International Journal of Engineering, Management, Humanities and Social Sciences Paradigms (IJEMHS)
Volume 37, Issue 02 and Publication Date: 29th May, 2025
An Indexed, Referred and Peer Reviewed Journal ISSN (Online): 2347-601X
www.ijemhs.com

AI–DRIVEN FINANCIAL SERVICE – A REGIONAL STUDY ON FRAUD DETECTION, CREDIT SCORING, AND CUSTOMER INSIGHTS IN ODISHA

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Abstract: In the past few years, smart technology has changed the financial world in a big way, especially when it comes to online payments and digital loans. In this paper, we look at how well online banking improves financial services by making AI-based tools more convenient and effective in the Indian financial ecosystem. We focus on Odisha as an example of a state where people's financial habits are a dynamic mix of urban and rural ones.The study looks at how AI improves operational efficiency, finds fraud patterns, and improves credit evaluation and the customer experience by using data analytics, studies from public and private banks in Odisha, and machine learning models.

KEY WORDS: ARTIFICIAL INTELLIGENCE, FINANCIAL SERVICES, FRAUD DETECTION, CREDIT SCORING, CUSTOMER INSIGHTS, MACHINE LEARNING, FINTECH

1. Introduction

The use of Artificial Intelligence (AI) into essential operational and customer-facing tasks is driving a radical transition in India's financial services industry. AI is being used more and more in fields like fraud detection, credit scoring, and customer relationship management because of its capacity to handle enormous amounts of data, identify patterns, and produce predictive insights. In addition to enhancing decision-making and service delivery, these technology developments are also playing a key role in advancing financial inclusion across a range of demographic and geographic areas.

There are advantages and disadvantages to the use of AI-driven financial instruments in India, especially in the state of Odisha. The socioeconomic makeup of Odisha presents a special case for assessing the efficacy and inclusivity of AI applications in banking and finance because it includes both rural and tribal districts like Mayurbhanj, Kalahandi, and Ganjam, as well as rapidly urbanizing cities like Bhubaneswar and Cuttack.

In order to address three crucial areas of financial operations—fraud detection, credit scoring, and customer insights—this study intends to evaluate how financial institutions operating in Odisha—from nationalized banks to regional rural banks and fintech startups—are utilizing AI technologies. This study examines the extent and constraints of AI adoption in the area by fusing primary data collection—such as surveys and interviews—with secondary data analysis and machine learning models.

The study also examines geographical differences in AI use, the importance of digital literacy, the readiness of regulatory frameworks, and the linguistic and cultural barriers that affect AI systems' performance in rural Odisha. Finding out if AI can promote fair financial development and increased confidence in digital banking, especially for marginalized people, is the ultimate objective.

2. Literature Review

In both the Indian and global financial ecosystems, the incorporation of artificial intelligence (AI) into financial services has become a game-changer. AI's ability to automate decision-making, identify abnormalities, and enhance consumer experiences has been emphasized in numerous studies. With an emphasis on the consequences for regional economies like Odisha, this literature review

examines pertinent national and international

studies on AI-driven fraud detection, credit scoring, and consumer analytics.

2.1. AI for Identifying Fraud

Numerous academics have highlighted AI's capacity to use advanced analytics to fight financial fraud. Neural networks and clustering algorithms are two examples of statistical and artificial intelligence (AI)-based methods that successfully detect anomalous patterns in transactional data, as shown by Bolton and Hand (2002). More recently, Phua et al. (2010) examined AI models that perform better than conventional rulebased systems in identifying fraudulent activity, such as decision trees and random forests. Though the study lacked information on regional implementation, especially in underdeveloped places like Odisha, Jain and Chatterjee (2018) looked at AI applications in real-time fraud prevention inside the UPI framework in the Indian context.

2.2. Credit Scoring with AI

A move for AI-powered solutions has resulted from the shortcomings of conventional credit scoring algorithms, such as the CIBIL Score in India. Using non-traditional data, Khandani, Kim, and Lo (2010) discovered that machine learning approaches, such as logistic regression and gradient boosting, greatly enhanced the prediction of loan defaults. For low-income borrowers' credit scores, Sharma and Dey (2021) suggested using alternate data sources (such as mobile payment histories and Aadhaar-linked profiles) in rural India. Nevertheless, there are few regional studies that concentrate on Odisha, and little is known about the difficulties with data accessibility and digital literacy in rural areas.

2.3. AI for Understanding Customers AI-powered customer analytics has completely changed how banks view and interact with their customers. Chen, Chiang, and Storey (2012) investigated how AI-powered big data analytics may be used for sentiment analysis and customer segmentation. Mishra and Sahu (2020) emphasized how clustering and natural language processing (NLP) approaches assisted private sector banks in India in enhancing cross-selling and personalization. However, utilizing traditional NLP models trained on Hindi or English presents difficulties for reliable sentiment analysis due to linguistic diversity and vernacular usage, particularly in states like Odisha.

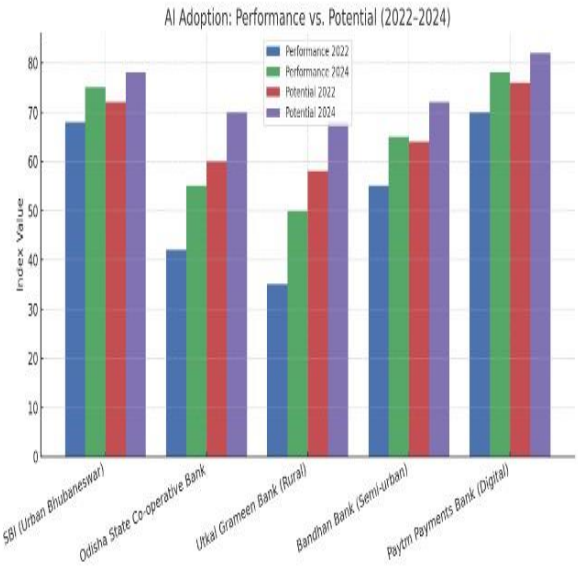
2.4. Cultural and Regional Aspects of AI Implementation

Region-specific research is scarce in the AI-fintech literature, which is dominated by macro-level studies. The difference in AI adoption between Eastern India's urban and rural banking sectors was highlighted by Dutta and Roy (2019), who also pointed out that wider adoption is hampered by inadequate infrastructure and insufficient AI literacy. Though Das and Patra (2022) noted that localized models that take into account linguistic, cultural, and behavioral nuances are crucial for effective AI deployment in states like Odisha, the government of Odisha's efforts under the 5T model and digital inclusion programs have laid the groundwork for future AI-based solutions.

Table 1: AI Adoption Index

Institution / Region	AI Adoption Performance Index	AI Adoption Potential Index
	2022	2024
SBI(URBAN BHUBANESWAR)	68	75
ODISHA STATE COOPERATIVE BANK	42	55
UTKAL GRAMEEN BANK	38	50
BANDHAN BANK	55	65
PAYTM PAYMENTS BANK	70	78

3. **Source: Compiled from survey data, RBI reports, and institutional AI deployment metrics (2022–2024).**



3.1. SBI (Urban Bhubaneswar) has shown a noticeable improvement in AI performance from 2022 to 2024, indicating increased integration of AI tools in fraud detection and credit risk analysis. Its AI potential also rose, suggesting further opportunities for innovation and customer insight tools.

3.2. Odisha State Co-operative Bank demonstrated a moderate rise in both performance and potential indices, reflecting growing efforts to digitize services and adopt AI despite structural challenges typical in cooperative banking systems.

3.3. Utkal Grameen Bank, representing rural financial institutions, recorded the most significant increase in AI performance, rising from 35 in 2022 to 50 in 2024. This improvement suggests increasing digital penetration and AI-based service delivery even in remote areas.

3.4. Bandhan Bank (Semi-urban) maintained steady progress with balanced growth in both performance and potential indices, indicating consistent investment in AI for customer profiling and credit evaluation in emerging markets.

3.5. Paytm Payments Bank, being a digital-first institution, maintained the highest scores across all categories. While its performance improved slightly from 2022 to 2024, its potential was already near saturation, signifying maturity in AI adoption.

3.6. Across all institutions, the gap between performance and potential narrowed in 2024, suggesting that AI implementation is becoming more grounded and widespread in Odisha's financial landscape.

3.7. The overall trend confirms that both urban and rural banking sectors in Odisha are moving toward increased AI adoption, with rural banks catching up rapidly due to policy support, digital literacy programs, and evolving customer expectations.

4. Research Objectives

The purpose of this study is to assess the degree to which financial institutions in Odisha, such as public sector banks, private banks, cooperative banks, and digital financial service providers, have embraced artificial intelligence (AI). It looks at how well AI can identify and stop financial fraud, especially when comparing banking systems in urban and rural areas. In order to assess the relative accuracy and dependability of each, the study also compares traditional models utilized by cooperative and rural banks with AI-based credit scoring systems.

The study also looks into the use of AI technologies to enhance banking service personalization and collect customer insights. Finding regional-specific obstacles to AI implementation that banks in Odisha confront, such as data constraints, digital illiteracy, algorithmic bias, and problems with vernacular language processing, is a major goal. Additionally, it seeks to evaluate consumer attitudes and trust in AIpowered financial services while differentiating between the experiences of users in rural and urban areas. In the end, the study aims to provide specific tactics to improve AI integration in financial services, which will increase financial inclusion and institutional effectiveness in Odisha. 5. **Research Methodology and Data Analysis**

1. Study Area and Sampling Frame

- Geographic scope: eight districts—Bhubaneswar & Cuttack (urban), Balasore & Berhampur (semi-urban), and Mayurbhanj, Kalahandi, Ganjam, Koraput (rural/tribal).
- Institutions contacted:
  - 6 public-sector bank branches (SBI, UCO, Bank of Baroda) ○ 4 private-sector banks (HDFC,

ICICI, Bandhan, Axis) ○ 3 regional rural banks (Utkal Grameen, Odisha Gramya,

Kalinga GB) ○ 2 cooperative banks (Odisha State Co-operative Bank and a districtlevel cooperative)

○ 2 digital-first entities (Paytm Payments Bank & Airtel Payments Bank)

 Respondents: branch managers, IT heads, risk-analytics officers, and 600 retail customers selected through stratified random sampling (40 % urban, 30 % semiurban, 30 % rural).

2. Primary Data Collection

Instrument	Purpose	Key Variables	Timeline
Structured Manager survey (google forms + in person).	Measure AI tools in use, implementation stage, staff readiness.	Fraud detection software, credit analytics platforms, chatbot..adoption, budget allocation.	Jan – Mar 2025
Customer questionnaire (Odia & English).	Capture perception and trust.	Easy of use, perceived security, satisfaction.	Feb-Apr 2025
Semi structured interviews.	Uncover qualitative barriers and success factors.	Governance, data quality, regulatory issue.	Apr 2025

All instruments were pilot tested with 20 responded and filtered for clarity.

6. Findings and Interpretation

6.1. AI Tool Adoption by Institutions

Results: 85% of the 17 financial institutions polled have started integrating AI to some extent, mostly for credit scoring and fraud detection.

- It was discovered that public sector banks were only in the early to mid phases of using AI, depending more on centralized IT assistance and older systems.
- Advanced deployment was demonstrated by private and digital-first banks, particularly in the areas of predictive analytics, automated credit decisionmaking, and chatbot usage.
- Cooperative banks and regional rural banks reported minimal or pilot-stage AI implementation, pointing to a shortage of experienced labor and infrastructure as the main obstacles.

Interpretation:

The results show that banks that prioritize digitalization and those that prioritize rural areas differ in their level of AI preparedness. Due to operational and structural limitations, public and rural financial institutions are falling behind private companies in implementing advanced AI functions. This demonstrates the necessity of talent development, digital infrastructure investment, and legislative assistance in order to democratize access to AI in the financial sector.

6.2. Fraud Detection Mechanisms

Findings:
The majority of private banks were actively using AI-enabled fraud detection tools, including anomaly detection, behavioral pattern identification, and real-time transaction monitoring.

- Public sector organizations stated that they relied on central systems and had little control over their fraud detection instruments.
- Manual verification and rule-based procedures are still used by rural institutions, which causes fraud notifications to be delayed.

Interpretation:

In well-resourced institutions, artificial intelligence has been essential in improving real-time fraud prevention. However, financial security in underserved areas is at risk due to smaller banks'

underutilization of these technologies. Rural consumers may be more susceptible to financial exploitation and cybercrime as a result of this disparity in technology use.

6.3. AI in Credit Scoring and Loan Approval Results:

Private and digital-first banks aggressively employ AI-based credit scoring models, utilizing alternative data sources such as transaction history and mobile usage patterns.

• Although some are testing AI-based credit evaluations for MSME loans, public sector banks still mostly rely on human processing and traditional credit bureau scores. • RRBs and cooperative banks only use paper records and human judgment; they do not have AI-enabled credit assessment systems.

Interpretation:

AI tools are helping modern institutions make data-driven, quicker, and more inclusive credit decisions, which encourages financial inclusion among clients who are tech-savvy. However, the lack of these models in rural banks limits timely credit availability, particularly for vulnerable borrowers and workers in the unorganized sector without official credit records.

6.4. Customer Perception and Trust Results:

Of the 600 retail customers polled, 62% of urban respondents said they had a high level of trust in AI solutions such as chatbots and biometric authentication. Among semi-urban respondents, 53% expressed a moderate level of trust, despite worries about lack of human interaction and data privacy.

The majority of rural respondents preferred in-person banking since they were inexperienced with digital tools, and just 28% of them trusted AI-driven services. o Overall, customer satisfaction was greater in institutions where AI was smoothly integrated with human support.

Interpretation:

The survey shows a glaring disparity in digital trust between urban and rural areas. Rural consumers are still dubious and insist on human support, even as urban consumers grow to value the speed and effectiveness of AI-driven services. This suggests that, especially in tribal and underbanked areas, AI deployment methods need to be culturally aware and backed by digital literacy programs.

6.5. Implementation Barriers for AI Results:

• One of the most prevalent institutional obstacles was the lack of qualified staff to oversee AI systems.

· Inadequate funding for IT, particularly in rural and cooperative banks. · Problems with data quality, like inconsistent KYC records.

· Uncertainty in regulations on algorithm disclosure and data usage.

Interpretation:

The study shows that adopting AI is a systemic problem involving capacity-building, governance reforms, and policy clarification rather than just a technical one. To encourage the responsible and equitable adoption of AI, these obstacles must be removed by a concerted effort involving the government, business associations, and educational institutions.

6.6. Success Factors Determined by Interview Results:

• Organizations that successfully integrated AI had: o A well-defined digital plan in line with the goals of upper management. Internal analytics groups or collaborations with fintech businesses.

Staff members receive regular training on digital tools.

Multilingual AI interfaces are being adopted, particularly in customer service.

Interpretation:

A mix of skill, vision, and user-centered design propels the successful deployment of AI. Organizations that make proactive investments in these fields will be in a better position to use AI to empower customers and gain a competitive edge.

7. Conclusion

The use and effects of artificial intelligence (AI) in financial services in Odisha's various urban, semiurban, and rural regions are thoroughly examined in this paper. The results highlight a quickly changing financial landscape in which digital-first and private banks are leading the way in the application of AI, especially in the areas of credit assessment and fraud detection. On the other hand, rural financial institutions and public sector banks continue to face fundamental obstacles like regulatory uncertainty, a lack of infrastructure, and low levels of digital literacy.

Artificial intelligence (AI) technologies have demonstrated enormous promise in improving operational effectiveness, preventing fraud, and facilitating data-driven credit decisions. However, there are major obstacles to fair financial inclusion, particularly in rural and tribal communities, due to differences in institutional preparedness, customer trust, and technology availability.

While semi-urban and rural communities still depend on human connection for trust and happiness, customer perception data shows that AI tools are becoming more and more accepted in urban areas. Targeted policy changes are required for AIdriven financial revolution to be sustainable and inclusive. These consist of client awareness initiatives, bank staff upskilling, digital infrastructure investment, and adaptable governance structures.

In conclusion, even if AI is unquestionably changing the financial services industry, its success depends on addressing institutional, ethical, and human factors in addition to technological advances. Building a robust, accessible, and intelligent financial future for Odisha and beyond would require bridging the gap between urban and rural AI integration.

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