	55%	45%	10%	13%	45%	32%	ER	ER
Continued and Acute Pollution	Pollution Continued	59%	48%	10%	24%	49%	24%	ER	ER
	Pollution Acute	64%	48%	18%	24%	46%	24%	ER	ER
Transparent Governance	Disclosure	55%	34%	8%	24%	47%	10%	ER	PR
Financial Inclusion	Financial Inclusion	73%	55%	40%	40%	33%	15%	PE	PE
Ageing Population	Ageing Populations	68%	77%	39%	40%	29%	37%	HC	PE

The materiality gap is expressed by the difference in percentage of respondents who consider the ESG risk is material and the awareness of product availability to any group of products[6]. ESG risks have different materiality for each group of insurance products (PSI, 2021; UNEPFI, 2009) and varies across sectors and industries (Kaiser, 2020). For example, GHG emissions risk is material for coal mining company liability insurance but not material for home insurance. The product groups (ER, PR, PE) in Table 9 were most frequently identified by respondents as material. The materiality gap provides an industry roadmap for innovative product development. As expected, the risk materiality perception in 2022 is greater

[5] BRL5.698/USD – https://www.bcb.gov.br/estabilidadefinanceira/historicocotacoes

[6] Table 9 presents product lines with a major materiality gap (ER: environmental risks; PR: property and casualty; PE: people/life; HC: healthcare).

than 2015 to all risks but ageing populations, which may be considered an established risk.

Besides extreme events and ecosystem degradation fewer respondents identified available products. This result may be influenced by higher expectations of the respondents in relation to new ESG products as shown in Table 7 and the ESG regulation circular letter nº 666 (SUSEP, 2022).

Constructs Assessment and Hypotheses Testing

The aim of this analysis is to test the hypotheses on the positive relationship between CESGR and IESGR. Insurer's size (SIZE) was operationalised by the Log10 of equities, revenues, profits, and workforce. A final sample of 84 responses was analysed and the constructs were operationalised and checked for validity and reliability.

The face validity was checked on pretesting with both researchers and practitioners that clearly understood the items on the questionnaire and their correct meaning, as discussed in section 4. Convergent validity was assured by the correlation values among constructs and their correspondent items. All values of the average variance extracted were above .700 indicating adequate convergent validity. Reliability was assessed by both composite reliability and Cronbach's alpha values – both above 0.700 for all constructs (Table 10). This instrument covers all ESG aspects and presents improved validity and reliability in comparison with Nogueira et al. (2018).

Table 10: Construct Validity and Reliability

Construct		*Items*	*AVE*	*Comp Reliability*	*Cronbach's Alpha*
CE	Consumer Environment	7	0.760	0.807	0.960
CS	Consumer Social	3	0.747	0.747	0.830
CG	Consumer Governance	6	0.805	0.805	0.952
IE	Insurer Environment	7	0.798	0.834	0.967
IS	Insurer Social	3	0.747	0.747	0.830
IG	Insurer Governance	6	0.782	0.782	0.944
SIZE	Insurance company size	4	0.796	0.796	0.915

Discriminant validity was assessed by both the Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio (Table 11). An HTMT of less than 0.85 is generally considered evidence of discriminant validity (Henseler et al., 2015). Although there is no standard value for discriminant validity, values not greater than 0.85 and ideally less than 0.70 suggest that discriminant validity likely exists between the two constructs.

Table 11: Construct Discriminant Validity

	CE	*CS*	*CG*
CE	0.898		
CS	0.426	0.864	
CG	0.370	0.612	0.897
IE	0.533	0.443	0.349
IS	0.376	0.695	0.500
IG	0.325	0.523	0.599
Size	0.017	0.205	0.182

The SEM was processed using IBM Amos 28 software with the recommendations of Hair et al. (2009) and Byrne (2010) for the procedures, steps, and assessments. The model fit was adequate, and the indices are presented in Table 12.

Table 12: Model Fit of the Indices

Model Fit Indices	*Values*
CMIN/DF: Discrepancy−Chi-square/degrees of freedom	1.882
CFI: comparative fit index	0.861
RMSEA: root mean square of error of approximation	0.103

Fit was examined by means of absolute, incremental, and parsimonious fit measures (see Table 10) and the absolute fit measurement, two-tailed bias-corrected confidence intervals, use CFI and RMSEA. Based on these values, the model was accepted. Path coefficients obtained by maximum likelihood estimation and bootstrapping were used to estimate errors and two-tailed bias-corrected confidence intervals (see Table 13).

Table 13: Hypothesis Testing Results

Hypothesis	*Std Path Coefficients*	*Error*	*P*	*Result*
Size -> IE	0.192	0.159	0.328	Not supported
CE -> IE	0.266	0.154	0.126	Not supported
CS -> IE	0.744	0.300	0.010	Supported
CG -> IE	−0.290	0.194	0.020	Supported
SIZE -> IS	0.136	0.151	0.492	Not supported
CS -> IS	0.885	0.118	0.012	Supported
SIZE -> IG	−0.017	0.100	0.912	Not supported
CE -> IG	−0.120	0.115	0.348	Not supported
CG -> IG	0.316	0.137	0.024	Supported
IE -> IG	0.168	0.187	0.312	Not supported
IS -> IG	0.515	0.237	0.051	Supported

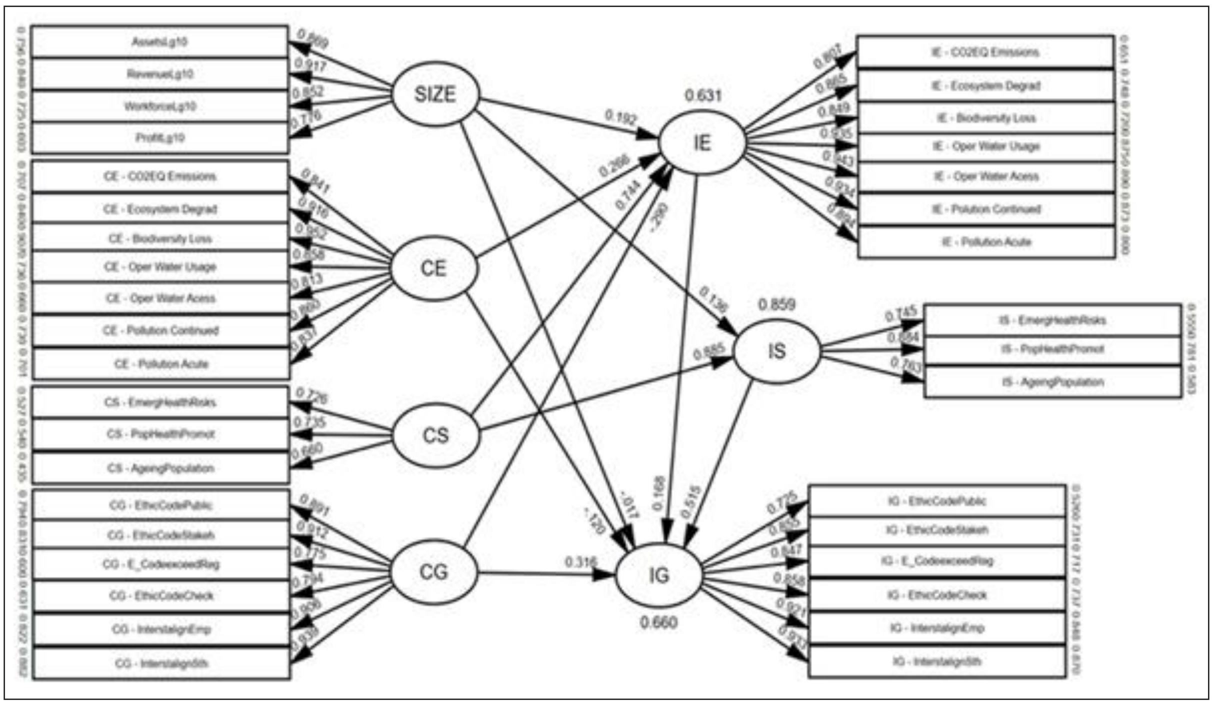

Fig. 3: Model with the Results

The final version of the model measured seven constructs through 36 items. The convergent and discriminant validity construct was accessed using CFA (see Tables 10 and 11). Statistics yielded adequate values, indicating that the constructs and the complete structural model were valid and reliable (see Table 12). SIZE and CESGR constructs explained variances in IESGR constructs (63% of IE, 86% of IS, 66% of IG). These results indicate an improvement on Nogueira et al. (2018) that explained just 28% of IE and 36% of IG variance (see Table 14).

The numbers in Fig. 3 beside the variable's boxes are the loading factors, the arrow points are the path coefficients to the construct represented by an ellipse, and the number close to it shows the amount of explained construct variance.

Two elements contribute to the incorporation of ESG risks into products and operations for insurance companies: first, a developed regulatory or legal framework, which was established in Brazil through Circular Letter No 666 (SUSEP, 2022); and second, the evolving risk perception of consumers, as shown in Table 7. In addition, other studies, such as Yu et al. (2019), have found that pro-environmental behaviour influences risk perception, which supports the capacity of CESGR to explain IESGR.

Table 14: Squared Multiple Correlations of the Dependent Constructs

Construct	*Sq Mult Corr*
IE	0.631
IS	0.859
IG	0.660

A squared multiple correlation of 0.50 or higher indicates a strong relationship, suggesting a 'good' model (Byrne, 2010; Hair et al., 2009).

The ESG factors are interconnected (Ceres, 2020; Nogueira et al., 2018; Shea & Hutchin, 2018; UNEPFI, 2009), which means that the risk perceptions of one ESG risk pillar can be perceived in other pillars.

The positive and significant relations between CS with IE and IS indicates that a greater social concern of ESG risks is driving the incorporation of these risks in insurance products and operations as in UNEPFI (2009). Pugnetti et al. (2022) showed that consumers are demanding new types of coverage in traditional product lines such as health and life insurance, as well cyber risks.

Environmental risks are increasing insurance demand (Landry & Turner, 2020; Mendes-Da-Silva et al., 2021) and improving social risk perceptions as observed in CS=>IE. The positive and significant relation between CG and IE was also captured by Nogueira et al. (2018). The positive relationship between IS and IG are consistent with an increase in demand for ethics and transparency in insurance companies' governance (Anderloni et al., 2020; COSO & WBCSD, 2018; Huang et al., 2022).

Despite inconsistency in ESG scores between service providers (Dorfleitner et al., 2015), some authors have observed a positive correlation between company size and ESG performance (Brogi et al., 2022; Scholtens, 2011). Conversely, other researchers (Çera et al., 2020; Nayak & Venkatraman, 2011) have not identified any significant relationship between these variables. Sung et al. (2022) found that the relationship may vary: it appears to be positive for larger companies when addressing national causes and for smaller companies when dealing with local causes.

Possible reasons why the model did not capture significant relationships between the size of the insurance company and the incorporation of ESG risks into the operations of the insurance companies are:

- SUSEP No 666 defined ESG risk management and reporting requirements for all insurance companies. Although these requirements differ based on the size of the companies, insurance professionals began to demand a greater focus on sustainability as discussed in item 5.2 (Table 8), no matter the size of the company.
- Consumer demands increased for insurance after the COVID-19 pandemic, particularly in relation to health (Agencia Brasil, 2023) and automobile (Reclame AQUI, n. d.) insurance, showing higher levels of satisfaction with smaller insurance companies. This was also observed in the Australian insurance market (Nayak & Venkatraman, 2011).
- The Brazilian insurance market showed a huge movement towards mergers and acquisitions (M&As) in different segments (Luiz, 2022) as well as the development of Insurtech, allowing the offer of green insurance for small companies (Redação, 2022).

Concluding Remarks

This paper examines the relationship between insurance consumers' ESG risk perceptions and the incorporation of these risks in the insurance companies' operations and products evolution between 2015 and 2022 in Brazil. Our sample comprised responses from 113 professionals across 40 insurance corporations, which collectively account for 65% of the premiums issued by SUSEP-supervised companies in 2022 (SUSEP, n.d.).

The sample description presented in section 4.1 shows an increase in the number of female respondents in 2022 versus 2015. Respondents are older and senior than in the market (Tables 2 and 5). The participation of underwriters and sustainability managers also increased. This profile suggests that professionals with higher ESG requirements may explain the lower (although not significant) progress in underwriting, as shown in Table 8.

Consumers' and insurers' environmental risk perceptions had increased since 2015 (Table 7). Among environmental risks, GHG emissions and extreme climatic events increased in the underwriting process (Table 8) and insurance demand (Fig. 2).

The final version of the model (Fig. 3) measured seven constructs (one for each ESG pillar for consumers and insurers and the size construct) through 36 items versus five constructs through 17 items, enabling the inclusion of social risks construct for consumers and insurers. The model was able to explain the 63% variance of IE, 86% of IS, and 66% of IG. The best predictor of IESGR variance was CS, validating the hypotheses of a positive relation between CS and IE, CG and IE, and CS and IS (Table 13).

Our model does not indicate significant relations between SIZE and IESGR constructs as in Çera et al. (2020), Nayak and Venkatraman (2011), and Sung et al. (2022). The possible reasons for this include new ESG regulations affecting all insurance companies, the growth in customer complaints against insurance companies, the post-COVID-19 era, the growth in M&As in the insurance industry, and the rise in Insurtech ESG services. ESG risk underwriting assessment highlights the evolution of GHG emissions and extreme events risks (Table 8). The results show that there is a lack of products for GHG emissions risks, ecosystem degradation, and continued pollution (Table 9).

This study contributes to the literature with the development of an ESG risk perceptions assessment framework and models. It also improves the discussion on the evolution of ESG risk perceptions over time and the relationship between insurance product availability and ESG risk materiality and underwriting. Our research contributes to strategic ESG risk management and product development within the context of new regulations.

In accordance with the mindset 'If you can't measure you can't improve', the insurance industry (companies and regulators) should keep ESG risk claims data as primary risks, for example: claims cost in property insurance are available from the SUSEP database, but not disclosures on specific climate risk such as heat waves, precipitation volume, or wind speed. This measurement would enable new products development as parametric insurance (available just for a few agricultural products).

The integration of ESG risks in the insurance business is a process that is evolving globally (Nobanee et al., 2021, 2022; Pugnetti et al., 2022; Stricker et al., 2022). Indian banks are increasingly focusing on adopting an integrated approach to risk management (Bhatt et al., 2023). Since 2015, Brazil's insurance industry has seen an increase in sustainability initiatives and committees (CNseg, 2022b), adherence to international protocols, especially the PSI (UNEPFI, 2018), and improvements in climate risk management and disclosure (UNEPFI, 2018; CNseg, 2022a).

We would like to make the following suggestions for Brazil's insurance industry:

- Work with the regulator to define standards for recording specific causes of ESG risk claims: for example, the rain volume in flood-associated claims in auto and properties and casualty policies.
- Increase risk analysis for climate risks related to extreme events, focusing on droughts and floods.
- Define standards for recording specific causes of ESG risk claims: for example, precipitation volume in flood-associated claims in auto and properties and casualty policies.
- Adhere to international standards of ESG performance as proposed by the International Sustainability Standards Board (ISSB).
- Create an open-access ESG products and performance (claims ratio) database.
- Increase investment in ESG risks research in universities and scientific research initiatives such as the Integrated Assessment Modeling Consortium (IAMC) for the development and analysis of scenarios for climate-related financial analysis.

Limitations

This study captures the perceptions of the respondents about a phenomenon, without measuring the phenomenon. Although some insurers work for international insurance companies, the results are pertinent to Brazil and should be viewed in relation to the country and similar economies. The results should not be generalised across the entire industry, as the sample, while covering over 65% of premiums within the Brazilian market, may still lack complete representativeness. Although this coverage renders the findings highly relevant, the model reflects insurance consumers' perspectives indirectly – filtered through the lens of insurers – making it secondary information.

Future Studies

For new research we suggest improving the assessment of global warming-associated risks especially extreme climate events (floods, drought, windstorms); incorporation of ESG Apria in insurance companies' investments and, finally, the effects of ESG regulations in risk management and financial performance.

Assess ESG risks perception directly from insurance consumers and the relationship between ESG performance and ESG risk claims ratios.

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Conflicts of Interest Statement

The authors declare that they have no conflicts of interest related to the insurance organisations that participated in this research.

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Unveiling the Financial Performance of Bank of Baroda, Vijaya Bank, and Dena Bank in Pre- and Post-Merger Through CAMEL Model

Jalpa Ukabhai Chauhan*, Brijrajsinh P. Gohil**

Abstract

The main aim of this study on the Pre- and Post-Merger of "Bank of Baroda, Vijaya Bank, and Dena Bank", and their performance before and following five years of the Merger. The 21st century is the span of rapidly advancing technology which increases competition between Companies, banks, and businesses. Mergers and Acquisitions are effective strategies to survive in the market and beat the competition. The current study used a camel model for evaluating financial performance impact due to merger for selected merged banks which considers a period of 2013-14 to 2023-24. "CAMEL stands for Capital Adequacy, Assets Quality, Management Efficiency, Earnings Quality, and Liquidity". The finding shows that the influence on economic outcomes due to mergers are combination of positive and negative effects. It shows considerable changes in Capital Adequacy Ratio, overall total business per employee, Total Investment on Total Assets, Operating Profit on average working funds, Total Advances on Total deposits, Net interest to total assets, and Liquid Assets on Demand Deposits in the pre-post-merger period.

Keywords: Merger & Acquisition, Banking Sector, CAMEL Model

Introduction

Merger and Acquisition is an extremely helpful practice for business growth and expansion. It is not just for hiding weaknesses but it is done to strengthen their capacities to beat the competition at the global level. Banking sector mergers become vital and useful for growing and developing a country's economic level. These mergers provide synergy benefits and consolidate assets, core systems, technology, market share, capital, etc. which facilitate larger credit and reduction of market risk that a single bank cannot achieve. Weak banks can endure by merging with strong banks. The Indian Banking Sector is vital in ensuring growth in the economy of Our country. "Indian Banking sector is divided into two categories: scheduled commercial banking institutions and non-schedule commercial banking institutions". "As per RBI, 1934, banks registered in Schedule II are considered scheduled banks and others are non-scheduled banks. Schedule banks are mainly categorized into three categories which are foreign banks, private sector banks, and public sector banks. Public sector banks are those banks that are majorly owned by the government i.e. Ministry of Finance Central Government or State government. Private sector banks are categorized into two bases which are new private sector banks and old private sector banks. Foreign banks are those banks which are headquartered in different countries but have operations in India".

RBI approved the CAMEL's measuring for the performance of Indian Commercial banks which evaluates sustainable growth and development and reflects the financial viability of banks. The camel model considers all components that measure the

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ability of banks to endure losses from risky investment or financial leverage, the profitability of stockholder's investment, borrowing ratio, and the capacity to transform its deposits into higher return advances, etc. Thus, this model considers all aspects of bank soundness in concern of financial performance.

Review of Literature

(Baburam Adhikari, 2023) Have examined the economic results of chosen banks in Nepal before and after mergers and acquisitions. They studied bank and financial institution mergers which took place in Nepal between 2013 to 2020. They implemented paired sample t-tests and accounting ratios for analysis. (Ajabani, 2023) Studied selected 15 IT Sector Institutions for Preceding and Following Merger and Acquisition performance. He has considered ten years of data from which five years as preceding the merger period and five years as following period. He used various ratios and Paired t-tests for analysis purposes. The researcher concluded that EBIT to sales Proportion, Current Asset Ratio, Margin of Net Profit, Interest Coverage Ratio, and ratio of return on assets have an unfavorable effect due to Merger and Acquisition whereas Return on Capital Employed has a favorable impact due to Merger and Acquisition. (Patel, 2018) Has evaluated five banks' pre- and post-merger analysis based on eight variables. Researchers encountered the SBI, BOB, IOB, OBC, and IDBI.

(Mirvis, 2011) Have conducted a study on Organizational, Cultural, and Human Components of mergers & acquisitions. They focused on the manner in which human factors affect their success and failure and also determined the components that enhance the success rate. (Chandani, 2014) They have focused on factors that lead to effectively managing change throughout an acquisition as well as a merger. They discussed reasons behind failed Mergers and Acquisition and also provided strategies that led to the success of the merger's identifiable Vision, strategy for integration, Involvement of Employees, HR reorganizing and retrenchment, and emphasis on customer-centered services, they did Bank of Madura and ICICI Bank and AOL and Time Warner Merger Case study based on changed management.

(Pandian, 2020) Has conducted the before and after mergers comparative examinations of the consolidated nationalized banks in India from 2000 to 2010. They do research for IDBI Bank, SBI, and BOB. (Ambica, 2017) Has looked at the financial results of Kotak Mahindra Bank's Strengths and Weaknesses in the context of its financial performance simultaneously prior to and following the merger. They evaluated statistics according to profitability as well as efficiency effects due to the merger and concluded it had a positive impact. (Edi, 2019) Have described the consequences of acquisitions and mergers on the quality and productivity of businesses. Various variables were utilized to gauge the company's success after its merger between 2010 to 2014. They concluded that the organization's performance had dropped after the merger, and the quality of returns had changed. (Paul, 2017) Has investigated the financial position of Indian banks that merged from 2000 to 2012. For ten commercial banks, he partitioned the time into three prior-merger and three following-merger periods. (KP, 2020) Have analyzed the financial position of chosen Indian companies prior to and following mergers like Tata Steel, Vodafone, TCS, ICICI Bank, and Sun Pharma. They concluded that post-mergers among many companies have favorable and unfavorable impacts together.

(Philip Ayagre, 2024) Evaluates how mergers and acquisitions have impacted performance in Sub-Saharan Africa from 2003 to 2019. Regulation – induces M&As, in which banks consolidated as a consequence of government attempts to reinforce the banking industry. The Study includes profitability measures which include ROE, ROA, and NIM are employed in the research to gauge post-merger performance. (Georgios, 2023) examines the economic impact of Alpha Bank's acquisition of Emporiki Bank's Merger and Acquisition in Greek banking. Before and following the acquisition, the study measures whether increased crucial financial indicators involving Profitability, Liquidity, and Operational Efficiency. They concluded that the acquisition of Emporiki Banks supported to increase in the customer base in Alpha Bank but that did not lead to an improvement in financial ratio and the financial crisis weakened both banks, making the acquisition less effective in generating intended financial outcomes. (Abu Khan, 2016) examined how mergers and acquisitions have impacted U.S. Banks' Operational results, efficiency, and value creation since GLBA. They presented a new metric named Expected Economic Value Added (EVA) Enhancement and incorporated numerous techniques from M&A research. They analyzed M&A transactions between 1999 to 2009, The dataset initially included 1264 mergers being decreased to 79 mergers based on government-assisted mergers, minimum asset size, and eliminating multiple M&A within a year. (John Goddard, 2011) The Research paper focuses on 132 bank M&A that occurred in Asia and Latin America from 1998-2009. It found how shareholders' value received substantial benefits after M&A, and Acquirer enterprises' value either remained constant or expanded, so shareholders were not squeezed. Cross-border acquisition and geographic diversity are two significant variables that accelerate value for acquirers, etc. (Bakir, 2019) studies how bank merger regulations and legislation specifically in Australia and Canada, enhance financial stability. This shows how competition laws prohibiting mega-bank mergers promote stability and caution banking, even though an extensive portion subsequently of the global financial crisis literature has concentrated on monetary regulatory failures.

Research Methodology

Objectives of Study

- To empathize with the mergers and acquisitions conceptual framework.
- To examine the merger's pre- and post-merger effect on the specified bank's financial outcomes through the CAMEL Model.
- To comprehend the impacts Before and After the merger employing Profitability Analysis.

Model

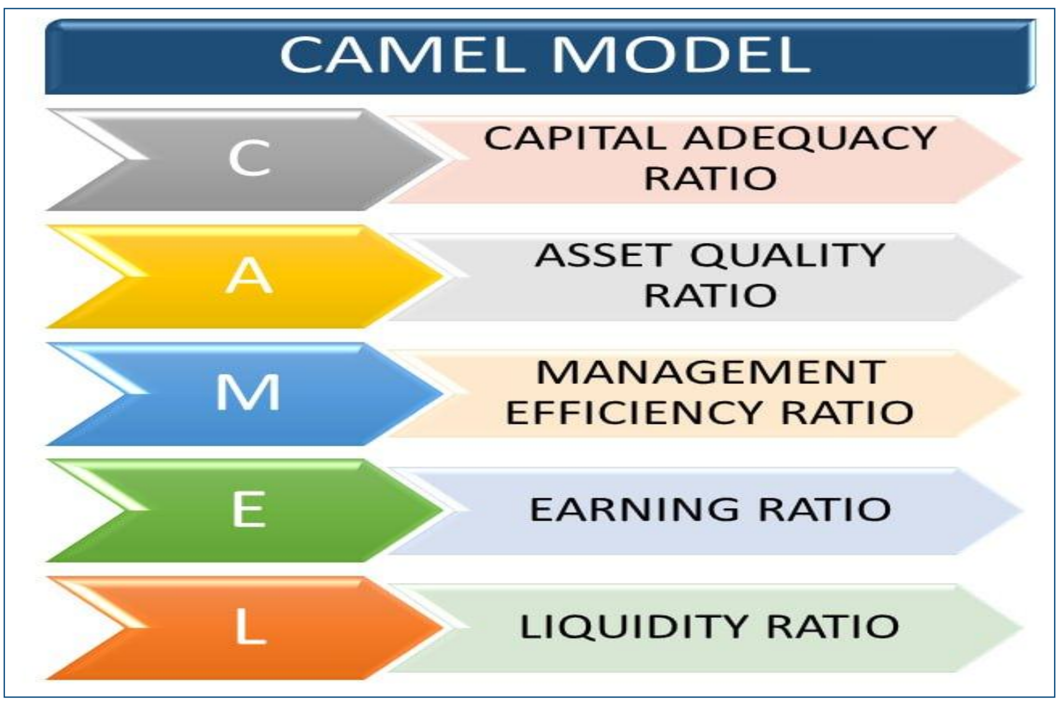

Fig. 1: Camel Model

Need for the Study

Understanding prior and following mergers impact on the consolidated bank's financial performance which are BOB, Vijaya Bank, and Dena Bank, it helps to government, Researchers, investors, and shareholders.

Research Design

This Research Paper is on the basis of Descriptive and Analytical methods of study. BOB effectively merged with Dena Bank and Vijaya Bank on 1st April, 2019. Here, five years are considered as a pre-merger and five years are considered as a post-merger whiz respectively from 2013-14 to 2017-18 as a prior-merger period and 2019-20 to 2023-24 as a following-merger period. 2018-19 is considered as a base year for the study. The data collected from secondary data which are from prowess software, annual reports of banks, newspapers, journals, websites, etc.

Statistical Test

Researchers have worked with parametric data so applied the paired t-test in analysis and testing the hypothesis considering the appropriateness of the prior to and following merger data.

Limitations of Study

Since secondary data is considered the core of the study, all conclusions and results are entirely reliant upon it. The analysis is about prior to and following the merger of five-five years, so financial performance impact may vary in the future.

Data Analysis and Interpretation

To examine the impact caused by the merger, both pre- and post-on on BOB, Dena Bank, and Vijaya Bank's Financial performance which is according to paired t-test and Camel Model and Profitability analysis based on ROA, ROE, and NIM.

Table 1: Significant Variables for the Research

Variables	*Formula*
Capital Adequacy Ratio	(Tier-I Capital +Tier-II Capital)/Risk Weighted Assets
Debt- Equity Ratio	Debt/ Equity
Advances to Assets Ratio	Advances/Assets
Return on Equity	Net Interest Income/Shareholder's Equity Growth Rate
Gross NPAs to Total Advances"	Gross NPA/Total Advances
Net NPAs to Net Advances	Net NPA/Net Advances
Net NPAs to Total Assets	' Net NPA/Total assets"
Total Investments to Total Assets	Total Investment/Total Assets
Total Advances to Total Deposits Ratio"	Total Advances/Total Deposits
Business per Employee	Total Business/Total number of employees
Profit per Employee"	Profit after Tax/Total number of employees
Operating Profit to Average Working Funds	Operating Profit/verage Working Funds
Spread to Total Assets	Net Interest Income/Total Assets
Return on Asset	Net Interest Income/Total Assets
Liquid Assets to Total Assets"	Liquid Assets/Total Assets
Govt. Securities to Total Assets	Government Security/Total assets
Liquid Assets to Demand Deposits	Liquid Assets/Demand Deposits

Table 2: Pre-Merger Descriptive Analysis of BOB, Vijaya Bank and Dena Bank

PRE_MERGER	"Descriptive Statistics"								
	"N"	"Minimum"	"Maximum"	"Mean"	"Std. Deviation"	"Skewness"		"Kurtosis"	
	"Statistic"	"Statistic"	"Statistic"	"Statistic"	"Statistic"	"Statistic"	"Std. Error"	"Statistic"	"Std. Error"
Capital_Adequacy_Ratio	5	11.33	12.37	11.9440	.43861	-.718	.913	-1.507	2.000
Debt_Equity_Ratio	5	.84	1.11	.9300	.11769	1.141	.913	-.224	2.000
Advances_to_Assets_Ratio	5	57.41	60.55	59.6260	1.28792	-1.839	.913	3.528	2.000
Return_on_Equity	5	-8.13	9.93	.2980	8.03604	.127	.913	-2.545	2.000
Gross_NPAs_to_Total_Advances	5	2.89	13.55	8.1640	4.64108	-.105	.913	-2.476	2.000
Net_NPAs_to_Net_Advances	5	1.81	7.25	4.7180	2.42678	-.347	.913	-2.689	2.000
Net_NPAs_to_Total_Assets	5	1.09	4.19	2.7140	1.35412	-.265	.913	-2.528	2.000
Total_Investments_to_Total_Assets	5	24.37	26.01	25.4340	.66560	-1.203	.913	1.430	2.000
Total_Advances_to_Total_Deposits	5	66.16	69.31	68.4120	1.30156	-1.884	.913	3.759	2.000
Business_Per_Employee	5	15.33	16.64	16.0980	.61320	-.530	.913	-2.734	2.000
Profit_Per_Employee	5	-4.71	1.46	-.6740	2.40639	-1.592	.913	2.798	2.000
Operating_Profits_to_Average_Working_Funds	5	1.04	1.54	1.3060	.19680	-.309	.913	-.981	2.000
Spread_Total_Asset	5	1.03	2.21	1.7860	.45192	-1.544	.913	2.851	2.000
Return_on_Asset	5	-.50	.54	-.0040	.45840	.049	.913	-2.515	2.000
Liquid_Asset_To_Total_Asset	5	6.88	11.12	9.6460	1.65730	-1.553	.913	2.632	2.000
Govt_Securities_To_Total_Assets	5	20.09	22.97	21.1880	1.10649	1.274	.913	1.709	2.000
Liquid_Assets_To_Demand_Deposits	5	23.44	50.41	40.3960	11.18247	-.924	.913	.084	2.000

Table 3: Post-Merger Descriptive Analysis of BOB, Vijaya Bank, and Dena Bank

“Descriptive Statistics”									
POST_MERGER	*“N”*	*“Minimum”*	*“Maximum”*	*“Mean”*	*“Std. Deviation”*	*“Skewness”*		*“Kurtosis”*	
	“Statistic”	*“Statistic”*	*“Statistic”*	*“Statistic”*	*“Statistic”*	*“Statistic”*	*“Std. Error”*	*“Statistic”*	*“Statistic”*
Capital_Adequacy_Ratio	5	13.30	16.31	15.3040	1.23937	-1.354	.913	1.510	2.000
Debt_Equity_Ratio	5	.80	1.30	1.0400	.20736	.236	.913	-1.963	2.000
Advances_to_Assets_Ratio	5	59.60	67.21	62.6540	3.13404	.850	.913	-.914	2.000
Return_on_Equity	5	.76	15.85	8.1000	7.11822	-.037	.913	-2.893	2.000
Gross_NPAs_to_Total_Advances	5	2.92	9.40	6.3180	2.91693	-.159	.913	-2.702	2.000
Net_NPAs_to_Net_Advances	5	.68	3.13	1.9020	1.16939	.172	.913	-2.956	2.000
Net_NPAs_to_Total_Assets	5	.45	1.89	1.1640	.68686	.186	.913	-2.962	2.000
Total_Investments_to_Total_Assets	5	22.61	24.85	23.8420	.94534	-.166	.913	-1.773	2.000
Total_Advances_to_Total_Deposits	5	72.95	80.32	75.7580	3.31949	.727	.913	-1.938	2.000
Business_Per_Employee	5	18.77	30.46	23.5020	4.95851	.679	.913	-1.407	2.000
Profit_Per_Employee	5	.01	.24	.1060	.10262	.400	.913	-2.111	2.000
Operating_Profits_to_Average_Working_Funds	5	1.47	2.00	1.7640	.22810	-.321	.913	-2.102	2.000
Spread_Total_Asset	5	2.37	2.84	2.6140	.20768	.167	.913	-2.485	2.000
Return_on_Asset	5	.06	1.17	.5860	.51993	.011	.913	-2.824	2.000
Liquid_Asset_To_Total_Asset	5	5.99	10.53	8.6200	2.17997	-.531	.913	-2.986	2.000
Govt_Securities_To_Total_Assets	5	20.02	22.00	21.2200	.81960	-.803	.913	-.666	2.000
Liquid_Assets_To_Demand_Deposits	5	18.49	36.52	26.8900	7.54642	.063	.913	-1.854	2.000

Table 4: Pre- and Post-Merger Capital Adequacy Ratios According to Paired T-Test Financial Performance

Sr. No.	*Ratio*	*"Pre-Merger Mean"*	*"Post Merger Mean"*	*"t-Value"*	*"Significant Level (2 Tailed)"*	*"Remarks"*
1	Capital Adequacy Ratio"	11.9440	15.3040	-8.899	0.001	Reject H0
2	Debt- Equity Ratio	0.9300	1.0400	-1.217	0.291	Accept H0
3	Advances to Assets Ratio	59.6260	62.6540	-1.701	0.164	Accept H0
4	Return on Equity	0.2980	8.1000	-1.210	0.293	Accept H0

Table 4 represents paired t-test analysis of Capital Adequacy Ratios of prior to and following the -merger in concern of BOB, Dena Bank, and Vijaya Bank. The Capital Adequacy ratio had a notable increase, with a pre-mean of 11.94 to a post-mean of 15.30. This change returns a t-value (-8.899) and the magnitude p-value is 0.001 so there is substantial change during pre- and post-merger so it rejects the null hypothesis. The debt-equity ratio shows a significant increase from a before-mean 0.93 to an after-mean 1.04 after the merger. The null hypothesis is accepted considering no discernible change as shown t-test and the p-value is 0.291. Similarly Advances on assets ratio suggests a slightly positive evolution in the pre-and post-mean from 59.63 to 62.65, the t-value is -1.701 and the significant value is 0.164 describing no statistically significant change so it accepts the null hypothesis and the Return on Equity represents 0.30 as pre mean and 8.10 as post mean, 0.293 represents significance figure while t value is -1.210 means it's not had enough statistical evidence of change so it accepts null hypothesis.

Table 5: Pre- and Post-Merger Asset Quality Ratios According to Paired T-Test Financial Performance

Sr. No.	*Ratio*	*"Pre-Merger Mean"*	*"Post Merger Mean"*	*"t-Value"*	*"Significant Level (2 Tailed)"*	*"Remarks"*
1	Gross NPAs to Total Advances	8.1640	6.3180	0.548	0.613	Accept H0
2	Net NPAs to Net Advances	4.7180	1.9020	1.754	0.154	Accept H0
3	Net NPAs to Total Assets	2.7140	1.1640	1.702	0.164	Accept H0
4	Total Investments to Total Assets	25.4340	23.8420	2.869	0.045	Reject H0

Table 5 reveals pre- and post-merger impact on the Asset Quality ratio through paired t-test analysis. The Gross NPAs to Total Advances have 8.16 and 6.32 as pre-mean and post-mean correspondingly. The significance p-value is 0.613 and the t-value is 0.548 so it accepts a null hypothesis. The Net NPAs on Net Advances have 4.71 as pre-mean and 1.90 as post-mean. The significance p-value is 0.154 and the t-value is 1.754 representing acceptance of a null hypothesis. Net NPAs to Total assets have pre-mean and post-means as 2.71 and 1.16 correspondingly. The p-value is 0.164 describing the adoption of the Ho but Total Investment on Total Assets has a pre-mean of 25.43 and post-mean of 23.84. the t-value is 2.869. the p-value is 0.045 and the t-value is 2.869 which reflects a rejection of a null hypothesis and there is a substantial change prior to and following investment to assets.

Table 6: Pre- and Post-Merger Management Efficiency Ratios According to Paired T-Test Financial Performance

Sr. No.	*Ratio*	*"Pre-Merger Mean"*	*"Post Merger Mean"*	*"t-Value"*	*"Significant Level (2 Tailed)"*	*"Remarks"*
1	Total Advances to Total Deposits Ratio	68.4120	75.7580	-4.287	0.013	Reject H0
2	Business Per Employee	16.0980	23.5020	-3.203	0.033	Reject H0
3	Profit Per Employee	-0.6740	0.1060	-0.700	0.523	Accept H0

Table 6 describes Pre- and Post-Merger Management Efficiency ratios through Paired t-test analysis. Total Advances to Total Deposits represent a notable change in prior to the merger and following to merger mean as

68.41 to 75.76 correspondingly. The significance p-value is 0.013 and the t-value is -4.287 showing changes so it rejects a null hypothesis. Business each Employee has 16.10 as pre mean and 23.50 as the post mean, t value as -3.203 and P-value is 0.033 so it denies a null hypothesis, and Profit per Employee shows -0.67 as pre mean and 0.11 as the post mean, p-value is 0.523 and t value is -0.70 statistically significance thereby suggests it accepts null hypothesis.

Table 7: Pre- and Post-Merger Earnings Ratios According to Paired T-Test Financial Performance

Sr. No.	*Ratio*	*"Pre-Merger Mean"*	*"Post Merger Mean"*	*"t-Value"*	*"Significant Level (2 Tailed)"*	*"Remarks"*
1	Operating Profits to Average Working Funds	1.3060	1.7640	-4.652	0.01	Reject H0
2	Spread to Total Assets	1.7860	2.6140	-5.077	0.007	Reject H0
3	Return on Asset	-0.0040	0.5860	-1.423	0.228	Accept H0

Table 7 represents pre- and post-merger earnings ratios through paired t-test analysis. Operating profits to Average working funds have 1.31 as pre-mean and 1.76 as post mean so there is a change and spreads to Total Assets have 1.79 as pre-mean and 2.61 as post mean so it also shows the change. Thus, the ratio of Spread on total assets and Ope. Profits on Average Working capital have significant changes prior to and following the merger period so it rejects the null hypothesis by having significance values of 0.01 and 0.007 respectively. While Return on Assets has -1.423 as the t value and 0.228 as the significance value so it reveals there is no important alteration during the prior to and following merger period so it accepts the null hypothesis.

Table 8: Pre- and Post-Merger Liquidity Ratios According to Paired T-Test Financial Performance

Sr. No.	*Ratio*	*"Pre-Merger Mean"*	*"Post Merger Mean"*	*"t-Value"*	*"Significant Level (2 Tailed)"*	*"Remarks"*
1	Liquid Assets to Total Assets	9.6460	8.6200	1.561	0.193	Accept H0
2	Govt. Securities to Total Assets	21.1880	21.2200	-0.080	0.94	Accept H0
3	Liquid Assets to Demand Deposits	40.3960	26.8900	5.821	0.004	Reject H0

Table 8 illustrates pre-post-merger analysis through paired t-test techniques. Liquid Assets to Total Assets has 9.65 as the pre-mean and 8.62 as the post-mean. The significance p Value is 0.193 and the t-value is 1.561 that leads to acceptance of the null hypothesis. Government Securities to Total Assets show a slight change in pre-mean and post-mean which is 21.19 and 21.22 consequently. The p-value is 0.94 and t-value is -0.080 which shows no noteworthy change so it accepts the null hypothesis. Liquid assets on Demand Deposits have pre-mean and post-mean as 40.40 and 26.89 respectively. The t-value is 5.821 and the P-value is 0.004 showing a noteworthy change in pre- and post-merger so it rejects the null hypothesis.

Profitability Analysis

Profitability analysis can evaluate a bank's competence to earn a profit based on its equity, assets, and interest-earning capabilities. It evaluates whether a merger has enhanced efficiency and return requires assessing economic outcomes before and after the merger of anchor banks. The three crucial profitability measures were used in this analysis:

- *ROA:* Evaluate how well the bank utilized assets to create a profit.
- *ROE:* It assesses Profitability from the perspective about Shareholders.

- *NIM:* It evaluates the efficiency of interest income creation in the context of earning assets.

Table 9: Profitability Analysis

	Year	*ROA (%)*	*ROE*	*NIM (%)*
Pre-Merger (year -5)	2013-14	0.75	12.61	2.36
Pre-Merger (year -4)	2014-15	0.49	8.53	2.31
Pre-Merger (year -3)	2015-16	-0.78	-13.42	2.05
Pre-Merger (year -2)	2016-17	0.20	3.43	2.19
Pre-Merger (year -1)	2017-18	-0.34	-5.60	2.43
Merger Year	2018-19	-	-	-
Post-Merger (year -5)	2019-20	0.06	0.76	2.73
Post-Merger (year -4)	2020-21	0.07	1.07	2.71
Post-Merger (year -3)	2021-22	0.6	8.46	3.03
Post-Merger (year -2)	2022-23	1.03	14.36	3.31
Post-Merger (year -1)	2023-24	1.17	15.85	3.18

Table 10: Pre- and Post-Merger Profitability Analysis According to Paired T-Test Financial Performance

Sr. No.	*Ratio*	*"Pre-Merger Mean"*	*"Post Merger Mean"*	*"t-Value"*	*"Significant Level (2 Tailed)"*	*"Remarks"*
1	Return on Asset	0.0640	0.5860	-1.144	0.316	H0 Accepted
2	Return on Equity	1.1100	8.1000	-0.984	0.381	H0 Accepted
3	Net Interest Margin	2.2680	2.9920	-4.809	0.009	H0 Rejected

Table 9 and 10 exhibits pre-and post-merger profitability analysis based on paired t-tests according to five years prior to the merger period and five years preceding to merger period. Based on Return on assets which has 0.0640 as the pre-mean and 0.5860 as the post-mean and it has 0.316 as the p-value which justifies there is no substantial change in the variable. Return on Equity has a pre-merger mean and post-merger mean of 1.1100 and 8.100 respectively and a p-value of 0.381 and t-value of -0.984 that results in a null hypothesis being accepted another variable Net Interest Margin presents 2.2680 and 2.9920 as before-merger mean and after-merger mean simultaneously. It exhibits -4.809 and 0.009 as t value and p value which results into there is significant modification in net interest margin prior to and preceding the merger period.

Conclusion

The key to merger & acquisition success depends on an acquiring bank's competence to manage the acquiring bank's cohesion with the existing banks. The statistical finding shows a very tricky and rosy picture of mixed effects on bank's financial performance as a consequence of mergers. Financial Performance has been evaluated by camel model components like capital adequacy, business each employee, return on equity, Profit per employee, return on assets, liquid assets on total assets, etc. after analyzing a comparative study between prior- and following-merger for the period of 2013-14 to 2023-24. it is observed that capital adequacy ratio, spreads on total assets, Total investment on total assets, liquid assets on demand deposit ratio, business per employee, etc. have significant impacts on prior-to-merger and preceding-to-merger financial performance. The profitability analysis shows no significant change in return on assets and return on equity and substantial change in the Net Interest margin.

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A Factor Analysis Approach to an Investigation of Odisha's Co-Operative Banks

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Abstract

In India's rural and semi-urban financial system, co-operative banks are vital, especially in regions such as Odisha where they provide low-income individuals, small enterprises, and farmers with vital loans. These banks, however, confront a number of difficulties, including unstable finances, ineffective governance, technology constraints, and disgruntled customers. This study uses factor analysis, a multivariate statistical technique, to assess the major factors influencing the performance of co-operative banks in Odisha. To find out how 200 respondents – including co-operative bank customers and staff – perceived banking services, governance, financial stability, and technology adoption, a primary survey was carried out. The appropriateness of factor analysis was validated by the Bartlett's test of sphericity ($p < 0.05$) and the Kaiser-Meyer-Olkin (KMO) test (0.812). Five key elements were identified through Principal Component Analysis (PCA): (1) risk management and financial stability; (2) governance and regulatory compliance; (3) digital banking and technological adoption; (4) customer satisfaction and service quality; and (5) operational efficiency and human resource management. Together, these variables accounted for 77.7% of the variance, demonstrating their significant impact on the operation of co-operative banks. The results emphasise how urgently governance frameworks must be strengthened, financial risk management must be improved, and digital transformation must be accelerated to increase banking efficiency. To increase client trust and retention, the report also emphasises the significance of customer-centric strategies, such as expedited loan processing and grievance redressal procedures. These insights can be used by regulators, policymakers, and bank management to create focused actions that would increase the competitiveness and sustainability of Odisha's co-operative banks.

Keywords: Co-Operative Banks, Odisha, Factor Analysis, Financial Stability, Governance, Digital Banking, Customer Satisfaction

Introduction

Co-operative banks occupy a pivotal position in India's rural and semi-urban financial ecosystem, particularly in states such as Odisha, where a significant portion of the population depends on agriculture and small-scale enterprises for their livelihoods. Established as member-owned institutions, co-operative banks are designed not merely for profit but to foster financial inclusion, offering essential services such as savings accounts, low-interest loans, and financial literacy programmes to underserved communities. Unlike commercial banks, which primarily focus on profitability, co-operative banks empower small farmers, self-help groups, micro-entrepreneurs, and low-income households, contributing directly to rural development and poverty alleviation (NABARD, 2022; Patil & Kumar, 2020).

In Odisha, co-operative banks form the backbone of the rural economy by providing short-term and long-term credit, facilitating investment in productive assets, and promoting financial literacy among local populations.

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Despite their critical role, these banks face a variety of operational challenges, including rising non-performing assets (NPAs), weak governance, limited technological adoption, and declining customer trust. Operational inefficiencies, inadequate risk management frameworks, and insufficient professional management practices further hinder their competitiveness compared with public and private sector banks. These challenges highlight the need for an empirical, data-driven analysis of the factors influencing co-operative banks' performance in Odisha.

This study provides a comprehensive empirical investigation into Odisha's co-operative banking sector, addressing a significant research gap. While much of the existing literature has focused on co-operative banks at the national or multi-state level, Odisha's unique socio-economic and agrarian context has been relatively underexplored. By concentrating specifically on this state, the research delivers a detailed, data-driven understanding of the operational, financial, and technological challenges faced by co-operative banks. This state-specific focus is especially important because a large rural population relies heavily on these institutions for access to credit and other financial services, making the study highly relevant for policymakers, bank managers, and other stakeholders seeking to enhance the efficiency and sustainability of co-operative banking in Odisha.

In addition to providing empirical evidence, the study undertakes a quantitative identification of key performance factors. Utilising Principal Component Analysis (PCA), a widely recognised multivariate statistical technique, the research systematically identifies the underlying determinants driving co-operative banks' effectiveness. Unlike qualitative approaches that often rely on anecdotal evidence or subjective assessments, PCA enables the extraction of statistically validated factors, including financial stability, governance, technological adoption, customer satisfaction, and operational efficiency. This approach strengthens the reliability of the findings and provides a precise understanding of how different variables interact to influence overall bank performance.

The findings also offer practical and actionable insights for stakeholders, including regulators, policymakers, and bank management. By highlighting critical dimensions such as governance mechanisms, digital banking infrastructure, risk management practices, and customer-focused services, the study informs targeted interventions that can enhance operational performance, increase customer trust, and improve competitiveness. These insights equip stakeholders with evidence-based recommendations, enabling more effective decision making and strategic planning to address both current operational challenges and long-term sustainability concerns.

Moreover, the research emphasises the broader role of co-operative banks in promoting financial inclusion and rural development. Strengthening these institutions can expand access to financial services for underserved and marginalised populations, reduce rural indebtedness, and foster greater economic resilience among small-scale farmers, self-help groups, and micro-entrepreneurs. In Odisha's agrarian economy, such improvements have far-reaching implications for livelihood security, poverty alleviation, and inclusive growth, highlighting the socio-economic significance of co-operative banking beyond financial performance metrics.

Finally, the study outlines clear policy and strategic implications for improving Odisha's co-operative banking ecosystem. Practical interventions, such as accelerating digital banking adoption, implementing structured human resource training programmes, and enhancing governance and regulatory oversight, are recommended to strengthen operational and financial infrastructure. By focusing on these key areas, the study provides a roadmap for creating robust, efficient, and inclusive co-operative banks capable of meeting the evolving needs of rural and semi-urban populations. These recommendations are intended to guide policymakers, regulators, and bank management in fostering sustainable growth, improving service quality, and ensuring long-term viability, thereby contributing to both economic development and financial inclusion goals.

Need for the Study

Co-operative banks in Odisha have not received much attention from researchers employing sophisticated statistical methods, despite their crucial role in financial inclusion. By using factor analysis, a statistical technique that aids in determining the fundamental elements impacting bank performance, this study closes the gap.

The results of the study will assist bank management, regulators, and policymakers in enhancing their operating plans and guaranteeing the long-term survival of co-operative banks in Odisha.

Research Questions

The following questions are the focus of this study:

- What are the main determinants of Odisha's co-operative banks' performance?
- How do governance, financial stability, technological adoption, and consumer happiness affect these banks?
- What steps may be made to make Odisha's co-operative banking system more sustainable and efficient?

Objectives of the Study

- To determine the main elements influencing Odisha's co-operative banks' performance.
- To examine operational effectiveness, financial stability, and customer happiness.
- To offer suggestions on how to increase co-operative banking's efficacy.

Literature Review

In India and around the world, a lot of research has been done on the sustainability and performance of co-operative banks. Prior studies have looked at a number of topics, including customer satisfaction, technology adoption, governance, and financial stability. With an emphasis on studies pertinent to Odisha and factor analysis in banking research, this section examines the major body of literature on co-operative banking.

Co-Operative Banks and Financial Inclusion

By offering loans and banking services to people living in rural and semi-urban areas, co-operative banks contribute significantly to financial inclusion (NABARD, 2022). By providing loans to small farmers and business owners who do not have access to commercial banking services, co-operative banks make a substantial contribution to the rural economy (Patil & Kumar, 2020). Research by Sharma and Gupta (2021) and Mohan (2019) highlights how financial inclusion via co-operative banks has aided in rural economic development and poverty reduction. However, their operations are frequently hampered by a lack of funding, difficulties with regulations, and ineffective risk management. As an agrarian state, Odisha depends heavily on co-operative banks for rural financing and agricultural lending. Over 70% of rural residents are served by co-operative banks, which offer loans for self-help organisations, small businesses, and farming, according to a report published by the Odisha State Co-operative Bank in 2021. Nonetheless, a number of academics (Das & Mishra, 2019; Swain, 2020) draw attention to issues that have an impact on these banks' performance, including high NPA rates, insufficient capital infusion, a lack of professional management, and operational inefficiencies.

Financial Stability and Risk Management in Co-Operative Banks

Numerous studies have looked into the co-op banks' financial soundness, focusing on problems with liquidity management and NPAs. High NPAs have a substantial impact on sustainability and profitability, according to Bhatia's (2021) analysis of the financial health of Indian co-operative banks. Stronger risk management techniques are required because of the significant loan default rates that Odisha's co-operative banks have experienced, according to Reserve Bank of India (RBI) (2022) data. According to research by Mehta and Patel (2020), preserving financial stability in co-operative banking requires better loan recovery procedures and accurate credit appraisal. One important element affecting the long-term viability of co-operative banks is their financial stability. One of the main issues facing Indian co-operative banks is the increase in NPAs, which affects their capacity to distribute loans and remain profitable (Singh & Agarwal, 2017). According to a study by Kale and Mukherjee (2020), co-operative banks are susceptible to financial hardship because of their inadequate risk management frameworks, ineffective loan recovery procedures, and heavy reliance on short-term deposits. These worries are even more acute in

Odisha because agriculture, which is risky by nature because of climatic uncertainties, accounts for a sizable amount of the loan portfolio (Panda & Rath, 2021).

Governance and Regulatory Compliance

One of the biggest problems facing co-operative banks has been governance. According to Singh and Verma (2018), these banks' operating structure is weakened by political meddling, ineffective governance, and a lack of transparency. According to Jain & Das (2020), upholding financial discipline requires adherence to the RBI's and National Bank for Agriculture and Rural Development's (NABARD's) instructions. Financial mismanagement and operational difficulties have resulted from internal inefficiencies and inadequate governance frameworks in Odisha (NABARD Report, 2023). In academic literature, governance concerns in co-operative banks have received a lot of attention. Mohanty and Swain (2018) stated that the main causes of governance failures in the co-operative banking industry of Odisha are political meddling and a lack of qualified management. Co-operative banks are frequently beset by subpar decision making, insufficient regulatory supervision, and restricted adoption of corporate governance norms, according to a report published by the RBI in 2022. Nonetheless, researchers such as Reddy and Ramesh (2021) contend that these institutions' governance structures might be enhanced by fortifying regulatory frameworks and guaranteeing improved adherence to RBI and NABARD norms.

Technological Adoption and Digital Banking in Co-Operative Banks

Compared with commercial banks, co-operative banks have been slower to adopt digital banking services. Co-operative banks need to combine digital payment systems, mobile banking, and core banking solutions (CBSs) to be competitive, according to studies by Reddy et al. (2021) and Pandey and Roy (2022). According to a study by Sahoo and Nayak (2023), a large number of Odisha's co-operative banks continue to use antiquated banking procedures, which result in ineffective service delivery and unhappy customers. Expanding banking outreach, decreasing fraud, and improving operational efficiency all depend on digital transformation. The banking industry has undergone a technological revolution, yet co-ops have been slow to embrace digital banking solutions (Ghosh & Chatterjee, 2020). According to studies, financial limitations, a lack of technological know-how, and opposition to change make it difficult for Odisha's co-operative banks to adopt digital banking services (Patnaik & Behera, 2022). According to a comparative analysis by Jain (2019), co-operative banks still use traditional banking models, which limit their ability to compete and operate efficiently, whereas commercial banks have made a successful move to digital platforms.

Customer Satisfaction and Service Quality

One of the main factors influencing banking success is customer happiness. According to Kotler and Keller (2020), to keep clients, financial institutions should prioritise accessibility, service quality, and grievance redressal procedures. According to a poll done in Odisha by Mishra and Das (2021), consumers like co-operative banks because of their individualised services and cheaper interest rates. However, bad customer service, insufficient infrastructure, and lengthy processing times have a detrimental effect on client retention. According to Zeithaml et al. (2022), to enhance the quality of their services, co-operative banks should make investments in customer relationship management, training, and technology. One of the most important factors influencing co-operative banks' performance is customer happiness. Customers of co-operative banks place a higher value on features such as ease of access, individualised services, and reduced interest rates than on cutting-edge digital services, per a poll by Srivastava and Sharma (2018). However, research shows that in Odisha's co-operative banks, low service quality, loan processing delays, and lack of grievance redressal procedures frequently result in dissatisfied customers (Sinha & Nanda, 2021). According to research by Gupta and Mehta (2020), using digital solutions, increasing transparency, and strengthening customer-centric services can all greatly increase customer retention and trust.

Factor Analysis in Banking Research

In banking research, factor analysis has been utilised extensively to pinpoint the main factors influencing bank performance. Using factor analysis, Malhotra and Agarwal (2017) examined Indian commercial banks and found that financial performance, customer happiness, and governance were important determinants. When Raj and Menon (2020) used factor analysis on rural co-operative banks, they discovered that adopting technology and managing risk were important components. PCA and factor extraction techniques are used in the current study to identify the most important performance elements in Odisha's co-operative banks. In banking research, factor analysis is frequently used to pinpoint important factors that influence both customer happiness and financial performance. Factor analysis aids in breaking down complicated variables into essential underlying components, offering insightful information for decision making (Hair et al., 2019). Factor analysis has been effectively used in studies by Banerjee and Gupta (2020) and Sharma and Rao (2021) to assess the performance of Indian banks, highlighting important variables such as technological adoption, financial risk, governance, and customer service.

Effects of External Factors and Government Policies

The state of the economy and governmental regulations have a big impact on how well co-operative banks perform. The effect of government loan waivers on co-operative banks was investigated by Mukherjee and Saha (2020), who came to the conclusion that although these programmes are advantageous in the short run, they increase bank failure rates and financial strain. Furthermore, the financial health of Odisha's co-operative banks is significantly influenced by external factors such as macroeconomic conditions, agricultural fluctuations, and climate risks (Patnaik, 2022).

Management of Human Resources and Efficiency in Operations

A key factor in co-operative banks' success is effective human resource management. Co-operative banks frequently struggle to recruit and maintain qualified staff because they lack professional training programmes and offer few financial incentives (Kumar & Sen, 2020). Bhattacharya's (2019) research emphasises how bureaucratic delays and personnel inefficiency affect co-op banks' overall effectiveness. Swain and Das (2021) discovered that a large number of bank workers in Odisha are not sufficiently knowledgeable about digital banking services and regulatory compliance, which has an impact on operational efficiency and service quality.

Development and Expansion of Indian Co-Operative Banks

With the passage of the Co-operative Societies Act of 1904, India's co-operative banking system had its start in the early 1900s (Deshpande, 2009). State Co-operative Banks (SCBs), District Central Co-operative Banks (DCCBs), and Primary Agricultural Credit Societies (PACS) make up the multitiered structure that these institutions have developed over time (NABARD, 2020). The governance of these banks has been strengthened by a number of policy changes, including the Banking Regulation Act, 1949 (Amendment in 1966) and the Vaidyanathan Committee recommendations (2004, 2006) (Mohan, 2012).

Research Gaps and Contribution of Study

Few studies have employed factor analysis to examine Odisha's co-operative banking industry, despite the fact that co-operative banking has been the subject of much research. The majority of research has been qualitative or has examined financial metrics without determining the fundamental causes of performance. By using quantitative statistical methods to identify important factors influencing the effectiveness of co-operative banks in Odisha, this study fills the knowledge gap. The results will offer policy suggestions for enhancing the industry's customer satisfaction, digital banking, financial stability, and governance.

There are still a number of gaps in the literature despite the substantial amount of study on co-operative banking. First, there are fewer studies that particularly address Odisha's co-operative banks; instead, the majority of studies concentrate on the federal or state level. Second, while research has examined particular aspects such as customer happiness, governance, and NPAs, very few have employed factor analysis to thoroughly evaluate a variety of factors affecting bank performance. Last, given the changing financial landscape, more research is required to determine how market rivalry, regulatory changes, and digital transformation affect Odisha's co-operative banks.

With an emphasis on Odisha specifically, this literature study offers a thorough examination of the variables affecting co-operative banks' success. The results show that the main factors influencing bank success are financial stability, governance, technology adoption, customer happiness, and human resource management. Growth is nevertheless hampered by issues such as NPAs, political meddling, lack of digital adoption, and operational inefficiencies. By using factor analysis to determine the most important elements influencing the performance of co-operative banks in Odisha, this study seeks to close the current research gaps and offer insightful information to researchers, financial institutions, and policymakers.

Methodology

Data Collection

Both primary and secondary data sources are used in the study.

Primary data includes customers, bank staff, and management survey answers. Financial reports, RBI rules, NABARD reports, and earlier research on co-operative banking are examples of secondary data.

Sampling and Data Processing

About 200 clients and 50 bank workers from different districts in Odisha were asked to complete a standardised questionnaire. Responses on topics such as financial services, customer happiness, governance, and technology adoption were measured using a Likert scale (1–5).

Table 1: Demographic Profile of Survey Respondents

Demographic Variable	*Categories*	*Frequency (N = 200)*	*Percentage (%)*
Gender	Male	120	60.0
	Female	80	40.0
Age group	18–30 years	50	25.0
	31–45 years	80	40.0
	46–60 years	45	22.5
	Above 60 years	25	12.5
Education level	No formal education	15	7.5
	High school	55	27.5
	Undergraduate	75	37.5
	Postgraduate and above	55	27.5
Occupation	Farmer/agricultural Worker	65	32.5
	Self-employed/business	50	25.0
	Salaried employee	55	27.5
	Student	20	10.0
	Retired	10	5.0
Annual income level (INR)	Below 1,00,000	60	30.0
	1,00,000–3,00,000	80	40.0
	3,00,000–5,00,000	40	20.0
	Above 5,00,000	20	10.0
Banking relationship with co-operative bank	Less than 1 year	30	15.0
	1 – 5 years	85	42.5
	6 – 10 years	50	25.0
	More than 10 years	35	17.5

Source: Author's own calculation.

Interpretation: To ensure fair gender representation, the sample is composed of 40% female respondents and 60% male respondents. The majority of respondents (40%) are between the ages of 31 and 45, making them important co-operative banking stakeholders. The largest occupational groupings are self-employed people (25%) and agricultural labourers (32.5%), underscoring the financial reliance of rural areas on co-operative banks. Seventy per cent of respondents earn less than INR3,00,000 annually, highlighting the importance of co-operative banks in helping lower-income populations. A considerable percentage of respondents (42.5%) are relatively new customers, having been clients for one to five years.

Factor Analysis Approach

A popular multivariate statistical method for determining the underlying relationships between observable variables is factor analysis. The extraction of latent components influencing bank performance is especially helpful in banking research. Exploratory factor analysis (EFA) is used in this study to identify the main variables influencing Odisha's co-operative banks' performance.

Tests for Sphericity by Bartlett and Kaiser-Meyer-Olkin: The Kaiser-Meyer-Olkin (KMO) measure of sample adequacy and Bartlett's test of sphericity were used to evaluate the dataset's suitability prior to factor analysis. A significant Bartlett's test ($p < 0.05$) verifies the existence of correlations appropriate for factor extraction, while a KMO value above 0.6 suggests that the sample is sufficient for factor analysis.

Factor Extraction – Scree Plot Analysis and Eigenvalue Criterion: PCA was used to extract factors, and the selection criterion was an eigenvalue larger than 1. By locating the 'elbow point' at which the variance explained by extra variables levelled out, the scree plot further confirmed the number of maintained elements.

Component Matrix Rotation with factor Loadings: Varimax rotation, a popular orthogonal rotation technique, was applied to the derived elements to enhance interpretability. Variables were categorised under corresponding latent factors according to their highest loadings, with factor loadings greater than 0.5 being deemed significant.

PCA: One popular dimension reduction method for determining the most important variables influencing the dataset's variance is PCA. For PCA to function, correlated variables must be broken down into a smaller group of uncorrelated elements called principle components. These elements minimise information loss while capturing the most variance in the data (Jolliffe & Cadima, 2016).

The following are the steps in PCA:

- *Variable Standardisation:* The dataset is standardised to guarantee that each variable has an equal weight because PCA is sensitive to the scale of measurement.
- *Covariance Matrix Computation:* The covariance matrix is a useful tool for analysing the relationships between variables.
- *Calculating Eigenvalues and Eigenvectors:* Eigenvalues indicate the relative importance of each principal component, and eigenvectors show which way the component axes point.
- P*rincipal Component Selection:* Only components that explain a significant amount of the dataset's variation (eigenvalues greater than 1) are kept for additional analysis.
- *Data Transformation:* Using the chosen principal components, the original dataset is modified to reduce complexity while preserving important information.

PCA assists in determining the primary determinants of bank performance in the context of Odisha's co-operative banks, including technological adoption, governance, customer happiness, and financial health. By emphasising important areas for development and policy action, the extracted components help make better decisions.

PCA is used in component analysis to distil a large number of variables into a smaller number of underlying factors. The actions consist of:

- *Data Adequacy Check:* Bartlett's test of sphericity and KMO test.
- Factor extraction using scree plot analysis and the eigenvalue criterion.
- *Factor Rotation:* To improve interpretability, use varimax rotation.

Based on a sample dataset, the KMO test and Bartlett's test of sphericity are shown in Table 2.

Table 2: KMO and Bartlett's Test Results

Test	Value	Interpretation
KMO measure	0.812	Adequate for factor analysis (above 0.7 is acceptable)
Bartlett's test of sphericity	Chi-square = 865.29	Significant correlation between variables
	df = 120	
	Sig = 0.000	($p < 0.05$ indicates factor analysis is suitable)

Source: Author's own calculation.

Interpretation: A KMO value of 0.812 indicates that factor analysis can be performed on the sample data. Good adequacy is indicated by values greater than 0.7. The applicability of factor analysis is supported by the substantial results of Bartlett's test of sphericity ($p < 0.05$), which indicate that the correlation matrix is not an identity matrix.

Table 3: Extraction of Factors – Eigenvalue Criterion

Factor	Eigenvalue	% of Variance Explained	Cumulative % of Variance
1	4.52	22.6	22.6
2	3.78	18.9	41.5
3	2.95	14.7	56.2
4	2.41	12.1	68.3
5	1.89	9.4	77.7
6	1.45	7.2	84.9
7	1.12	5.6	90.5
8	0.85	4.2	94.7
9	0.64	3.2	97.9
10	0.41	2.1	100

Source: Author's own calculation.

Interpretation: According to Kaiser's rule, the eigenvalue criterion recommends keeping factors with eigenvalues higher than 1. Five factors are derived from this as they account for 77.7% of the cumulative variance, which is deemed adequate for factor analysis.

Table 4: Extracted Factors Affecting the Performance of Co-Operative Banks in Odisha

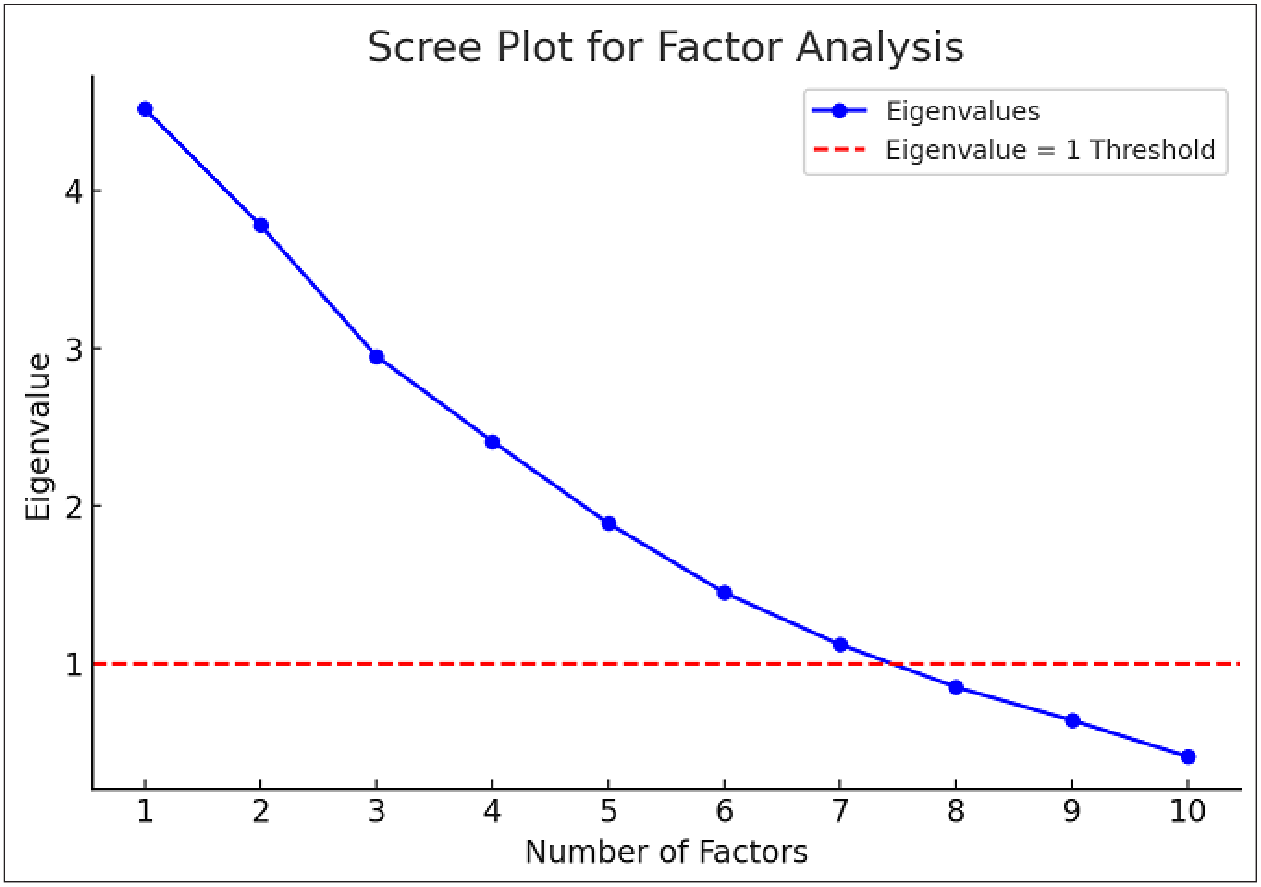
Factor	Key Variables Loaded	Factor Loading Range	Variance Explained (%)
Factor 1: Financial stability and risk management	Loan recovery rate, capital adequacy, NPAs, liquidity ratio	0.65–0.85	22.6
Factor 2: Governance and regulatory compliance	Board effectiveness, transparency, audit mechanisms, RBI/NABARD compliance	0.60–0.82	18.9
Factor 3: Technological adoption and digital banking	Internet banking, mobile banking, core banking system, information technology (IT) infrastructure	0.58–0.79	14.7
Factor 4: Customer satisfaction and service quality	Loan processing speed, Customer support, Accessibility, Grievance redressal	0.62–0.81	12.1
Factor 5: Operational efficiency and human resource management	Staff training, cost efficiency, automation, workload management	0.55–0.77	9.4

Interpretation:

- These five extracted factors together explain 77.7% of the total variance, making them crucial in understanding co-operative banks' performance.
- Factor 1 (financial stability) contributes the highest variance, indicating its strong influence.
- Factor 2 (governance) and Factor 3 (technology) are also significant, emphasising regulatory compliance and digital transformation.

Scree Plot Analysis

The eigenvalues are graphically represented using a scree plot, which also aids in identifying the number of important components. The ideal number of elements to keep is shown by the elbow point, where the eigenvalues start to level out. This is the factor analysis's scree plot. Since the eigenvalues drastically decrease beyond Factor 5, the 'elbow point' around Factor 5 indicates that keeping five factors is ideal.



Source: Author's own calculation.

Fig. 1

Results and Discussion

Key Factors Identified

Five key elements influencing Odisha's co-operative banks' performance were identified by the factor analysis:

- *Financial Stability and Risk Management:* NPAs, capital adequacy, and loan recovery rates.
- *Governance and Regulatory Compliance:* Efficiency, openness, and compliance of the board with RBI regulations.
- *Digital Banking and Technological Adoption:* Deployment of core banking systems, mobile banking, and internet banking.
- *Customer Satisfaction and Service Quality:* Speed at which loans are processed, resolution of complaints, and availability of services.
- *Human Resources and Operational Efficiency:* Automation, cost control, and employee training.

Policy Implications

- According to the study, financial risk management techniques need to be strengthened.
- Internal control systems and governance need to be enhanced.
- Infrastructure for digital banking is being improved
- Programmes to raise customer awareness are increasing.
- Training programmes to increase employee productivity need to be put in place.

A number of policy considerations must be taken into account in light of the difficulties Odisha's co-operative banks face to improve their sustainability and performance:

- *Enhancing Regulatory Oversight:* To guarantee financial discipline in co-operative banks, the RBI and NABARD should put in place stronger regulatory frameworks. This entails strengthening auditing procedures, implementing capital sufficiency standards, and increasing operational openness.
- *Improving Credit Risk Management:* To examine loan applications, policymakers should promote the use of cutting-edge risk assessment methods such as predictive analytics. This can increase loan recovery rates and decrease NPAs.
- *Promoting Digital Transformation:* Co-operative banks should get financial and technical support from the government to deploy digital payment services, mobile banking, and CBSs. Banks that use fintech solutions should be given special incentives.
- *Enhancing Professional Management and Governance:* Steps should be taken to lessen political meddling in co-operative banks. Rather than political affiliations, board members ought to be chosen on the basis of their qualifications and experience. To improve their ability to make decisions, bank managers should also be required to participate in training programmes.
- *Providing Capital Infusion and Financial Assistance:* To assist co-operative banks in fortifying their balance sheets, the government ought to design unique financial packages and liquidity assistance initiatives. To guarantee sufficient lending capability, low-interest credit lines ought to be offered.
- *Encouraging Financial Inclusion:* It is important to support co-operative banks in reaching out to underbanked and unbanked communities. Banks that offer loans and microfinance services to underserved communities can receive incentives from the government.
- *Promoting Customer-Centric Services:* By cutting down on loan processing times, streamlining banking processes, and strengthening customer support systems, co-operative banks may concentrate on raising the quality of their services. To find and fix service shortcomings, regular customer feedback surveys should be carried out.
- *Creating a Sturdy Human Resource Strategy:* Co-operative banks should hire qualified personnel, provide performance-based incentives, and fund employee training initiatives to increase operational effectiveness. To guarantee the seamless integration of contemporary financial technologies, employees should also receive training in digital literacy.
- *Managing Climate and Agricultural Risks:* Because of the significant reliance on agricultural loans, co-operative banks ought to work with insurance companies to provide risk-reduction products such as weather-based lending options and crop insurance.
- *Increasing Public Knowledge and Trust:* To inform the public about the advantages and offerings of co-operative banks, government organisations and financial institutions should launch awareness programmes. Customers' long-term trust will be bolstered by ethical banking practices and transparency in financial operations.

Conclusion and Recommendations

Using factor analysis, this study has determined the main elements impacting Odisha's co-operative banks' performance. Customer satisfaction and service quality, governance and regulatory compliance, technological adoption and digital banking, financial stability and risk management, and operational efficiency and human resource management were the five main criteria identified by the analysis. Together, these elements account for a sizeable amount of the variation in banking performance, underscoring their significance in determining the direction of co-operative banks in the future. According to the research, co-operative banks are essential to financial inclusion, but they also face a number of difficulties, such as poor governance, sluggish adoption of new technology, disgruntled customers, and financial risk. To increase these banks' efficiency and competitiveness, the report highlights the necessity of tighter regulatory control, greater financial risk management, better customer service, and faster digital transformation. Enhancing digital banking infrastructure, lowering NPAs, strengthening governance systems, and funding staff development are some of the policy recommendations made by this study. Co-operative banks may improve their financial viability and maintain their position as an essential part of Odisha's rural and semi-urban banking system by putting these strategies into practice. To create more comprehensive policy insights, future study might compare co-operative banks in different states and further examine how government policies, macroeconomic factors, and competitive pressures affect co-operative banking performance.

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Forecasting Gross Premium in India: Comparative ARIMA Model Analysis for New India Assurance

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Abstract

This research assesses the predictive efficacy of ARIMA models for projecting Gross Premium Collected in India (GPI) by New India Assurance. The study utilizes historical data from 2002 to 2023 and includes stationarity testing, model selection, and residual diagnostics. The study designates ARIMA(1,1,5) as the most efficacious model, shown by its optimal performance measures, which include the minimal Akaike Information Criterion (AIC) value and the maximal R-squared among the assessed alternatives. The projection anticipates consistent rise in GPI from 2024 to 2027, suggesting possible revenue enhancements driven by elements such as market development and heightened insurance penetration. This study enhances the current literature by underscoring the applicability of ARIMA models in projecting public sector insurance, therefore addressing a gap identified in previous studies centered on macroeconomic and efficiency evaluations. The findings corroborate the current research about ARIMA's forecasting efficacy, endorsing its use in strategic planning and risk management in the insurance sector.

Keywords: ARIMA, Gross Premium, Forecasting, Insurance Sector, New India Assurance

Introduction

The insurance sector in India is strong and varied, attributed to legislative changes, market growth, and evolving customer behavior. It is a key performance indicator that signifies the income stream of an insurance firm and its market penetration. The expansion and fortitude of New India Assurance as a leading public sector insurer, among these ongoing difficulties, is praiseworthy. The capacity to forecast future GPI based on the patterns found in this study is essential for strategic decision-making and resource allocation. Forecasting trends in GPI may provide better informed policy and operational planning within the firm and among other insurers.

Consequently, improved forecasting of their GPIs for strategic management planning, risk detection, and evaluation is essential for competitive positioning. The GPI is often influenced by macroeconomic circumstances and industry-specific variables, necessitating a predictive modeling system that can include these elements. This prognosis is seen significant by both traders and risk managers, as well as planners. Previous studies conducted by the RBI assigned comparable significance. Muthumeena and Muthusamy (2018) concentrated on the economic factors influencing public sector insurers, while Veerakumar et al. (2024) emphasized the competitive pressures between public and private insurers in India in this systematic study. These results highlight the need of specialized models to identify patterns in time series data, therefore assisting insurance companies in navigating both economic challenges and advantages.

This study seeks to determine the appropriate ARIMA model from the available alternatives for forecasting the GPI at New India Assurance. The outcome will identify the

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optimal model characterized by the minimal AIC or HIC value. This study is essential for advancing the company's entertainment projections, thereby enhancing its strategic planning. This study aims to determine the most effective method for evaluating GPI patterns and predicting them through ARIMA models, relevant for both short-term business strategies and long-term planning.

Literature Review

The Indian insurance market has seen substantial development and transition in recent decades, leading to considerable study on macroeconomic factors, financial efficiency, regulatory consequences, and operational effectiveness. Muthumeena and Muthusamy (2018) examined macroeconomic factors influencing public sector non-life insurance, highlighting the effect of external economic variables on gross premium performance. Ghose and Kumar (2019) examined the relative performance of public and private insurers, highlighting significant operational advantages and drawbacks. Yadav (2023) offered historical insights by examining general insurance patterns in the pre-liberalization period, so laying a framework for comprehending the industry's development trajectory. Veerakumar et al. (2024) performed a multivariate study comparing the performance of public and private insurance companies, while Kumar, Afifa and Sharma (2016) illustrated the efficacy of VAR modeling in predicting life insurance rates.

Investigations into financial efficiency have enhanced comprehension of the sector's production and obstacles. Chakraborty (2016) assessed the financial efficiency of public-sector insurance companies, while Sinha (2005, 2007) established the foundation for examining the development of the insurance sector, focusing on regulatory issues and structural transformations that arose after liberalization. Mathur (2001) addressed regulatory repercussions and variables affecting insurance growth, while Rao and Srinivasulu (2013) highlighted the sector's contribution to India's economic development. Ahmed et al. (2019) elucidated the difficulties and strategic transformations ensuing from industrial changes. Rajeswari and Kartheeswari (2011) observed the growing influence of private entities in defining the competitive environment, enhancing the examination of market engagement and dynamics. Gamage and Dayabandara (2013) further contributed by exploring the impact of vehicle make-based pricing in the motor insurance sector in Sri Lanka help understand premium setting in emerging markets like India.

Numerous studies have examined certain insurance sectors. Studies conducted by Nadkarni, Shetty, and Gadia (2017) and Radhika (2012) examined life insurance, addressing premium trends and the regulatory impact of the IRDA. Rajgopal (2013) explored whether life insurance acts more as a social security mechanism or an investment tool in post-reform Karnataka, contributing valuable socio-economic perspectives to the discourse on life insurance behavior. Nagaraju (2014) and Shahi and Gill (2013) examined the expansion of health insurance, emphasizing strategic innovations, while Binny and Gupta (2017) and Ramamoorthy and Kumar (2018) evaluated sector-specific obstacles and possibilities within health insurance. Dash (2018) performed perceptual mapping of health insurance companies, showing customer-focused evaluation trends. Priya (2018) analyzed benefit payouts using statistical techniques like ANOVA, underlining the need for robust analytical models in insurance operations. Kait and Sheoran (2022) elucidate the complexities of crop insurance schemes in rural regions, highlighting possible opportunities for expansion in these specialized insurance products. Karunarathne and Dayabandara (2013) studied the impact of policy and claims dates on investment terms, demonstrating time-sensitive variables relevant in non-life insurance operations

The theoretical underpinnings of time series forecasting have been established via seminal research, notably the ARIMA model created by Box and Jenkins (1976). The efficacy of ARIMA in managing data patterns, trends, and seasonality renders it particularly appropriate for predicting financial series like gross premiums (Stevenson, 2007). The efficacy of this model was further emphasized by Vandaele (1983) and Brockwell and Davis (2006), who demonstrated the applicability of ARIMA in time series analysis. Fattah et al. (2018) have shown applications in the insurance industry for demand forecasting, whereas Kumar et al. (2020) have focused on estimating insurance claim amounts. Li, Zhao and Zheng (2024) substantiated the model's significance by illustrating its efficacy in predicting industry trends. Vevek, Selvam and Kirithiga (2017) demonstrated the impact of sectoral volatility (e.g., auto and forex) on returns, emphasizing macro-financial linkages that are critical in modeling. The persistence of such volatility in stock indices, discussed by Vevek, Selvam and Sivaprakkash (2022), reinforces the importance of dynamic models like ARIMA for handling financial time series. Furthermore, the comparative study of stock market assimilation between India and China by Vevek, Selvam and Ganapathy (2024) provides an advanced perspective on inter-market dependencies that may influence insurance forecasting through spillover effects.

Despite comprehensive study on the performance of the Indian insurance business, deficiencies persist in the use of predictive modeling for public sector organizations such as New India Assurance. Negash, Venugopal and Asmare (2018) found variables influencing the rise of non-life insurance; however, they did not explore forecasting via sophisticated time series methodologies. Sood, Seth, and Grima (2022) examined portfolio performance without using forecasting methodologies such as ARIMA. The technical efficiency studies conducted by Siddiqui and Das (2019) and Khan and Mitra (2015) did not investigate predictive models, while Saminathan et al. (2013) and Izadi (2013) analyzed performance but restricted their focus to time series forecasting. This study seeks to fill the research vacuum by using comparable ARIMA models to determine the optimal model for predicting gross premium income (GPI) for New India Assurance.

This research posits that the ARIMA model will provide enhanced forecasting precision for GPI relative to less complex models. This theory is predicated on the seminal work of Box and Jenkins (1976), which demonstrated the dependability of ARIMA for intricate data patterns, along with additional corroborations by Stevenson (2007) and Ho and Xie (1998). Recent research by Vevek and Selvam (2021) and Hafiz et al. (2021) on economic indicators has shown the effectiveness of ARIMA in financial forecasting. The hypothesis asserts that a model combining autoregressive and moving average components would improve the precision of GPI predictions, hence aiding strategic decision-making in public sector insurance.

Data and Methodology

This study employs secondary data about Gross Premiums Collected by New India Assurance (GPI) in India. Annual reports, industry journals, and regulatory entities like the IRDAI guarantee data veracity. The period from 2002 to 2023 was selected for an in-depth examination of trends, seasonality, and structural alterations affecting GPI throughout the years. The primary variable analyzed is yearly GPI, which indicates market performance in the insurance industry. ARIMA modeling necessitates the evaluation of stationarity by the Augmented Dickey-Fuller (ADF) test, employing differencing until stationarity is established. The ADF test, in conjunction with ACF and PACF charts, informs the selection of ARIMA models, ranging from ARIMA(1,1,1) to ARIMA(1,1,5). The AIC, SC, and Hannan-Quinn Criterion assist in determining the optimal model by selecting the lowest values. Residual diagnostic assessments, such as the Ljung-Box Q-test and correlogram, validate the model's appropriateness by indicating that the residuals exhibit characteristics of white noise. The finalized model, evaluated and implemented, predicts GPI for 2024–2027, assisting New India Assurance's strategic strategy.

Result

Table 1: Stationarity Testing of Gross Premium in India (GPI) from New India Assurance

	ADF		*Test Critical Values*		
	t-Stat	*Prob*	*1% Level*	*5% Level*	*10% Level*
GPI (@ level)	-0.656	0.964	-4.468	-3.645	-3.261
D(GPI) (@ first Difference)	-4.601*	0.008	-4.498	-3.658	-3.269

Source: Author Compiled and calculated.

Table 1 displays the results of the Augmented Dickey-Fuller test performed to assess the stationarity of the Gross Premium in India (GPI) data from New India Assurance, analyzed at both its level and first difference. The GPI series exhibits a t-statistic of -0.656, exceeding the critical values at the one, five, and ten percent significance levels, accompanied by a p-value of 0.964, which exceeds the conventional threshold of 0.05. The elevated p-value indicates that we should maintain the null hypothesis, implying the existence of a unit root in the GPI series. This result indicates that the GPI series is non-stationary at its initial level, implying the presence of patterns or trends that do not converge to a constant mean over time.

The analysis of the first difference of GPI (D(GPI)) reveals an ADF test t-statistic of -4.601, which is below the critical values at all significance levels, accompanied by a p-value of 0.008. The low p-value enables the rejection of the null hypothesis, thereby confirming that D(GPI) is stationary. A single differencing of the GPI series effectively eliminates non-stationarity, rendering it appropriate for time series modeling. The findings indicate that GPI is an integrated series of order 1, I, 1, suggesting that an ARIMA (Autoregressive Integrated Moving Average) model is suitable for analyzing and forecasting this data, as it addresses both the autoregressive characteristics and the initial non-stationarity of the GPI series.

The correlogram of the differenced Gross Premium in India (GPI) series reveals substantial autocorrelation (AC) at lags 1 to 5, with a progressive decline, indicating an autoregressive (AR) component's existence. The partial autocorrelation (PAC) exhibits robust values at lag 1 and moderate significance at lags 2, 3, and 4, indicating a potential moving average (MA) component. The Q-statistics and associated p-values suggest substantial autocorrelation up to lag 4, with p-values below 0.05, hence justifying the inclusion of both AR and MA components. Potential ARIMA models that may encapsulate the underlying structure of the series, based on these patterns, include ARIMA (1,1,1), (1,1,2), (1,1,3), (1,1,4), and (1,1,5).

Table 2: Predictive Model Estimates and Fit Statistics for ARIMA Models of GPI

	ARIMA (p,d,q) (1,1,1)	*ARIMA (p,d,q) (1,1,2)*	*ARIMA (p,d,q) (1,1,3)*	*ARIMA (p,d,q) (1,1,4)*	*ARIMA (p,d,q) (1,1,5)*
C	1445.219	1457.664	1444.002	1470.458	1314.489
AR	0.907*	0.486	0.654*	0.412	0.456*
MA	-0.521	0.260	-0.164	0.453	0.754
SIGMASQ	826524.6	895174.2*	952252.8*	853661*	628908.5
AIC	16.880	16.949	17.011	16.930	16.770
SC	17.079	17.148	17.210	17.129	16.969
HQC	16.924	16.992	17.055	16.973	16.813
R-squared	0.440	0.393	0.355	0.422	0.574

Source: Author Compiled and Calculated.

Table 2 includes the estimates for many ARIMA models, such as ARIMA(1,1,1), (1,1,2), (1,1,3), (1,1,4), and (1,1,5). Finding the best model for forecasting the Gross Premium in India (GPI) series is the goal of this table 2. Notable variables include the AR coefficient in ARIMA(1,1,1) and ARIMA(1,1,5), among others. Each model has its own unique set of parameters for the AR and MA parts of the model. The ARIMA(1,1,5) model has the lowest AIC, score of 16.770 out of all the models that were considered. This means the model outperforms the alternatives in terms of data fit. This model outperforms the competition with an R-squared score of 0.574. A larger portion of the variation in the differenced GPI series may be explained by this. The ARIMA(1,1,5) model is appropriate for capturing the dynamics in the GPI data since the Schwarz Criterion (SC) and the Hannan-Quinn Criterion (HQC) have decreasing values. Taken into account, the ARIMA(1,1,5) model seems to be the most suitable prediction model for the series.

The correlogram of the residuals, in conjunction with the Ljung-Box Q-statistic test, indicates that the residuals from the fitted ARIMA(1,1,5) model display properties consistent with white noise. The autocorrelation (AC) and partial autocorrelation (PAC) values for the residuals across all lags are minimal and remain within the significance thresholds, indicating the absence of substantial spikes. The null hypothesis that the residuals are white noise cannot be rejected, since the Q-statistic p-values above the 0.05 level, indicating a lack of significant autocorrelation. The Ljung-Box Q-statistic supports this conclusion, as the high p-values indicate a lack of significant autocorrelation in the residuals, confirming their randomness and unpredictability. The

ARIMA(1,1,5) model effectively captures the intrinsic patterns in the Gross Premium in India (GPI) series, as evidenced by the absence of discernible patterns in the residuals. The presence of white noise in the residuals validates the appropriateness of the ARIMA(1,1,5) model for forecasting purposes.

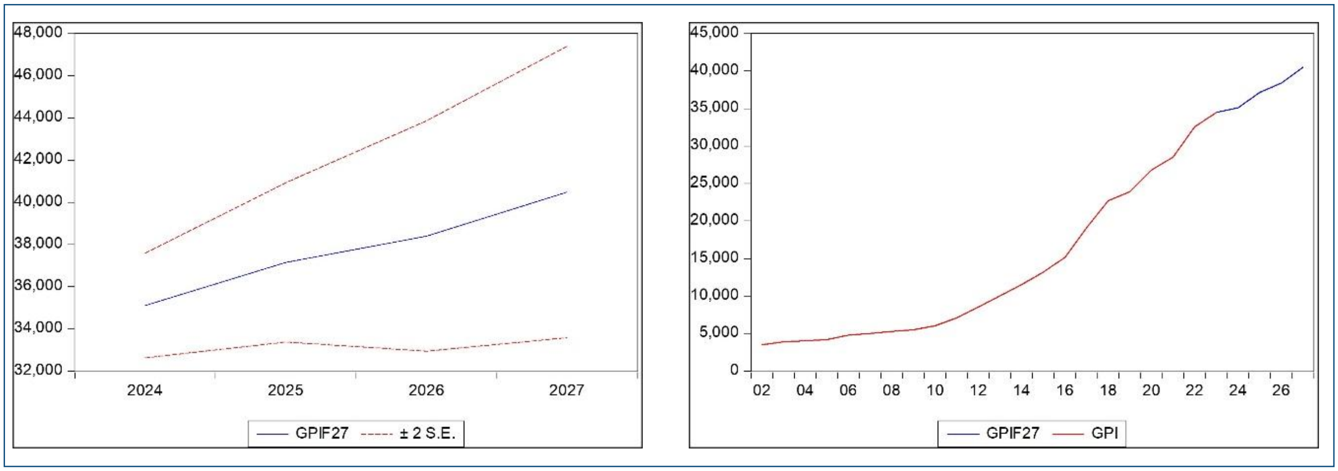

Fig. 1 and 2: Forecasted Growth of Gross Premium in India (GPI) Using ARIMA(1,1,5)

The ARIMA(1,1,5) model has generated forecasted values for Gross Premium in India (GPI) over a four-year period from 2024 to 2027. According to the forecast, GPI is expected to increase steadily each year. Starting from an estimated value of 35,107.76 in 2024, the GPI is projected to rise to 37,151.09 in 2025, followed by 38,399.94 in 2026, and reaching 40,487.81 in 2027. This consistent upward trend suggests a gradual increase in gross premium collections over time, indicating growth within the industry. The forecasted growth may reflect underlying factors such as expanding market demand, inflation, or increasing insurance penetration within India. However, it is essential to consider the model assumptions, as unexpected economic or industry-specific changes could impact the accuracy of these predictions. These results provide a useful baseline for planning and strategy within New India Assurance or the broader insurance industry, particularly for resource allocation and risk management.

Limitations and Future Research

This study has few limitations making its generalizability narrow because it is based on secondary data information only from New India Assurance so the same may not represent well about bigger picture of industry or differences with other companies. Further, the study uses a univariate ARIMA model to forecast Gross Premium Collected in India (GPI) and does not take into account external variables like economic changes, regulatory regulations or competition between other insurance players which may have substantial impact on GPI. ARIMA models, since they are built only on historical data, assume that the patterns worth considering in past will also exist in future — a hypothesis which might not always hold true; especially when you have to deal with rapidly changing business ecosystems. Additionally, the estimates reflect data as recorded at that point in time and may not account for updates to a company's filings over time.

As a next step, it suggests the collection of data from all major Indian insurance companies would be recommended to provide an overall picture of market conditions. Adopting multivariate models like Vector Autoregression (VAR) or ARIMAX would allow inclusion of external economic data, regulatory forces and competitive parameters; making the predictions advanced. Additionally, applying machine learning methods such as Neural Networks or Long Short-Term Memory (LSTM) models could be beneficial for detecting more intricate patterns in GPI An ongoing data refresh needed to take place allowing a more regular model evaluation that would allow corrections and tuning in predictions more especially under market volatility where past trend based estimates may lose relevance.

Conclusion

This research sought to determine the optimal ARIMA model for predicting Gross Premium Collected in India (GPI) by New India Assurance. The findings reveal that ARIMA(1,1,5) is the superior model, surpassing other configurations because to its decreased Akaike Information Criterion (AIC) values and elevated R-squared metrics. Thorough stationarity tests and diagnostic assessments confirmed the model's resilience in identifying the intrinsic patterns within the GPI data, establishing it as a dependable instrument for strategic forecasting. The anticipated GPI growth from 2024 to 2027 indicates a consistent rise driven by expected economic stability and increasing market needs. The results correspond with the findings of Kumar, Afifa and Sharma (2016), who illustrated the effectiveness of predictive modeling in insurance trends, and Stevenson (2007), who validated ARIMA's capability in managing intricate time series data. This research builds upon previous evaluations by concentrating on public sector data and correcting the deficiencies identified in the works of Negash, Venugopal and Asmare (2018), which overlooked sophisticated forecasting methodologies. Furthermore, it opposes the narrow emphasis shown in Sood, Seth and Grima (2022), whereby predictive analysis was not included despite the evaluation of performance measures.

Contribution to Literature entails addressing a significant deficiency in research pertaining to predictive modeling in the Indian public insurance industry. This research uniquely blends performance measurements, regulatory implications, and macroeconomic trends with advanced time series forecasting, in contrast to most of the prior work that has focused on analyzing these elements separately. The study demonstrates that the use of ARIMA modeling to GPI data may improve forecasting accuracy for public insurers using customized time series methodologies. This study enhances the scholarly discourse on financial forecasting and offers a pragmatic framework for insurers aiming to bolster strategic planning. It emphasizes the conclusions of Box and Jenkins (1976) about the efficacy of ARIMA in time series forecasting, corroborating its significance as noted in research such as Vevek and Selvam (2021). These contributions provide the groundwork for future research to integrate multivariate or machine learning methodologies, guaranteeing responsiveness to changing economic situations and data trends.

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Exploring Key Factors Influencing Financial Inclusion Among Customers of Rural Banking Agents

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Abstract

Financial inclusion provides easy and affordable access to financial products and services and has been identified as an enabler for 7 of the 17 Global Sustainable Development Goals. Agent banking has become a powerful catalyst for improving financial inclusion, especially in rural and under-banked areas. Thus, identifying the determinants of financial inclusion for the rural banking customers would help the policymakers and government in bringing them into the formal financial system. The study has been conducted in the Darjeeling district of West Bengal, India. Primary data was collected for the present study using questionnaires on a five-point scale, and statistical analysis was done using EFA, CFA & SEM. Statistical tools like SPSS 20, AMOS 23, and Microsoft Excel were used to conduct the investigation. The study identified four constructs i.e. affordability, accessibility, trust, and availability as important determinants of financial inclusion and found statistically significant for the banking agent customers. These findings highlight the vital role of agent banking in breaking down barriers to financial inclusion and expanding access to formal financial services.

Keywords: Financial Inclusion, Business Correspondents, Banking Agents, Rural Finance

JEL: G21, D14, R51

Introduction

Financial Inclusion is the process of delivering financial services to the unbanked population so that they can have access to basic banking products and services in a formal financial system (Ozili, 2020) and is one of the important factors in eradicating poverty and achieving sustainable economic growth. Several studies undertaken by academics in various countries have discovered that those with a higher degree of financial inclusion in terms of affordable access and adequate financial services had higher GDP growth rates and lower levels of income inequality (Clarke et al., 2006, Beck et al., 2007, Demirguc-Kunt et al., 2017). A well-functioning financial system should be inclusive and easily accessible to the large population, improving the financial condition of the poor and deprived sections (Dahiya & Kumar, 2020). Financial Inclusion has been identified as an important catalyst for 7 of the 17 Global Sustainable Development Goals, considering it a key enabler to reduce extreme poverty and boost shared prosperity (World Bank, 2018). Demirgüç-Kunt et al. (2015) conducted a study on the relationship between financial inclusion and poverty alleviation and found that access to financial services is positively correlated with economic empowerment, enabling individuals to invest in education, health, and business opportunities, thereby contributing to poverty reduction in the economy.

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Vishwakarma (2024) stated that financial inclusion and overall well-being are critical components in empowering women, as they significantly contribute to enhancing their financial autonomy. According to the Global Findex Database (2017) report around 79.9% of our population have formal bank accounts, compared to 53.1% in 2014. Furthermore, 23.4% of those without an account cited the distance between the financial institution and their home, 21.7% cited a lack of necessary documents, and 51.6% stated that someone in their family has an account with a formal financial institution. Thus, the major thrust of policymakers should be to increase the economic access of the deprived section living at the bottom of the pyramid and provide uninterrupted services at their doorstep at an affordable cost, which can potentially be a viable business opportunity for the banks.

RBI introduced the Information and Communication Technology based Business Correspondents model vide a circular DBOD.No.BL.BC.58/22.01.001/2005-06 dated January 25, 2006, based on the recommendation of the Internal Credit Group on Microfinance to provide doorstep delivery of financial products and services at a reasonable cost. Banking Agents were permitted to carry out their transactions on behalf of the banks as agents (RBI, 2006). In this model, the banks enter into third-party contracts with the Corporate BC and are entrusted with the task of appointing, training and managing the banking agents and providing banking services to the customers residing in the unbanked locations including the urban areas through the Banking Agents.It uses a Laptop/Desktop to handle transactions together with a biometric device, Pinpad Device, Printer, Inverter and Cash Counting Machine. They operate from a fixed establishment which is set up as a rural banking outlet and also have the option to execute transactions from other places. It also employs a GPRS-equipped mobile set which includes biometric authentication and a Bluetooth-enabled portable printer to execute banking transactions. The introduction of agent banking has enhanced access to financial services by enabling customers to use non-bank intermediaries, particularly in regions where formal bank branches are absent (Ivatury & Mas, 2008). Further, the study also highlights that the fintech companies, through innovative and customer-focused technologies, improve the efficiency of banking services and play a significant role in advancing financial inclusion (Baporikar, 2023).

Literature Review and Hypothesis Formulation

Financial Inclusion has been considered a major strategy for achieving UN Sustainable Development Goals (Demirduc-Kunt & Singer, 2017). A well-functioning financial system should be inclusive and easily available to the populace so that it can alleviate poverty or uplift marginalized sections of society. Rangarajan (2008) states financial inclusion is the process of ensuring access to financial services from the formal financial institution in an adequate and affordable manner. Sharma (2016) examines the relationship between the different dimensions of financial inclusion and economic development. The study found that higher banking penetration, availability of banking services and deposit usage of banking services resulted in higher economic growth. Availability and Accessibility are important factors in a financially well-included society (Dixit & Ghosh, 2013). High fees for basic services, such as account maintenance, withdrawals, and transfers, often deter poorer individuals from engaging with formal financial institutions thus by reducing these costs via digital platforms, financial service usage has notably increased, particularly in low-income countries (Porteous, 2006). According to Muniarty et al. (2020), the agent banking system efficiently connects unbanked and under-banked inhabitants within the formal financial system at a reduced cost and motivates them to avail services physically for cash transactions, account registration, micro-insurance, etc. at agent outlets. This method has been predominantly pushed by banks working with Corporate Business Correspondents to expand their banking coverage to the country's major unbanked areas through BC Agents. Gitau (2014) investigated the role of agency banking and its influence on commercial banks' operational performance. The study revealed that banking agents were effective in diverting existing customers from overcrowded branches, providing a supplementary and convenient channel and tapping into clients from different geographical areas, which was an expensive undertaking for bank branches. Agency banks have increased the performance of commercial banks by reducing expenses related to building premises, human resources, training, and equipment such as furniture and computers. Zins and Weill (2016) observed that trust in the overall financial system, especially in the safety and reliability of digital transactions, is essential for advancing financial inclusion. To foster this trust, banking agents must be seamlessly integrated into secure and transparent systems, ensuring that customers feel confident in the security of their deposits and transactions. Further Khalti (2019) opined that agent banking has proven to be a cost-effective approach for providing banking services to the rural population, allowing them to access formal banking services and alleviating poverty. While the agency banking system has been in place in India for almost a decade and significant progress has been achieved, it falls well short of expectations (Qazi, 2019). Goud (2022) observed that enhancing financial inclusion empowers individuals to make more informed and confident financial decisions. As a result, a framework that may accelerate the financial inclusion of business correspondent customers in India must be identified. Thus, this study tries to identify the factors influencing the financial inclusion among the customers of rural banking agents.

Hypothesis

Accessibility is the ability of individuals to obtain various financial products and services without paying extra money with minimum barriers to accessing the bank account and conducting deposits or withdrawals. According to Allen, Demirgüç-Kunt, Klapper and Peria (2016), accessibility plays a crucial role in influencing individuals' decisions to engage with formal financial services, especially in developing nations where challenges such as stringent documentation requirements and financial illiteracy are more prevalent. The proper access to banking products and services with less documentation and proximity will result in greater financial inclusion (Demirguc-Kunt & Klapper 2013). As a result, this study hypothesizes:

H1: Accessibility is the determinant of financial inclusion.

Affordability is considered as an important barrier to financial inclusion as the higher cost of accessing financial products and services will deprive marginalized people of availing the services. Similarly, the compulsion of maintaining a higher balance in the bank account and the charges associated with it result in the exclusion of poor people (Beck et al., 2008). It is the affordability of the services that encourage people to access and use the product that influences financial inclusion (Claessens, 2006). Similarly, Porteous (2006) also noted that innovative solutions like mobile banking and agent banking can effectively lower the costs of financial services, thereby enhancing financial inclusion for low-income populations. As a result, this study hypothesizes:

H2: Affordability is the determinant of financial inclusion.

Availability refers to the physical presence of financial institutions, like bank branches, ATMs, and banking agents in areas with limited access to financial services. This financial infrastructure plays a crucial role in promoting financial inclusion, particularly in rural and remote regions. Beck, Demirgüç-Kunt and Martinez Peria (2007) emphasized that expanding banking services through the growth of branches enhances financial inclusion by offering easier access to essential financial services for previously excluded populations. Most of the literature focuses on the availability of bank branches, ATMs, and other services as the strategic policy to enhance financial inclusion (Chakraborty & Pal, 2013). The availability of banking products and services to poor and unbanked people at ease brings them within the system's financial domain, increasing their transaction power. Therefore, this study hypothesizes that:

H3: Availability is the determinant of financial inclusion.

Trust reflects a belief that the opponent will behave according to what has been promised and will not take undue advantage of the person he is dealing with (Guiso, 2010). Any shortage of distrust in the financial system will be a barrier preventing the individual from accessing the services. Trust in financial service providers tends to improve when agents come from the local community, as customers are more at ease interacting with familiar individuals (Suri & Jack, 2016). This is especially crucial in rural areas where social capital heavily influences financial decision-making. Trust can be strengthened through transparency, secure handling of deposits, and positive customer experiences with financial services. It was also indicated by nearly 13% of unbanked individuals as one of the main reasons for not having a bank account (Demirguc-Kunt et al., 2015). Thus, trust can play a crucial role in enhancing financial inclusion. As a result, this study hypothesizes:

H4: Trust is the determinant of financial inclusion.

Methodology

The study aims to find out the attributes that accelerate the financial inclusion of rural banking agent customers who use information and communication technology-based agency banking services. The current research is primarily based on primary and secondary data. All those rural customers availing the services from the banking agents in the Darjeeling district of West Bengal, comprises the population of the study. Banking agent data was obtained from the Business Correspondents registry and the bank websites after which their customers were approached for the primary study. A well-structured questionnaire has been personally administered to the sample customers on a five-point Likert-type scale measurement ranging from "1 (strongly disagree)" to "5 (Strongly Disagree)."A pre-test was conducted with three domain experts with experience in financial inclusion to confirm that the questionnaire had no semantic issues. The instrument was further pilot-tested with 20 banking agent customers to test the validity and reliability of the survey instruments, and it was statistically evaluated to find out its feasibility. Nearly 460 responses were received, out of which 37 questionnaires were rejected due to incomplete details or outliers. As a result, the total sample size was 423. The survey data was examined using statistical techniques such as exploratory factor analysis, confirmatory factor analysis, and structural equation modeling using statistical tools such as SPSS 23, Amos 20 and Microsoft Excel.

Results and Discussions

The exploratory factor analysis was first used to identify the main factors that are thought to influence rural customers' intentions to use agent banking services. The purpose of using factor analysis is to reduce a large number of variables into a small collection of factors while retaining all of the information contained in the variables (Hair et al., 2010). The core argument behind the application of exploratory factor analysis is that it helps build a construct using different items and effectively contributes to creating instruments and validating a questionnaire (Davis, 2016). The findings of factor analysis are generated through principal component analysis using varimax rotation. The sampling adequacy is measured by the KMO (Kaiser-Meyer-Olkin) test and Bartlett's test of sphericity. The KMO value (0.840) is acceptable and Bartlett's test of sphericity is significant at a 5% level and is found satisfactory to extract attributes using EFA. According to Kaiser (1960), all factors whose criterion is above the eigenvalue of one are to be retained. Five factors are extracted from 20 observed variables out of which 03 variables are dropped from the analysis due to their factor loading being less than 0.5 and the cumulative percentage variation of 72.450 percent is obtained which is beyond the acceptable variance of 60% (Hair et al., 2014). As a result, the measurements are suitable for carrying out CFA (Byrne, 2010).

Table 1: EFA & CFA Factor Loadings, Validity & Reliability of Items

	Coefficient of Loading	
Factors	*Exploratory Factor Analysis*	*Confirmatory Factor Analysis*
Accessibility (ACCE): Eigen Values - 5.555; CR - 0.878; AVE - 0.643		
ACCE4	0.837	0.811
ACCE1	0.833	0.845
ACCE2	0.822	0.816
ACCE3	0.796	0.73
Availability (AVAIL): Eigen Values - 2.179; CR - 0.844; AVE - 0.575		
AVAIL2	0.821	0.769
AVAIL4	0.815	0.81
AVAIL1	0.768	0.751
AVAIL3	0.765	0.7

Factors	*Coefficient of Loading*	
	Exploratory Factor Analysis	*Confirmatory Factor Analysis*
Trust (TRUS): Eigen Values - 2.179; CR - 1.790; AVE - 0.622		
TRUS1	0.885	0.738
TRUS3	0.842	0.834
TRUS2	0.746	0.791
Affordability (AFFO): Eigen Values - 1.664; CR - 0.797; AVE - 0.568		
AFFO2	0.857	0.79
AFFO3	0.847	0.809
AFFO1	0.777	0.653
Financial Inclusion (FIN): Eigen Values - 1.129; CR - 0.816; AVE - 0.597		
FIN1	0.816	0.78
FIN2	0.781	0.799
FIN3	0.776	0.738

Source: Author calculation.

Confirmatory factor analysis validates the measurement model created by exploratory factor analysis. The measurement model helps to determine the reliability and validity of the measuring instruments and evaluates the fit observed between the observed and estimated covariance matrices (Hair et al., 2014). The maximum likelihood estimation approach was utilized to perform confirmatory factor analysis on the five-component model retrieved from EFA. Confirmatory factor analysis is used to assess the model data fit on four factors with 14 observed variables. The empirical results are as follows: CMIN/DF = 2.310, CFI = 0.956, TLI = 0.946, GFI = 0.935 and RMSEA = 0.056 which support the measurement model being compatible with the data (Hair et al., 2014). The standardised factor loading, which should be greater than 0.6, is used to determine reliability, and the factor loading in our study is greater than 0.6. (Hair et al., 2014). Further to assess the validity measures composite reliability (CR) was tested and the obtained value was more than 0.7 with the highest CR of 0.878 and the lowest CR of 0.790 (Table 1) satisfying the internal consistency of the latent construct. Similarly, convergent validity is assessed by calculating the AVE value with the acceptable value being 0.5 for each construct. The study found the AVE values ranging from 0.568 to 0.643 which concludes adequate convergent validity (Table 1).

Discriminant validity is measured to find out to what extent a construct is different from other constructs and it ensures that a construct is unique and captures specific phenomena. Each construct's square root is greater than the off-diagonal value of all correlation coefficients in our investigation. According to the factor correlation matrix, the lowest value of the square root of AVE is 0.754, which is more than the inter-construct correlation and so indicates that the construct is distinct from other constructs and hence fulfills the model discriminant validity (Fornell & Larcker, 1981). The result of discriminant validity is presented in Table 2 below:

Table 2: Discriminant Validity

	CR	*AVE*	*MSV*	*MaxR(H)*	*AFFO*	*AVAIL*	*ACCE*	*TRUS*	*FIN*
AFFO	0.797	0.568	0.149	0.811	**0.754**				
AVAIL	0.844	0.575	0.227	0.849	0.183	**0.759**			
ACCE	0.878	0.643	0.227	0.883	0.174	0.476	**0.802**		
TRUS	0.831	0.622	0.285	0.837	0.183	0.349	0.325	**0.789**	
FIN	0.816	0.597	0.285	0.819	0.386	0.441	0.459	0.534	**0.773**

Source: Author calculation.

Note: Square root of AVE on diagonal values and off-diagonal value are inter-construct correlations.

Structural Equation Modeling (SEM)

The SEM was applied to test the proposed model on exploring the attributes resulting in the financial inclusion of business correspondent agents' customers. The model specification of the structural model found all the indicators favorable with normed chi-square value 1.696, CFI = 0.968, GFI = 0.934, NFI = 0.925 and RMSEA = 0.047 all within the cut-off value recommended earlier studies (Hair et al., 2014) and demonstrate that the proposed model is appropriate for the data collected. The standardised path coefficients for the structural equation model are shown in Fig. 2. The results of the structural equation model are shown in Table 3.

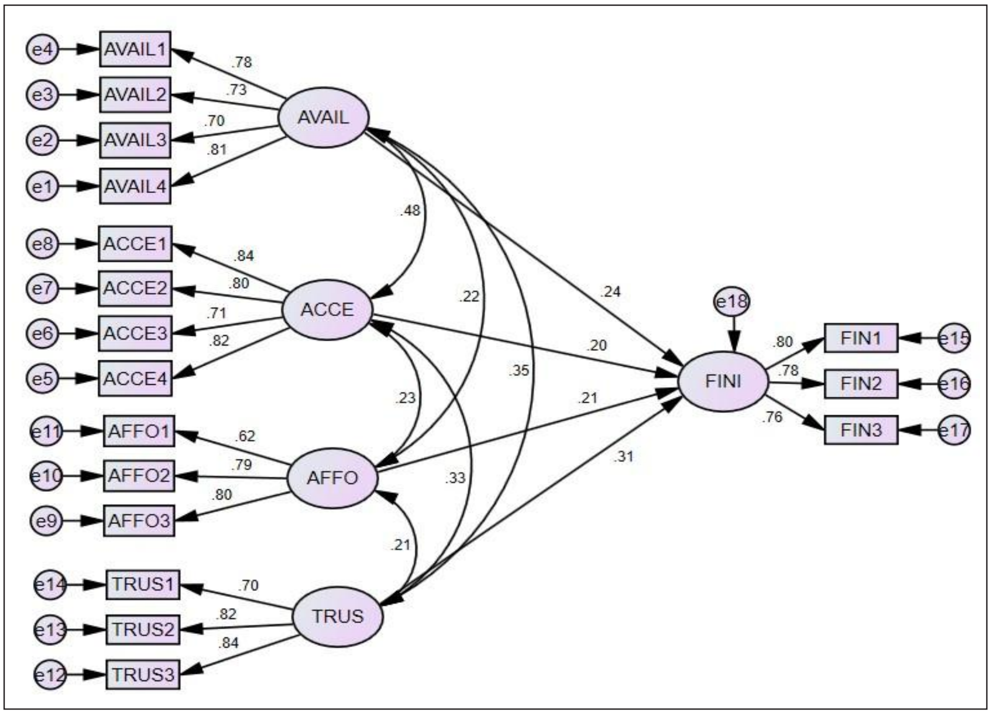

Fig. 1: Standardised Path Coefficient for Structural Equation Model

Table 3: Results of the Structural Equation Model

Hypotheses	*Relationship*	*Estimate*	*S.E.*	*Critical Ratio*	*P-Value*	*Results*
H1	AVAIL → FI	0.237	0.062	3.383	***	Accepted
H2	ACCE → FI	0.205	0.061	3.024	***	Accepted
H3	AFFO → FI	0.206	0.065	3.314	***	Accepted
H4	TRUS → FI	0.315	0.08	4.805	***	Accepted

Source: Author Calculation; Note: p-value is significant at 5 per cent level.

Conclusion

The findings reveal that availability, accessibility, affordability, and trust emerge as the most significant determinants driving financial inclusion. Table 3 shows the model hypothesis testing findings, including the path coefficients and their significant values. According to the study, trust emerges as the most significant factor influencing financial inclusion, demonstrating the highest degree of influence (0.315). This finding aligns with previous research by Ghosh (2021) and Koomson et al. (2023), both of whom emphasize the pivotal role of trust in enabling customers to engage confidently with banking agents. Trust is cultivated through regular interactions and the reputation that agents build within their local communities, ultimately shaping customers willingness to transact. Similarly, Masila et al. (2015) found that customers placed their trust in banking agents to deliver reliable and quality services, which in turn led to greater satisfaction and service adoption. Similarly, availability is the second highest determinant with a standardized regression weight of 0.237 as a majority of the customers depends on the agents to conduct banking transaction after the banking hour. Agents provide their services even from their homes in case of necessity to the customer and they also do not hesitate to approach them in case of any query regarding the banking product and services. This result is consistent with the prior studies. Ho (2017) has also found that the average rural customer has to travel between 8 to 20 km to access banking services from the nearest branch. In contrast, the availability of banking agents in close proximity to their homes has made it extremely convenient for rural customers to access the same services regularly.

Affordability is the third significant factor with a beta value of 0.206. The majority of the rural population hesitate to visit bank branches to conduct banking transactions due to their lower income and the cost required to travel to the branch while the banking agents are located within the villages making it easier for them to access the subsidies and other welfare schemes subsidy in their account without incurring any additional cost. This is consistent with past research (Gupte et al., 2012). The accessibility dimension is also found to be a significant determinant of financial inclusion with a regression weight of 0.205. Banking agents are very cooperative as they belong to the same village making it convenient to rural people to open their accounts comfortably and access the service at the ease of their convenience. They do not have to travel a long distance incurring additional charges, which motivates them to deposit or withdraw money with the local agents, and since the agents are accessible as per their requirements, it becomes easier to conduct transactions. They are the real heroes in the rural areas and far-fledged locations where the bank branches are not available. This result is similar to the studies conducted earlier (Camara & Tuesta, 2014). Kolloju (2014) also observed that Business Correspondent Agents offer significant exposure to financially illiterate rural individuals, facilitating their access to fundamental banking services without incurring any extra costs. Further, Dhar & Jaiswal (2021) pointed out that despite the expanding outreach of financial services through business correspondents, the system continues to experience qualitative gaps, including suboptimal usage, misinformation, and inappropriate financial behaviors. These issues underscore the need to not only strengthen trust, accessibility, affordability and availability but also enhance the quality and effectiveness of financial service delivery to ensure meaningful inclusion.

Limitations

The study focused on the factors affecting the financial inclusion of the banking agents customers in the Darjeeling district of West Bengal. The researchers can undertake further studies to identify the other determinants that can accelerate financial inclusion and the mediating and moderating factors influencing the banking agent customers. Similarly, longitudinal studies can be undertaken covering multiple states which will help to generalize the findings.

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Competitive Dynamics in the Indian Banking Sector: A Comparative Analysis Using Structural and NEIO Approaches

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Abstract

Purpose: The study examines competition in the Indian banking sector by analysing public, private, and foreign-owned banks from 2005 to 2023. It also explores the market structure of the Indian banking industry. *Design/methodology/approach:* The study employs both structural approaches – specifically, the concentration ratio (CR) and the Herfindahl-Hirschman Index (HHI) – and the New Empirical Industrial Organization (NEIO) framework, which includes the Lerner index (LI) and the Panzar-Rosse H statistic, to estimate bank competition. *Findings:* The findings indicate that competition levels vary based on ownership segments and the metrics employed. The HHI reveals that the differences in HHI values based on ownership are negligible, reflecting that the banking sector in India has remained highly competitive throughout the study period. In contrast, the LI, which utilises marginal cost, shows varying levels of market power. When examining total revenue, public sector banks are marginally more competitive than private sector banks, although the difference is minimal. *Originality/Value:* This paper offers new insights into the competitive dynamics of the Indian banking sector, contributing to the existing literature on banking efficiency. The application of structural and non-structural approaches, and a comparative analysis of the results obtained, provides a new perspective on bank competition in India. Policymakers can use the study's findings to enhance competition in the Indian banking industry and implement measures accordingly.

Keywords: Public Sector Banks, Banking Policy, Bank Competition, Lerner Index, Panzar-Rosse H Statistic, Financial Intermediation, Financial Markets

Introduction

India's banking system, forged through decades of development, now stands as a vast and dynamic network crucial to the country's economic engine (RBI, 2013). India's banking system, shaped over decades of development, now functions as a critical driver of the country's economic growth (RBI, 2013). Banks primarily serve to facilitate credit, ensure financial stability, and foster economic expansion (Ramanadh & Rajesham, 2013). The Indian banking sector underwent significant reforms following the Narasimham Committee report of 1991, which marked a pivotal shift in economic policies during the early 1990s. These reforms, driven by competitive pressures in emerging markets, introduced substantial changes in banking models. Key transformations included the privatisation of state-owned banks, a surge in mergers and acquisitions (M&As), and increased participation from foreign banks.

Since the first nationalisation wave in 1969, the sector has witnessed 54 M&As – 14 before the 1991 reforms and 40 thereafter (Leeladhar, 2008; Herwadkar et al., 2022). This consolidation process has yielded both positive outcomes and regulatory challenges for the banking industry. To address these, a second Narasimham Committee was formed in 1998 to oversee the ongoing reform trajectory. The forces of globalisation further fuelled mergers, significantly altering the banking landscape. Nonetheless, these structural shifts raise concerns about their impact on competition within India's banking sector.

Despite the profound changes in the Indian banking structure, prior literature reveals a scarcity of empirical

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studies comparing bank ownership in India using both the structural approach and the New Empirical Industrial Organization (NEIO) framework (Bhuyan, 2022). We aim to fill this gap and contribute to the limited body of research on the subject. The objectives are as follows:

- To assess the concentration and level of competition in the Indian banking sector with respect to total assets, total revenue, net interest income, marginal costs, and deposits using different matrices of measurement.
- To compare how the competitiveness differs across bank ownership segments.

The remaining sections of this study are organised as follows: Section 2 provides a review of the literature; Section 3 describes the data and the methodology; Section 4 presents the findings of the analyses estimating concentration ratio (CR), Herfindahl-Hirschman Index (HHI), Lerner index (LI), and Panzar-Rosse H statistic; and the final section, Section 5, presents the conclusion.

Literature Review

The empirical measurement of competition in the banking sector can be categorised into two main approaches: the structural approach and the non-structural approach (Bikker & Groeneveld, 2000; Tecles & Tabak, 2010; Prayoonrattana et al., 2020). Many studies (Amavilah, 2012; Bikker et al., 2006; Bikker & Haaf, 2002) use the structural approach based on traditional industrial organisation, which states that banking competition stems from the market structure, measured by the concentration ratio (CR) or the Herfindahl-Hirschman Index (HHI).

While these indicators have strengths, they also have limitations. For example, the CR considers only the data of the top n enterprises, neglecting the remaining firms and the internal distribution within the market (Prayoonrattana et al., 2020; Bikker & Haff, 2002; Lipczynski et al., 2017). The HHI, although widely used, does not distinguish between large banks and small banks and may misrepresent competition trends during bank consolidations (Xu et al., 2014). However, HHI is particularly effective in representing market concentration during structural changes such as M&As (Lipczynski et al., 2017). In addition, many studies have concluded that concentration is not a suitable proxy for competition and may not be the cause of high profitability (Bikker & Haaf, 2002; OECD, 2010).

The literature on non-structural measures of competition is commonly known as the NEIO approach. In contrast to the structural approach, the NEIO method does not directly rely on information about market structure (Anzoategui et al., 2010). Instead, this approach assesses parameters that consider the degree of competition in specific markets, stemming from bank-level data and certain assumptions about bank conduct, such as demand elasticity and market dynamism (Bikker & Groeneveld, 2000; Bikker & Haaf, 2002; Guevara et al., 2005; Carbo et al., 2009). This literature includes the Brenahan, Lau and Panzar-Rosse approaches, as well as the LI and PE elasticity (Demirguc-Kunt & Peria, 2010; Xu et al., 2014; Bandaranayake et al., 2020).

The LI has key limitations: the need for detailed firm-level cost and demand data and the challenge of calculating marginal costs, as only internal agents know marginal prices (Cetorelli, 1999). These indicators also fail to capture qualitative market factors such as market stability, product differentiation, and entry barriers (Carbo et al., 2009). However, the LI offers a key advantage by being bank-specific and varying over time, enabling the comparison of market power both among different banks and across different periods (Leon, 2015). The Panzar-Rosse H statistic, another NEIO indicator, is widely used globally but less so for Indian banks (Prasad & Ghosh, 2007; Bhuyan, 2022). Its main limitation is the assumption that markets are in long-run equilibrium and that bank products are homogeneous (Xu et al., 2014). Despite this, the Panzar-Rosse H statistic model is advantageous because it utilises bank-level data and accommodates bank-specific differences in production function (Claessens & Laeven, 2004).

Various studies for most countries conclude that market structure can be distinguished as monopolistic competition, a result obtained in many mature markets (Acikalin & Sakinc, 2015; Berger, 1995; Bikker & Groeneveld, 2000). Gelos and Roldos (2003) empirically deduced that the banking industry has become more competitive and argued that foreign bank penetration and competition have helped maintain competitive pressure. However, Yeyati and Micco (2007) inferred that foreign penetration has a negative and significant effect on competition and that increased concentration has no influence on competition and banking sector stability.

Some studies use both structural and non-structural approaches to determine concentration and measure the degree of competition, further attempting to compare the relationships between structural and non-structural measures (Bikker & Haaf, 2002; Carbo et al., 2009; Claessens, 2009; Guevara et al., 2005). A small or insignificant relationship is observed between the empirical results obtained from the structural and non-structural indicators (Bikker & Haaf, 2002; Carbo et al., 2009; Claessens, 2009; Guevara et al., 2005).

A limited number of empirical studies have investigated competition and concentration in the Indian banking sector. These studies use both approaches to measure bank competition, viz structural (Parida & Padhi, 2018; Rakshit & Bardhan, 2019) and non-structural approaches (Vinod & Azam, 2018; Li et al., 2019; Prasad & Ghosh, 2007; Arrawatia & Misra, 2019; Rakshit & Bardhan, 2019). Some studies empirically conclude that the Indian banking sector is characterised by monopolistic competition (Prasad & Ghosh, 2007; Rakshit & Bardhan, 2019; Li et al., 2019).

Parida and Padhi (2018), on the basis of structural measures, concluded that concentration is increasing and that competition in the Indian banking sector is decreasing. On the other hand, some studies deciphered that the Indian banking sector is competitive and shows an increasing trend in competitiveness (Arrawatia & Misra, 2019; Rakshit & Bardhan, 2019). Rakshit and Bardhan (2019), using the NEIO approach, employed the LI, adjusted LI, and Boone indicator along with the HHI and the CR (structural approach) to assess the degree of market competition (over the period 1996–2016). These findings align with those of Bolt and Humphrey (2010), who demonstrated that the degree of competition is lower in activities that generate non-interest income. The findings also indicated that a higher degree of bank competition erodes market power and decreases profit margins in Indian banking over time. The study does not support the structure-conduct-performance hypothesis. Robust findings also revealed that public sector banks in India exercise relatively less market power than private and foreign banks. Vinod and Azam (2018) asserted that increasing the number of banks in the banking industry will not lead to enhancing the competition-induced efficiency.

Despite the disadvantages of competition indices, they are significant indicators of concentration and competition in an industry (Maksimovic, 2012; Nuraini, 2019). While various measures have been broadly accepted, there is no consensus regarding the ‘best’ indicator for gauging bank competition (Carbo et al., 2009). Although many studies apply both structural and non-structural approaches to assess competitiveness in the banking sector, these studies predominantly focus on developed economies, particularly in Europe, rather than on developing countries. In addition, the literature measuring bank competition in the Indian banking sector relies on the HHI, CR, and LI. These studies compute the HHI and CR using variables such as total loans and total deposits. Our study offers a different perspective by calculating the LI using the base prime lending rate (BPLR), base rate, and marginal cost of funds based lending rate (MCLR) as proxies for marginal cost across the bank segments and also computing the Panzar-Rosse statistic. A comparison of these findings across different bank ownership segments offers a comprehensive analysis of competition within the Indian banking sector. This study provides new insights into the competitive dynamics, contributing to the broader literature on banking efficiency. As a result, it enhances the understanding of competition in Indian banking.

Data and Methodology

Data

Bank-level data for all variables, except for marginal cost, were obtained from the *Statistical Tables Relating to Banks in India* (STRBI), an annual publication by the Reserve Bank of India. Data on marginal costs were sourced from the interest rate data table provided in the Reserve Bank of India (RBI) database. The sample includes public sector banks, private banks, and foreign banks, covering the period from 2005 to 2023. The data were cleaned for inconsistencies and outliers by excluding certain foreign and private banks, resulting in an unbalanced panel dataset. A classification table showing the number of banks by ownership type is included in the appendix (Table 1).

Methodology

Methodology is categorised as follows:

Structural

The structural approach consists of two methods:

CR

The CR is the ratio of the sum of the assets of the five largest banks to the total assets of all banks.

$$CRn = \sum_{i=1}^{n} \frac{Si}{S}, n = 1, \ldots, 5$$

where n is the number of banks; Si denotes the market share of bank I; and S denotes the total market share of all banks in the banking industry.

We calculated the CRs as CR5-TA (total assets), CR5-TD (total deposits), and CR5-TL (total loans), similar to the methodology used by Acikalin and Sakinc (2015). The five largest banks on the basis of the 2020 assets database from the STRBI are the State Bank of India (SBI), HDFC Bank, Bank of Baroda, ICICI Bank, and Axis Bank.

HHI

The HHI is computed by summing the squares of asset shares of all banks in the banking system. The formula for HHI is as follows:

$$HHI = \sum_{i=1}^{n} [Si/S]^2$$

where Si denotes the total assets of bank i, n denotes the number of banks, and S denotes the total assets of all banks in the banking industry. Similar to the CR, we calculated and categorised the HHI into three types: HHI-TA, HHI-TD, and HHI-TL.

Non-Structural

The non-structural approach consists of the following steps:

LI

The LI measures the market power of a firm, as formalised by the Russian-British economist Abba P. Lerner. The index measures the percentage markup of the price that a firm can charge over its marginal cost. The LI is calculated via the following formula:

$$Lerner_{it} = (P_{it} - MC_{it})/P_{it}$$

where

P_{it} = ratio of total revenue to the number of advances (in percentage)

MC_{it} = marginal cost of the banks.

Since the marginal cost of banks is not directly observable, many studies use the translog cost function to proxy for the marginal cost (Coccorese, 1998; Prayoonrattana et al., 2020). Here, we take a different approach and use the following variables (values given in Table 2) as proxies for the marginal cost.

Table 2: Values for Proxy for Marginal Costs

MC Proxy	*Year*
MCLR	2016–2023
Base rate	2010–2016
BPLR	2003–2009

Source: Ratio and rates table (rbi.org.in).

Furthermore, we calculate the LI sector-wise: the public sector, private sector, and foreign sector.

Panzar-Rosse H Statistic

The Panzar-Rosse H statistic, a tool for measuring competition, falls under the NEIO literature. This method considers the relationship between the revenue and cost of a firm under the assumption of long-run equilibrium (Nathan & Neave, 1989; Wong et al., 2011). It is the sum of the elasticities of total revenue with respect to each input price (Bikker et al., 2012). The generalised least squares method (Models 1 and 2) is applied to estimate the equation using banks as fixed effects on the basis of Bhuyan (2022).

Model 1

$$\log(TR) = \alpha + \beta 1\log(AFR) + \beta 2\log(WR) + \beta 3\log(PFC) + \gamma 1\log(CL\_TA) + +\gamma 2\log(CD\_CDB) + \gamma 3\log(EQ\_TA) + \delta \log(TA) + \varepsilon$$

Model 2

$$\log(IR) = \mu + \omega 1\log(AFR) + \omega 2\log(WR) + \omega 3\log(PFC) + \varphi 1\log(CL\_TA) + +\varphi 2\log(CD\_CDB) + \varphi 3\log(EQ\_TA) + \rho \log(TA) + \epsilon$$

H-statistic is the sum of the coefficients of all the input prices used in the model. The formula for calculating the H statistic is as follows:

$$H = \sum\nolimits^{n}_{i=1} \beta i$$

Description of Variables

The dependent variable used in Model 1 is the logarithm of total revenue (log (TR)). The independent variables used are as given in Table 3.

Table 3: List of Variables Used in the Panzar-Rosse H Statistics

Variable Abbreviation	*Variable Name*	*Calculation*
AFR	Average funding rate	Percentage ratio of expenses incurred on payment of interest to the total fund (deposits + borrowings)
WR	Wage rate	Percentage ratio of total expenses incurred on employees to the total number of employees
PFC	Price of fixed capital	Percentage of other operating expenses (operating expenses excluding expenses on employees) to the total number of employees
Control variables		
CL_TA	Control variable for customer loans	Ratio of customer loans (total loans excluding inter-bank loans) to the total assets
CL_CDB	Control variable for customer deposits	Ratio of total customer deposits excluding inter-bank deposits to the total of customer deposits and short-term borrowing
EQ_TA	Control variable for equity	Ratio of capital and reserves and surplus to total assets
TA	Total assets	Total assets

Interpretation of Competition by CR, HHI, LI, and Panzar-Rosse H Statistic

The CR indicates the size of firms relative to the industry as a whole. CRs, based on companies' market shares within a given industry, are used to assess market concentration. The CR considers the size distribution of the five largest banks. It can range from '0' to '1', with higher values indicating a more concentrated market, greater market power, and lower competitiveness.

In comparison, the HHI captures the market concentration of all banks, with values also ranging from '0' to '1'. The HHI is interpreted similarly to the CR, where lower values indicate a less concentrated market, lower market power, and greater competitiveness.

The LI measures the percentage markup a firm can charge over its marginal cost. Its values range from '0' to '1', with higher values indicating greater monopoly power. The interpretation of the LI is presented in Table 4.

Table 4: Classifying the Market Power of Industries with the LI

Market Power	*Value*
Monopoly	L = 1
Perfect competition	L = 0

Source: Prayoonrattana et al., 2020; Lipczynski et al., 2017, p. 74.

The Panzar-Rosse H statistic is the summation of the coefficients of the inputs, representing the percentage variation in equilibrium revenue resulting from a unit percentage increase in the price of all factors used by the firm (Prasad & Ghosh, 2007). The H statistic values are interpreted as given in Table 5.

Table 5: Interpretation of Panzar-Rosse H Statistics

H-Value	*Interpretation*
$H \leq 0$	Monopoly or perfectly collusive oligopoly.
$H < 1$	Monopolistic competition.
$H = 1$	Perfect competition, natural monopoly in a perfectly contestable market, or sales-maximising firm subject to a break-even constraint.

Source: Anzoategui et al., 2010; Bikker et al., 2012.

Empirical Results

Analysis of Bank Competitiveness and Concentration in India

In this study, the CR is defined as the ratio of the total assets of the five largest banks to the total assets of all banks. We estimate this CR based on the total assets of the following five banks: SBI, HDFC Bank, Bank of Baroda, ICICI Bank, and Axis Bank. A CR lower than 0.5 indicates a higher level of competition in the market. As illustrated in Fig. 1, the CR values range from 0.32 in 2005 to 0.53 in 2023, suggesting that the banking sector is moderately concentrated.

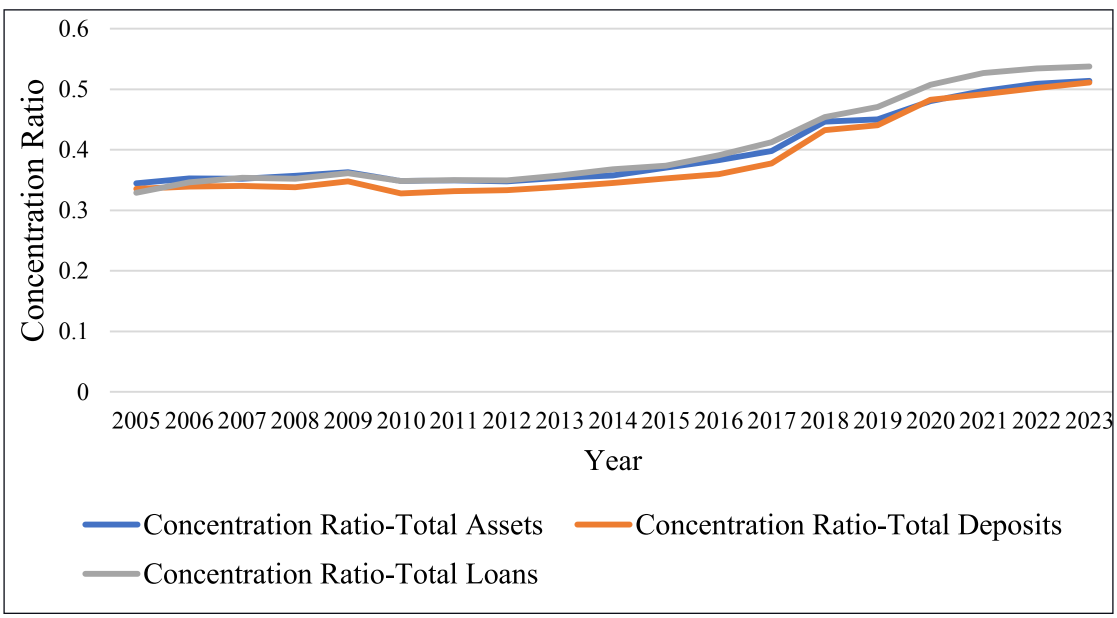


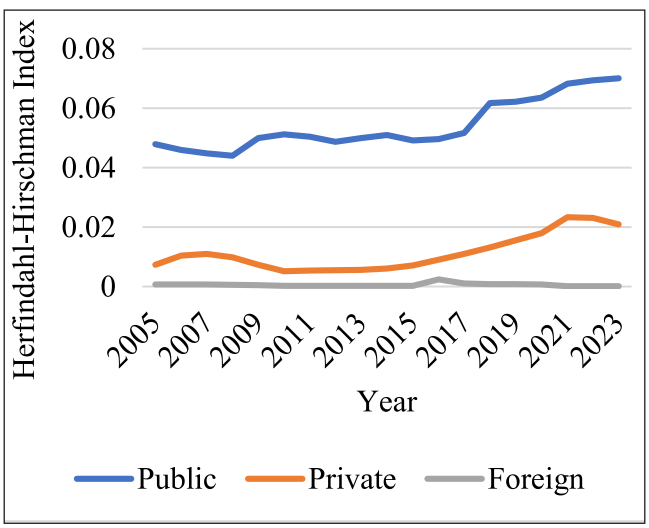
Fig. 1: Concentration Ratio

The data for these five banks from 2005 to 2023 show an increasing trend in the CR, implying that their market power is rising over the years. A comparison of CRs for total assets, total deposits, and total advances reveals negligible differences.

In addition, we estimated the HHI based on total deposits, total assets (which consist of cash on hand, balances, investments, advances, fixed assets, and other assets), and total loans and advances. The market approaches a monopoly when HHI values tend towards 1, indicating a highly concentrated market with low competition. Conversely, when HHI values approach 0, the market aligns more closely with perfect competition and is characterised by low concentration (Bhuyan, 2022).

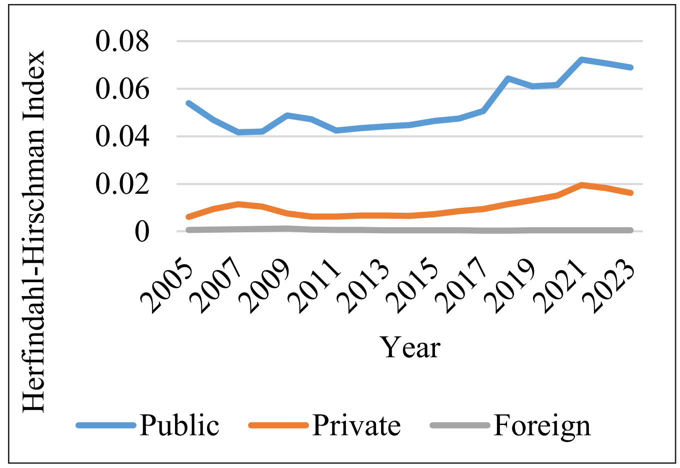
As shown in Fig. 2:

- The HHI for total loans (HHI-TL) for public sector banks ranges from 0.04 in 2005 to 0.07 in 2023, slightly exceeding the values for private and foreign banks. The HHI-TL values for all banks range from 0.0001 (for foreign banks in 2021) to 0.070 (for public banks in 2023).
- When we analyse HHI-TA, as illustrated in Fig. 3, it is evident that the public sector banks' value range is 0.041 in 2007 to 0.070 in 2022; this is slightly more concentrated than the foreign banks (value range is 0.0003 for 2017 to 0.001 for 2008).
- This suggests that the differences in HHI values based on ownership are negligible, reflecting that the banking sector in India has remained highly competitive throughout the study period.



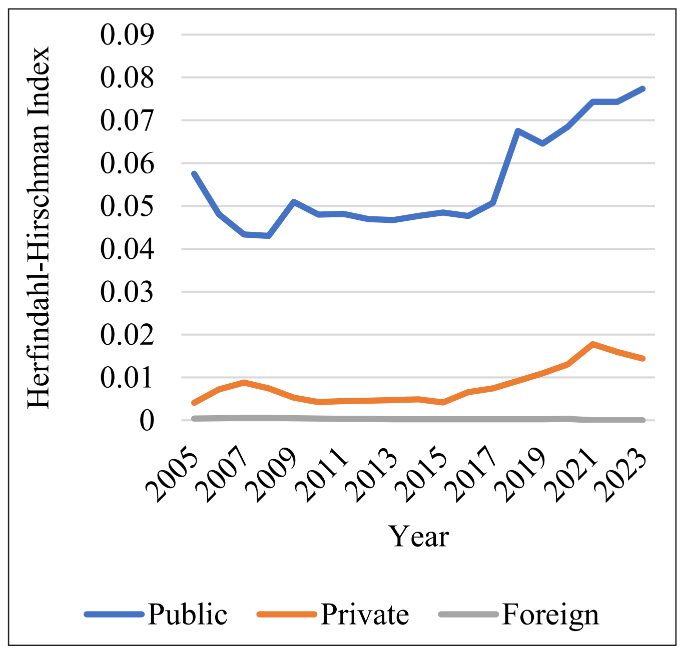
Source: Author's calculation.

Fig. 2: Hirfindahl-Hirshman Index (Total Loans) -Ownershipwise



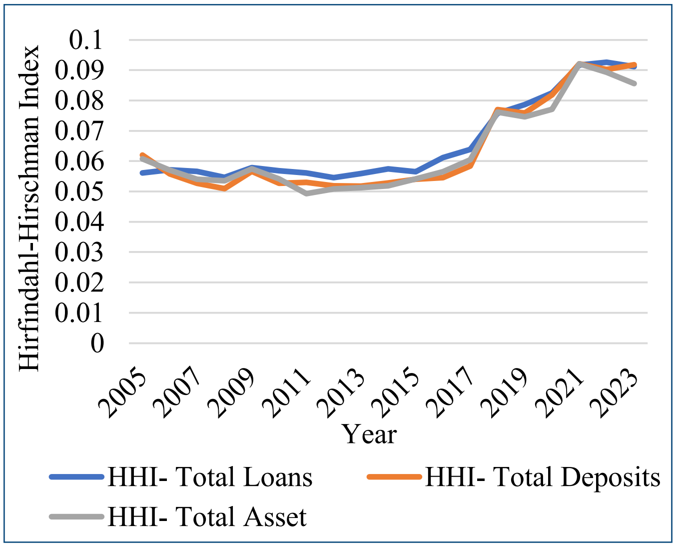
Source: Author's calculation.

Fig. 3: Hirfindahl-HirschmanIndex (Total Asset) -Ownershipwise



Source: Author's calculation.

Fig. 4: Hirfindahl-Hirschman Index (Total Deposits)-Ownership



Source: Author's calculation.

Fig. 5: Herfindahl-Hirschman Index - (All Banks)

As shown in Fig. 4, the empirical calculation of the HHI for total deposits (HHI-TD) indicates that HHI-TD values for:

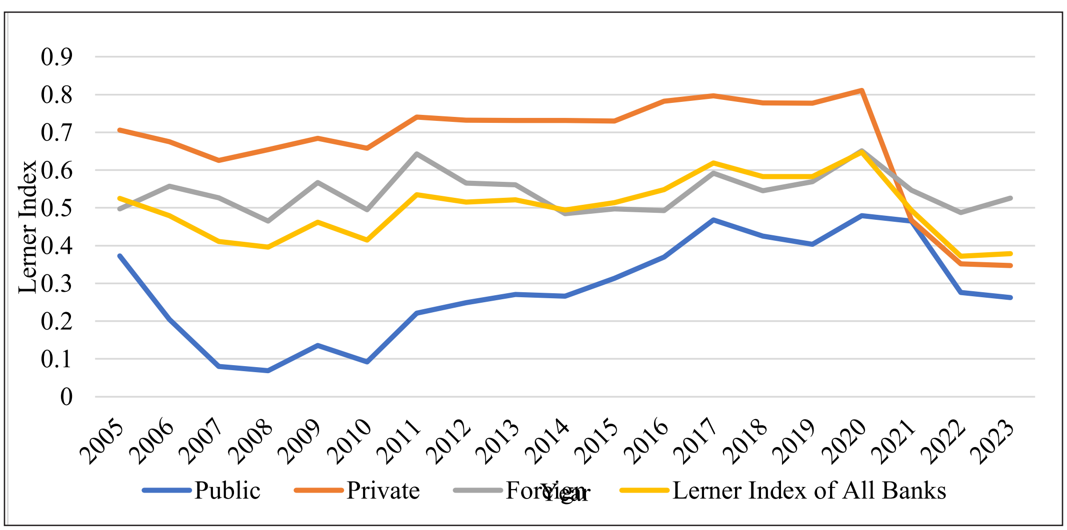
- Public sector banks range from 0.043 in 2008 to 0.077 in 2023.
- Foreign banks remain below 0.01 for all years under study.

Fig. 5 presents the HHI for all banks from 2005 to 2023.

- An upward trend is observed in all three indices from approximately 2014, indicating that although the market remains highly competitive, concentration has increased in the sector.
- The HHI for total loans was 0.06 in 2005, showing a slight decrease until around 2010; it remained relatively stable from 2010 to 2014 while it significantly increased post 2014, reaching 0.09 in 2023.
- The HHI for total deposits was slightly higher than the total loans index in 2005, at approximately 0.065. It followed a similar trend, decreasing until about 2012, then increasing to a peak close to 0.09 in 2021, with a slight decline in 2022 (0.08).
- The HHI for total assets exhibited a pattern similar to that of total deposits, gradually declining around 2012 (0.05) and then rising steadily.

Thus, all indices peaked at approximately 0.09 in 2021, followed by a slight decline to 0.08 in 2023, possibly due to stabilisation or a minor reduction in concentration. One interesting finding is the evident increase in HHI values after 2012, indicating a rise in concentration in the banking industry. This may be due to an increase in M&As of banks, leading to fewer but larger banks. Conversely, before 2012 all indices exhibited a declining or stable trend, suggesting a decrease or stability in market concentration during this period.

LI: The value of the LI lies between 0 and 1. An LI of '1' denotes a monopoly, whereas an LI of '0' denotes perfect competition.



Source: Author's calculation.

Fig. 6: Lerner Index

As evident from Fig. 6 the LI for all banks lies in the mid-range, with values of 0.371 for 2022 and 0.646 for 2020. These results indicate that the Indian banking sector is neither perfectly competitive nor monopolistic; rather, it exhibits a moderate competition.

Sectorally, the LI shows that private sector banks demonstrate less competitive behaviour and hold more market power, with LI values ranging from 0.62 in 2007 to 0.81 in 2020. However, after 2021 there was an increase in competition among private banks, as indicated by a significant decline in LI values to 0.49 in 2021.

According to the LI values, public sector banks exhibit the most competitive behaviour, carrying the least market power. The LI for public sector banks shows a general upward trend from 2008 to 2017, increasing from 0.06 to 0.46, which indicates rising market power. This trend suggests reduced competition among public sector banks, possibly due to M&As in 2017, which decreased the number of banks from 22 to 12. Foreign banks are moderately competitive, with LI values of 0.46 in 2008 and 0.65 in 2020.

The LI for public, private, and foreign banks, as well as the LI for all banks, indicates varying levels of market power from 2005 to 2023. Initially, all segments show a declining trend in market power until 2012, followed by a period of stabilisation and a slight increase in 2020. This trend may be attributed to M&As, which led to the consolidation of banks and the formation of larger, fewer institutions. Such changes affect the market structure and conduct, thereby influencing competition (Neuberger et al., 2008; Murthy & Deb, 2013).

Nevertheless, a significant reduction in market power is evident from 2021 to 2023, suggesting an increase in competitive behaviour among banks.

Interpretation of the Panzar-Rosse H Statistic

Contestable market theory, as stated by Baumol, Panzar and Willig (1972), asserts the presence of competition in the market, with conditions of free entry and exit of the firms from the industry without any legal or economic barriers. An H statistic value of '1' indicates perfect competition, whereas an H statistic value of '0' indicates monopoly. When the H statistic lies between 0 and 1, it indicates a monopolistic market structure due to the competitive nature of the market, supporting contestability theory (Bikker et al., 2012). It is assumed that existing banks set their prices near competitive levels, due to the possibility of new banks entering the market. This means potential competition keeps prices low. Even if the market is not highly competetive overall, the threat of new entrants forces current banks to act competitively (Prasad & Ghosh, 2007).

The value of the H statistic, as shown in Tables 6 and 7, lies between 0 and 1, supporting contestability theory for the Indian banking market structure. This finding is in consistent with the Prasad & Ghosh (2007) study.

The estimated coefficient of the variable AFR is positively significant for both models for all scheduled commercial banks and across all ownership types, which is consistent with the findings of Bikker et al. (2012) and Bhuyan (2022). The impact of TR on PFC is negative for public sector banks and insignificant for all other categories. Similarly, the impact of interest revenue (IR) on PFC is insignificant across categories, aligning with Bikker et al. (2012) and Bhuyan (2022).

The coefficient for WR is negative for Model 1 at the 10% significance level and positive for Model 2 at the 1% significance level. The control variable TA is positively significant for both models across all categories. The impact of TR on CL_TA is positively significant for all scheduled commercial banks and private banks, whereas EQ_TA is positively significant only for all scheduled commercial banks at the 1% significance level. In contrast, CD_CDB is negatively significant for all scheduled commercial banks at the 1% significance level. The impact of IR on CL_TA is positively significant for all categories but varies in significance level (1% for all scheduled commercial banks and foreign banks, 5% significant level for public and private sector banks). EQ_TA is positively significant only for all scheduled commercial banks at the 1% significance level; otherwise, it is insignificant for all other categories. CD_CDB is positively significant for private sector banks and otherwise insignificant.

Table 6: Panzar-Rosse H Statistic – Model 1 Results

Variables (Dependent Variable is IR)	*All Scheduled Commercial Banks*	*Public Sector*	*Private Sector*	*Foreign Banks*
Constant	−3.364	−5.524	−5.556	−3.268
Log (AFR)	0.253*** (0.045)	0.559*** (0.030)	0.562*** (0.022)	0.098*** (0.022)
Log (PFC)	0.162 (0.107)	0.002 (0.029)	−0.107*** (0.021)	−0.038 (0.054)
Log (WR)	−0.114 (0.904)	−0.028 (0.024)	0.105*** (0.021)	0.014 (0.052)
Log (CL_TA)	0.179*** (0.059)	0.138** (0.065)	0.103** (0.035)	0.131*** (0.036)
Log (CD_CDB)	−0.175 (0.106)	0.256*** (0.084)	0.335 (0.236)	0.013 (0.025)
Log (EQ_TA)	0.530*** (0.118)	0.034 (0.026)	0.020 (0.022)	0.029 (0.032)
Log (TA)	1.009*** (0.031)	1.025*** (0.014)	0.995*** (0.009)	0.954*** (0.019)
R^2	0.850	0.996	0.994	0.935
Adjusted R^2	0.850	0.996	0.994	0.935
S E of Regression	0.308	0.529	0.889	0.578
Prob (F-statistic)	0.000	0.000	0.000	0.000
H-statistic	0.301	0.533	0.560	0.074

Source: Author's estimates.

Note: (i) ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively; (ii) figures in brackets are standard errors of the corresponding estimates of the coefficients.

Table 7: Panzar-Rosse H Statistic – Model 2 Results

Variables (TR as Dependent Variable)	*All Scheduled Commercial Banks*	*Public Sector*	*Private Sector*	*Foreign Banks*
Constant	−0.1736	−4.990	−4.722	−2.494
Log (AFR)	0.224*** (0.039)	0.496*** (0.024)	0.473*** (0.027)	0.099*** (0.026)
Log (PFC)	0.150 (0.103)	0.048 (0.035)	−0.094 (0.016)	−0.051 (0.075)
Log (WR)	−0.086 (0.089)	−0.062* (0.0319)	0.095*** (0.016)	0.0424 (0.057)
Log (CL_TA)	0.125* (0.676)	0.125* (0.069)	−0.029 (0.033)	0.080 (0.048)
Log (CD_CDB)	−0.194* (0.095)	0.022 (0.140)	0.350 (0.210)	−0.028 (0.021)
Log (EQ_TA)	0.507*** (0.107)	0.037 (0.031)	0.020 (0.022)	0.052 (0.031)
Log (TA)	0.976*** (0.036)	1.014*** (0.016)	0.988*** (0.008)	0.924*** (0.025)

Variables (TR as Dependent Variable)	*All Scheduled Commercial Banks*	*Public Sector*	*Private Sector*	*Foreign Banks*
R^2	0.843	0.995	0.994	0.922
Adjusted R^2	0.843	0.995	0.994	0.922
S E of regression	0.180	0.361	0.744	0.228
Prob (F-statistic)	0.000	0.000	0.000	0.000
H-statistic	0.288	0.482	0.474	0.009

Source: Author's estimates

Note: (i) ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively; (ii) figures in brackets are standard errors of the corresponding estimates of the coefficients.

The results indicate that the average funding cost significantly contributes to the explanation of both IR and TR, thereby impacting the H statistic. Interestingly, the ratios of interest income to TR and non-interest income to TR do not show significant differences, with public sector banks deriving 87.61% of their revenue from interest income and 12.38% from non-interest income, compared to 84.24% and 15.75%, respectively, for private banks.

In both models, the H statistic for foreign banks is lower than that for private banks, public banks, and all scheduled commercial banks, suggesting that foreign banks are less competitive than other types of bank ownership. When examining TR, public sector banks are marginally more competitive than private sector banks, although the difference is minimal. However, when focusing solely on interest income, private sector banks show a slight edge in competitiveness over public sector banks, with this difference also being relatively small.

Conclusion

During the last few decades, the Indian banking industry has experienced significant transformation, marked by increasing privatisation and the emergence of new challenges. M&As are also reshaping the structure of the banking sector (Neuberger, 1997). Since the nationalisation of banks in India, a plethora of studies have compared public sector and private sector banks. However, there is a lack of literature on bank competition in the contemporary environment that measures competitiveness from various approaches. While various measures of competition are widely accepted, there remains no consensus on the 'best' indicator for evaluating bank competition (Carbo et al., 2009). Therefore, it is essential to assess market power using multiple indicators and explore the relationships among them. In this context, assessing concentration and competition within the banking sector is essential for informing policymakers and enriching the academic discourse.

This study aims to assess concentration and competition using four key indicators: the CR, the HHI, the LI, and the Panzar-Rosse H statistic. All indicators suggest a monopolistic nature in the Indian banking sector, aligning with the findings of Sinha et al. (2015), which indicate a decreasing trend in competition following deregulation.

Results of this analysis show that despite significant reforms, public sector banks continue to hold substantial market shares, with the SBI accounting for approximately 22% and Punjab National Bank (PNB) around 7% of total assets.

In contrast, the non-structural analysis utilising the LI reveals that public sector banks are more competitive than their private counterparts, which are identified as less competitive. The LI assesses banks' ability to set prices above marginal costs, indicating that public sector banks effectively leverage their pricing power.

Furthermore, the Panzar-Rosse H statistic suggests that private sector banks exhibit slightly higher competitiveness when assessing IR. However, when TR is taken into account, public sector banks appear marginally more competitive, although the difference is negligible. These findings are consistent with previous literature (Bikker & Haaf, 2000; Bikker et al., 2012; Bhuyan, 2022).

This subtle distinction in competitive dynamics – between IR and TR – can be attributed to the differing business models of public and private banks. Private sector banks typically adopt more aggressive pricing strategies and focus on profit-driven lending, whereas public sector banks follow a more traditional banking model. Their relatively higher total interest income can be linked to a greater emphasis on lending and a wider branch network, which provide them with stability and a broader customer base.

In conclusion, this study highlights notable discrepancies in the competitive dynamics of the Indian banking sector as revealed by different analytical approaches. The structural approach, particularly through the HHI, indicates minimal variation in HHI values across different ownership types, with all values remaining below 0.09. This suggests that the Indian banking landscape is fragmented rather than concentrated, reflecting a competitive environment.—investigating how M&As impact banks' pricing strategies and TR generation could be a fruitful avenue for future research.

Appendix

Table 1: Classification of Number of Banks According to Bank Ownership (Data are from STRBI)

Years	*Public*	*Private*	*Foreign*	*All*
2005	28	29	31	88
2006	28	28	29	85
2007	28	25	29	82
2008	28	23	28	79
2009	27	22	31	80
2010	27	22	32	81
2011	26	22	34	82
2012	26	20	41	87
2013	26	20	43	89
2014	27	20	43	90
2015	27	20	44	91
2016	27	21	46	94
2017	27	21	44	92
2018	21	21	46	88
2019	20	22	45	87
2020	18	23	46	87
2021	12	21	45	78
2022	12	21	45	78
2023	12	21	44	77

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Optimising Credit Risk Management: An In-Depth Exploration of the Expected Credit Loss Framework for Effective Credit Loss Provisioning

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Abstract

The banking sector in India currently relies on the incurred loss approach (ILA) for provisioning non-performing assets (NPAs), wherein credit losses are recognised only upon the occurrence of a loss event. While widely adopted, this reactive approach suffers from significant limitations, including delayed recognition of losses, inadequate early warning indicators, procyclicality, and the absence of forward-looking insights. These shortcomings impede effective risk management and highlight disparities with globally accepted standards. To address these gaps, the Reserve Bank of India (RBI) has proposed a transformative shift to the expected credit loss (ECL) framework, as outlined in its discussion paper. The ECL approach introduces a forward-looking, proactive provisioning methodology based on a three-stage model for categorising loans and advances. By emphasising early loss recognition and aligning with international best practices, this framework aims to enhance the resilience and stability of the banking system. This paper critically examines the limitations of the ILA and provides a comprehensive analysis of the ECL framework. It underscores the potential of the ECL approach to revolutionise credit risk management (CRM) in India, offering insights into its benefits, implementation challenges, and implications for the financial ecosystem.

Keywords: Banking Resilience, Credit Risk Management, Expected Credit Loss (ECL) Framework, Incurred Loss Approach (ILA), Non-Performing Assets (NPAS), Proactive Provisioning

JEL Classification: E58, G21, G28

Introduction

As an integral part of the financial system, banking institutions play a crucial role in economic development by serving as intermediaries between entities/individuals with surplus investable funds and those in need of financing. Lending, a primary business activity for banks, constitutes an integral and important part of their operations, with loans and advances making up over 55% of their total assets. In addition, investments also form a substantial part of a bank's assets, accounting for 25–30% of the total assets. Moreover, interest income from loans and advances contributes to approximately 85% of their total income. Therefore, loans and advances represent a significant and vital segment of the asset portfolios of banks. It is noteworthy that loans and advances are regarded as bank assets since they generate interest income during the credit period.

However, the loans provided by banking institutions are inherently subject to various types of risks, with credit risk being a significant concern. Credit risk refers to the potential for banks to experience losses on their loans/exposures. These credit losses, intrinsic to the banking business, stem from the lending business and are impacted by forecasts of the future performance of borrower entities. Due to the inherent uncertainty and potential variability in these projections, losses are inevitable. Similarly, investments are vulnerable to changes in their realisable, recoverable, or maturity values, sometimes resulting in decreased recoverable values and subsequent impairment losses.

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To manage credit risk, standard approaches classify potential losses in a bank's credit portfolio into expected and unexpected losses. Expected losses are typically managed through pricing strategies and loan loss provisions (LLPs), while unexpected losses are mitigated by maintaining adequate capital. Any expected losses not covered by provisions must be absorbed by the bank's capital. This dual requirement leaves banks vulnerable to unexpected losses, consequently increasing the risk of failure (Cohen & Edwards, 2017), randomized, double-blind, placebo-controlled clinical trial. SETTING: Large, urban pediatric emergency department between March 2002 and November 2003. PATIENTS: Children aged 5 to 18 years with moderate to severe pharyngitis (odynophagia or dysphagia), moderate to severe pharyngeal erythema or swelling, and a McGrath Facial Affective Scale score of 0.75 or higher [scale 0.0-1.0]. A study by Prakash and Swayam (2024) examines how factors such as bank size, profitability, capital adequacy, liquidity, and diversification impact credit risk. The findings reveal that larger banks and those with higher income diversification tend to face higher credit risk, while stronger profitability, healthier capital buffers, and prudent lending practices mitigate it.

It is crucial to understand that LLPs are funds allocated as allowances for potential uncollected loans. Essentially, provisioning involves setting aside profits (of banking institutions) to cover potential losses from bad loans, commonly referred to as non-performing assets (NPAs). These provisions contribute to the loan loss reserves, a component in the statement of financial position (also known as the balance sheet), with the total reflecting the cumulative amount of loan losses subtracted from the loans and advances of banking entities. Thus, robust loan loss provisioning practices play a vital role in ensuring the safety and stability of any banking institution (Bank for International Settlements, 2017; Behn & Couaillier, 2003). We test the small molecule flexible ligand docking program Glide on a set of 19 non-α-helical peptides and systematically improve pose prediction accuracy by enhancing Glide sampling for flexible polypeptides. In addition, scoring of the poses was improved by post-processing with physics-based implicit solvent MM-GBSA calculations. Using the best RMSD among the top 10 scoring poses as a metric, the success rate (RMSD ≤ 2.0 Å for the interface backbone atoms.

ILA – An Overview

There are two important methodologies for establishing LLPs: the incurred loss approach (ILA) and the expected credit loss approach (ECLA). Until recently, the ILA was the standard practice globally. However, several countries, including the United States, have transitioned to the ECLA. In India, the ECLA is mandated only for non-banking financial companies (NBFCs).

Therefore, banking companies in India, including the scheduled commercial banks (SCBs), currently adhere to the ILA for their loan loss provisioning. The Reserve Bank of India (RBI), the country's banking regulator, is now considering extending ECLA to all SCBs. In light of this, we aim to provide an overview of the developments in the ILA in India, followed by an analysis of the expected credit loss (ECL) framework.

Until the mid-1980s, India lacked standardised guidelines for assessing the quality of individual loans and making adequate provisions for bad loans. The management of such loans was left to the discretion of banking companies. However, following the recommendations of the *Pendharkar Working Group on the System of Inspection of Banks* (1985), which were reiterated by the *Committee to Consider Final Accounts of Banks* under the chairmanship of Shri A. Ghosh, the RBI introduced significant changes during 1985–86, effective from November 7, 1985.

Accordingly, the RBI advised all commercial banks (excluding branches of foreign banks in India, which already had similar mechanisms) to classify loans into eight categories under the Health Code System. This system was introduced to facilitate closer monitoring of credit quality. Furthermore, the Health Code System mandated all commercial banks to categorise their problematic loans into three distinct categories: (i) advances classified as 'bad and doubtful', (ii) advances where suits were filed and/or decrees were obtained, and (iii) advances with 'undesirable features'.

However, this system faced practical challenges due to a lack of transparency, objectivity, and uniformity in the criteria for assessing NPAs (Gowda, Inchara, 2020). Recognising these shortcomings and in line with the recommendations of the M. Narasimham *Committee* *on the Financial System*, the central bank issued comprehensive prudential guidelines in 1992. The central bank mandated banks to classify loans into two main categories: standard assets and NPAs, further classifying the latter into substandard assets, doubtful assets, and loss assets based on the compression of health codes.

Subsequent revisions and modifications aimed to refine the definition of NPAs and enhance the mechanism for provisioning against them. These revisions also prescribed rates for provisioning against loans in different categories and sub-categories. Currently, the *Master Circular on Income Recognition, Asset Classification, and Provisioning*, effective April 1, 2022, governs these provisions, outlining varying provisioning rates ranging from 0.25% to 100%. Some details are summarised in Table 1.

Table 1: Loan Categories and Rates of Provisions

Categories of Loan Assets					*Rate of Provisioning (%)*
Standard assets:					
	(i)	Farm credit and SME sectors			0.25
	(ii)	Advances to the commercial real estate (CRE) sector			1.00
	(iii)	Advances to the commercial real estate (residential housing) sector			0.75
	(iv)	Housing loans extended at teaser rates and restructured advances			2.00
	(v)	In all other loans and advances [not included in (i) to (iii) above]			0.40
NPAs:					
	Sub-standard assets:				
		(i)	On total outstanding loan without making any allowance for securities available		15.00
		(ii)	On the unsecured exposures		25.00
	Doubtful assets:				
		(i)	On the advance not covered by the realisable value of the security		100.00
		(ii)	In the case of the secured portion of doubtful loans, and the period for which the advance has remained in the 'doubtful' category		
			(a)	Up to one year	25.00
			(b)	One to three years	40.00
			(c)	More than three years	100.00
	Loss assets – it should be written-off fully; otherwise, the provision at,				100.00

Source: RBI (2022).

Extant ILA – Shortcomings

Per existing prudential guidelines, asset classification is intricately tied to recovery records, providing insight into banking companies' risk exposure only after the credit risk materialises. As a result, banks create provisions against loans using the ILA, which involves considering the asset classification of specific exposures and the corresponding provisioning rate.

Under this framework, banks recognise LLPs in response to borrower payment delays stemming from financial distress, thereby amplifying the credit risk faced by lenders. Notably, loan loss provisioning occurs after the escalation of credit risk to the lender banks, with loan classification as NPA serving as the prerequisite trigger for provision creation. The ILA model recognises credit losses only after default or impairment (Frykström & Li, 2018). This backward-looking approach proved inadequate during the 2008 financial crisis, leading to significant delays in loss recognition and exacerbating the crisis's severity (Oreshkova, 2018; Joseph Mcphail & Lihong Mcphail, 2014). The incurred loss model's reliance on historical data and inability to anticipate future economic downturns were key weaknesses (Oreshkova, 2018).

This suggests that under the ILA, banking companies make provisions for actualised loan defaults/losses, thereby highlighting a temporal gap between the escalation of credit risk and the recognition of the provision. It is imperative to recognise that while underlying default or credit risk may precede actual default events, mitigation efforts remain deferred until regulatory mandates for loan loss provisioning are activated upon exposure classification as NPA (Reserve Bank of India, 2023).

This delay in recognising expected losses under the ILA, coupled with a systemic increase in defaults, is compelling banks to bolster provisions to higher levels and poses a potential risk to their resilience. This trend erodes the capital maintained by banks precisely at a juncture where capital reinforcement is crucial, consequently impinging upon their resilience and posing systemic risks. Examining the impact of revised LLPs under International Financial Reporting Standards (IFRS) and generally accepted accounting principles (GAAPs) on Tier-1 capital reveals that these changes lead to a reduction in Tier-1 capital, particularly during economic downturns and for low-quality credit portfolios. The findings suggest that the provisioning rules exacerbate the procyclicality of bank capital requirements. Therefore, adjustments to significant increases in credit risk thresholds or capital buffers are recommended to mitigate the regulatory pressure resulting from the reduction of regulatory capital (Krüger et al., 2018).

Moreover, the delay in loan loss recognition inflates banks' reported income, exacerbated by dividend payouts, thereby diminishing internal accruals and further undermining banks' capital base, subsequently compromising their resilience. The ILA engenders provisioning shortfalls, necessitating adjustments in the calculation of capital requirements.

In addition, this practice leads to loans being presented on banks' balance sheets at inflated values relative to their realisable amounts. Such deviation from financial valuation principles, where asset value is determined by the present value of anticipated cash flows over the asset's lifespan, underscores the inconsistency of the ILA for LLPs. As a result, the traditional way of thinking about NPAs/non-performing loans (NPLs) and provision models is not working well. This is because different types of loans have different effects on how credit quality is judged (Beatty & Liao, 2020).

With empirical insights from 230 respondents (event management firms) in the Salem district, Krishnakumar & Arul (2024) effectively demonstrated that access to bank credit significantly improves business outcomes such as profitability, capacity expansion, technology adoption, and competitive advantage.

IFRS 9/IND as 109: Financial Instruments

The situation described above, among others, prompted the G-20 and the Basel Committee on Banking Supervision (BCBS) to recommend that accounting standard setters (International Accounting Standards Board [IASB] and Financial Accounting Standards Board [FASB], among others) modify provisioning practices to adopt a more "forward-looking approach" rather than the ILA. Consequently, the standard setters have developed and issued accounting standards that incorporate methodologies for quantifying and including expected credit losses in provisioning. The relevant standards are:

- *IFRS 9: Financial Instruments* by IASB, effective from January 1, 2018.
- *Current Expected Credit Losses* by FASB, effective from January 1, 2020, and *Topic 326: Financial Instruments – Credit Losses.*
- *Ind AS 109: Financial Instruments* by the Institute of Chartered Accountants of India (ICAI) for NBFCs, effective January 16, 2023.

For India, IFRS 9 is particularly relevant, and it is noteworthy that Ind AS 109 closely mirrors IFRS 9. This standard (IFRS 9) specifies that the classification and measurement of an entity's financial assets should be based on the entity's business model for managing the financial assets and the contractual cash flow characteristics of these financial assets. The standard also provides detailed criteria for measuring financial assets at cost, fair value through other comprehensive income (OCI), and fair value through profit and loss. In addition, it outlines the effective interest rate method for computing interest income and the ECLA for impairment, measurement of loss allowance, and treatment of credit-impaired financial assets (Deloitte, 2016; PWC, 2014; Tayler & Zilberman, 2021). It is important to note that financial assets primarily include loans, advances, irrecoverable loan commitments, and investments categorised as held-to-maturity or available-for-sale. Moreover, the aggregate loan disbursed encompasses irrevocable loan commitments, including sanctioned limits within revolving credit facilities. Against this backdrop, the RBI is making necessary preparations to transition commercial banks from the existing ILA to the ECLA for creating and maintaining credit loss provisions.

Literature Review – Global Experience

The ECL framework is a big change in how credit loss is calculated. It replaces the old ILA with a more forward-looking method that fits with new global accounting standards such as IFRS 9 and the current ECL standard in the US. This transition underscores the growing emphasis on proactive risk management and early recognition of potential credit losses to enhance the stability and resilience of the banking sector.

While the ECL framework is a relatively recent development, it has garnered significant academic and professional attention, particularly in the context of its implementation, challenges, and implications for financial institutions. Researchers have extensively explored its theoretical underpinnings, comparative effectiveness against the ILA, and practical application across jurisdictions.

This literature review, presented thematically, seeks to provide a comprehensive overview of existing research on the ILA and ECL framework, focusing on its operational mechanics, advantages over traditional models, and challenges in adoption. In addition, it highlights notable studies that examine the framework's impact on the banking sector, offering critical insights into its transformative potential in credit risk management (CRM).

A study on 10 Nigerian banks (2008–19) revealed that substandard and loss loans adversely affect financial performance, while doubtful loans do not. Strengthened risk assessment and loan repayment enforcement were recommended (Odeh et al., 2023). In Italian banks, LLPs are driven primarily by expected credit risk, with regional banks facing higher LLPs due to loan concentration and reduced competition. Income smoothing practices were also noted (Aristei & Gallo, 2019). An analysis of 15,931 European bank loan portfolio observations showed that provision reversals during recessions impacted reported income (Aggelopoulos et al., 2023).

Heightened economic policy uncertainty (EPU) led to increased LLPs in 6,384 US banks (2009–19), reflecting its use for income smoothing and capital management (Danisman et al., 2021). LLPs and bank lending significantly influenced business cycle fluctuations across 12 Organisation for Economic Co-operation and Development (OECD) countries (Pool et al., 2015). Fiscal measures during the COVID-19 pandemic, such as tax relief, reduced loan portfolio risks, while liquidity support had minimal impact (Degryse & Huylebroek, 2023).

Post-great financial crisis reforms improved stability through capital buffers, reducing domestic credit activity, especially in weaker institutional frameworks (Fratzscher et al., 2016). LLP regulations in Chile's mortgage market reduced loan-to-value ratios and highlighted the competition's role in lending standards (Calani & Paillacar, 2022). IFRS 9 increased Tier-1 capital in Spanish banks, benefiting larger institutions but with procyclical effects (López-Espinosa & Penalva, 2023).

Australian banks strategically increased LLPs for future growth, leveraging surplus capital and discretionary power (Cummings & Durrani, 2016). Simplified ECL models are advised to address procyclicality and ensure comparability (Jacobs, 2019). Dynamic provisioning, combined with credit gap-augmented Taylor rules, effectively curbs financial procyclicality (Agénor & Zilberman, 2015). Transitioning to ECL reduced stock price crash risks in banks with lower opportunistic incentives and opaque information environments (Jin & Wu, 2023). Md Nasim Ansari & Jamaluddeen (2025) assess bank performance with a focus on both interest and non-interest income efficiencies. While most public sector banks (PSBs) perform well in generating interest income, a notable efficiency gap exists in their ability to generate non-interest income, which adversely affects overall efficiency levels. The study underscores the need for PSBs to diversify income sources and improve internal financial management to remain viable in an increasingly competitive environment.

Adopting ECL under IFRS enhanced loss recognition timeliness, particularly in riskier institutions, with global influence seen in subsidiaries (Rakhaev, 2020). However, Portuguese banks reported procyclical tendencies and reduced capital adequacy under ECL (Resende et al., 2024). Current ECL (CECL) adoption during COVID-19 slowed economic recovery in areas with high market share banks (Chen & Ryan, 2024). Forward-looking provisioning practices globally showed mixed effects on risk discipline, enhancing it through timely loss recognition but reducing transparency with earnings smoothing (Bushman & Williams, 2012).

ECL adoption increased loan loss allowances due to forward-looking assessments but challenged comparability due to modelling variations (Jacobs, 2020). This shift improved credit risk assessment timeliness and financial reporting accuracy while necessitating advanced forecasting models and technology investments (Kim et al., 2022; Gee et al., 2022). However, adoption varied due to preparedness, interpretations, and institutional risk appetites (Rafika Sari & Dwitayanti, 2023).

This literature review has examined the evolution of credit loss provisioning frameworks, with a particular focus on the ECL model and its implications for effective risk management in the banking sector. While existing studies have extensively analysed the theoretical foundations, comparative advantages, and practical challenges of transitioning from the ILA to ECL, most research has been centred on global or Western banking systems. This has resulted in limited insights into the operationalisation of ECL in the unique regulatory, economic, and credit environments of emerging markets, including India. This study seeks to address this gap by focusing on the application, challenges, and implications of the ECL framework within the Indian banking sector. By doing so, it aims to contribute to the broader discourse on optimising CRM and fostering resilience in emerging economies.

A Few Aspects of Methodology

The primary objective of this study is to evaluate the efficacy of the proposed ECL framework in facilitating effective credit loss provisioning. This includes a full review of the method, especially compared with the current incurred credit loss model, with the main goal of finding its flaws and ways to improve it. The primary source of literature for this study is the RBI, which offers authoritative information and insights into various aspects of credit loss provisioning. In addition, relevant details are collected from a range of secondary sources, including scholarly articles, websites, industry reports, and specialised literature.

This study adopts a predominantly theoretical and qualitative approach, aiming to explore different dimensions of the proposed ECL model. Through rigorous analysis and synthesis of existing literature and regulatory frameworks, it seeks to provide a comprehensive understanding of the conceptual underpinnings and potential implications of the proposed framework.

Optimising CRM: Exploration of ECL Framework for Effective Cl Provisioning

The ECL model fundamentally employs a forward-looking approach to estimating potential credit losses. Unlike its predecessor, the incurred loss model, it does not wait for defaults before recognising losses. Instead, it requires financial institutions to estimate expected losses over a loan's lifetime from its origination (Cohen, 2017; Frykström & Li, 2018). This forward-looking perspective is a key improvement over previous incurred loss methods, aiming to provide a more realistic and timely reflection of credit risk in financial statements, enhancing their predictive power and usefulness for investors (Gee & Neilson, Jed J., 2022).

The discussion paper of the RBI outlines the current ILA and the proposed ECL mechanism. The ECL model uses a forward-looking perspective, requiring institutions to estimate potential losses from loan inception (Cohen, 2017). This proactive approach aims to provide a more timely and accurate reflection of credit risk (Gee & Neilson, Jed J., 2022). The ECL model also incorporates a broader range of information, including macroeconomic forecasts and forward-looking assessments of creditworthiness (Frykström & Li, 2018). This forward-looking aspect aims to mitigate the procyclicality of loan loss provisioning – the tendency for LLPs to increase during economic downturns, exacerbating the cycle (Abad & Suarez, 2018; Michael Jacobs, 2020). Given the constraints in providing an exhaustive analysis of the discussion paper, this paper aims to highlight the key features of the proposed framework. Specifically, it delves into two critical components: the ECL mechanism and the classification of financial assets, offering a concise yet insightful examination of these aspects.

ECL refers to the probability-weighted estimate of the present value of all cash shortfalls arising from a financial instrument. Cash shortfalls occur when the actual cash receipts a bank expects from an instrument fall below the contractual cash flow expectations. As cash shortfalls are discounted, a delay in payment – even without an actual shortfall in the payment amount – can also contribute to an ECL.

Contractual cash flow receipts refer to the payments that a lender expects to receive from the borrower as outlined in the loan agreement. To correctly figure out the ECL of an asset or loan, banks have to look at a few variables. These include (i) a probability-weighted amount that comes from evaluating a range of possible outcomes; (ii) the time value of money, which means figuring out the present value of future cash flows – this is a basic idea in financial analysis; and (iii) information that is relevant at the time of reporting, such as events that have happened in the past, the current state of the economy, and predictions for the future.

The estimation of ECL involves considering three key components: (i) exposure at default, (ii) loss given default, and (iii) probability of default:

$$\text{ECL} = (\text{EAD} \times \text{LGD} \times \text{PD}) \tag{1}$$

EAD (exposure at default) represents the predicted outstanding loan amount at default. Estimating EAD requires forecasting future loan behaviour, such as prepayments or drawdowns, depending on the financial instrument (Engelmann, 2021). For revolving credit facilities, such as credit cards, estimating EAD is particularly challenging due to fluctuating outstanding balances (Canals-Cerdá, 2020). Accurate EAD estimation is important for determining the total amount of potential loss associated with a default. Accurate EAD forecasting also requires considering macroeconomic factors influencing borrower behaviour, such as changes in interest rates or economic growth (Lu & Nikolaev, 2019). In the context of a loan, EAD typically represents the difference between the disbursed loan amount and the repayments received. Therefore,

$$\text{EAD} = (\text{disbursed loan amount} - \text{repayment received}) \tag{2}$$

LGD (loss given default) refers to the percentage of exposure expected to be lost in the case of default. Estimating LGD involves considering factors such as collateral value, recovery rates, and legal and administrative costs associated with debt recovery (Engelmann, 2021). Determining LGD can be complex, especially for loans with complex collateral or in jurisdictions with varying legal frameworks governing debt recovery. Accurate estimation often requires detailed historical data on defaults and recovery processes (Guamán-Chumaina & Vásconez-Acuña, 2024). The accuracy of LGD estimation is crucial for determining the severity of potential losses associated with a default. It is expressed as a percentage, calculated by dividing the net loss (that is, loan disbursed − repayment received − realisable value of collateral) by the outstanding loan amount (that is, amount of loan disbursed − repayment received). Therefore,

$$\text{LGD} = \left[\frac{\begin{Bmatrix}\text{loan}\\ \text{disbursed}\end{Bmatrix} - \begin{Bmatrix}\text{repayment}\\ \text{received}\end{Bmatrix} - \begin{Bmatrix}\text{realisable value}\\ \text{of collateral}\end{Bmatrix}}{\begin{Bmatrix}\text{amount of}\\ \text{loan disbursed}\end{Bmatrix} - \begin{Bmatrix}\text{repayment}\\ \text{received}\end{Bmatrix}}\right] \tag{3}$$

PD (probability of default) denotes the likelihood of a borrower failing to meet his contractual obligations. Its estimation often involves sophisticated statistical techniques and incorporates a few factors such as borrower credit history, macroeconomic conditions, and industry-specific risks (S. Drin, 2023; Xin Xu, 2016). The accuracy of PD estimation is paramount, as it directly impacts the overall ECL calculation. Different models exist, ranging from simple linear regressions to complex machine-learning algorithms (Chen, 2024). The model choice depends on available data, loan portfolio complexity, and the institution's risk appetite (S. Drin, 2023).

The discussion paper includes relevant parts of IFRS 9 and Ind AS 109 that specify to banks what they need to do about loss allowances for financial instruments:

- *Lifetime ECL:* If the credit risk of a financial asset has increased significantly since it was first recognised, banks must set the loss allowance for that asset at the same level as its lifetime ECLs. This mandate guarantees that the provisioning mirrors the heightened risk profile, thereby improving the precision of CRM and adhering to forward-looking accounting standards.
- *12-Month ECL:* If a financial asset's credit risk has not significantly increased since its initial

recognition, we should determine the loss allowance to match the 12-month ECLs. This method upholds a foundational level of provisioning that mirrors the credit risk of the asset for the upcoming 12 months, guaranteeing cautious risk management in line with accounting standards (IASB, 2022; Ministry of Corporate Affairs, 2015).

Another significant aspect of the discussion paper is the proposal to categorise financial assets (based on the evolution of credit risk relative to their initial recognition) into three groups, as outlined below:

- *Stage 1 – Financial Assets with Stable/Low Credit Risk:* This category includes financial assets that have minimal credit risk, have maintained their original quality since their recognition, or have been assessed as low risk at the reporting date. Under standards such as IFRS 9/Ind AS 109, banks are mandated to set aside provisions for ECLs over the next 12 months (12-month ECL). This proactive approach ensures that potential losses are anticipated and disclosed in financial statements, bolstering stability and investor confidence. Strategically, holding a significant portion of assets in Stage 1 supports a bank's steady income stream.
- *Stage 2 – Financial Instruments with Increased Credit Risk:* This category includes financial instruments that have shown a significant increase in credit risk since their initial recognition, but they do not meet the criteria for low credit risk at the reporting date, nor do they provide clear evidence of impairment. Mainly comprising loans or debt securities, this stage mandates banks to establish an allowance for credit losses representing ECLs over the asset's remaining lifetime, termed as Lifetime ECL. This framework makes sure that banks properly reflect the higher risk in these instruments, which accurately shows possible losses in their financial statements and makes financial reporting clearer and more reliable.
- *Stage 3 – Financial Instruments with Objective Evidence of Impairment:* This category pertains to financial instruments that demonstrate clear indicators of impairment at the reporting date. Specifically, all financial assets identified as being in a 'default' status fall under the classification of Stage 3 assets. For these assets, financial institutions are obligated to acknowledge an allowance for credit losses that correspond to the anticipated credit losses throughout the entirety of the remaining lifespan of the asset (referred to as Lifetime ECL).

The proposed model represents a significant improvement over the current ILA for credit loss provisioning, which is known for its delayed recognition of impairment losses on financial assets. In contrast, the ECL model aims to promptly acknowledge credit losses by requiring banking entities to recognise allowances for anticipated lifetime credit losses. While ECL offers an integrated solution for IFRS 9 compliance and ECL-compatible estimation, its implementation may introduce procyclicality. This could have substantial effects on banks' regulatory capital ratios and lending practices during financial crises (Covas & Nelson, 2018). A study on the transition from the ILA to the ECL approach in European banks found that the ECL model outperforms the ILKA method in predicting future banking risk. Therefore, it is felt that adopting the ECL provisioning approach provides better insights for assessing bank risk, especially during periods of credit deterioration (Salazar et al., 2023).

Observations and Challenges in ECL Implementation

The transition to the ECL model presents a few significant challenges, as outlined below:

- *Methodological Challenges:* Implementing the ECL model requires sophisticated modelling techniques and substantial data. Key components such as PD, LGD, and EAD must be estimated using advanced statistical models. Incorporating macroeconomic factors and addressing uncertainties are critical yet complex tasks (Wolfgang Reitgruber, 2016; Joseph & Lihong McPhail, 2014). In addition, robust validation algorithms and techniques to separate risk costs into their primary components are necessary to ensure accuracy and reliability (Rathnakar, 2020). Furthermore, while macroeconomic factors are vital for capturing economic cycles' impact on credit risk, their inclusion introduces substantial uncertainty. Forecasting inaccuracies and subjective judgements by management regarding future economic conditions can bias ECL estimates, reducing comparability and transparency (Lu & Nikolaev, 2019; Oreshkova, 2018; Jacobs, 2019). In addition, although the ECL framework aims to mitigate procyclicality, it can inadvertently exacerbate this phenomenon, especially for banks with low regulatory capital or heterogeneous loan portfolios (Jacobs, 2019; Chen et al., 2022). Robust monitoring and back-testing processes, alongside stress testing, are essential to counteract such risks (Reitgruber, 2015).

- *Data-Related Challenges:* Implementing ECL relies heavily on comprehensive and high-quality data, including historical defaults, recovery rates, and forward-looking information (Guamán-Chumaina & Vásconez-Acuña, 2024; Jacobs, 2019). Many institutions, particularly smaller ones, lack access to such datasets, leading to inaccurate model calibrations (Swanson et al., 2021). Besides, inconsistent reporting practices, potential biases in historical data, and variability in macroeconomic forecasts further complicate ECL estimations (Engelmann, 2021; Frykström & Li, 2018).
- *Governance and Operational Challenges:* Subjective judgements by management in estimating ECLs introduce potential biases and reduce transparency. Enhanced disclosure of assumptions, inputs, and methodologies is essential to improve accountability and comparability across institutions (Oreshkova, 2018; Jacobs, 2019). Furthermore, sophisticated ECL models demand significant computational resources and technical expertise, posing challenges for institutions with limited infrastructure (Gubareva & Silva, 2019). Smaller entities may struggle to align their internal risk management frameworks with the complexities of ECL estimation (Swanson et al., 2021).
- *Capital Management Implications:* The forward-looking nature of ECL provisioning increases banks' capital requirements, affecting their lending capacity and potentially amplifying procyclicality during economic downturns (Hsiang-Chieh Yang, 2024; Chen & Ryan, 2024). Institutions must refine capital allocation strategies and enhance risk management frameworks to address these pressures (Resende et al., 2024). In addition, aligning ECL methodologies with regulatory frameworks such as Basel III is critical to avoid adverse impacts on banks' capital adequacy and lending behaviour. Greater collaboration between standard setters and regulators is necessary to optimise provisioning requirements (Mahieux et al., 2023; Rugilo, 2021).

Conclusion

Loan losses are an inherent and recurring aspect of banking operations, necessitating robust methodologies for credit loss provisioning. The transition from the ILA to ECL framework represents a paradigm shift in managing credit risk, offering more timely and forward-looking loss recognition.

The ECL framework provides superior insights into bank risk, particularly during periods of credit deterioration, compared with the ILA. Despite its merits, the ECL model poses significant challenges, including increased complexity in modelling, stringent data requirements, and heightened resource demands. Institutions must also navigate governance issues, procyclicality risks, and the interplay between accounting standards and regulatory frameworks.

To overcome these challenges, financial institutions must invest in data quality, enhance modelling techniques, adopt robust governance structures, and align strategic objectives with regulatory requirements. The RBI's proactive steps in promoting ECL implementation signal a positive direction, and with adequate support, scheduled commercial banks in India are well-positioned to navigate this transition. By addressing these challenges effectively, the banking sector can strengthen its risk management capabilities, build investor confidence, and foster long-term financial stability.

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