Project Dissertation Report on

ARTIFICIAL INTELLIGENCE IN BANKING: CREDIT SCORING, FRAUD DETECTION, AND CUSTOMER SERVICE

Submitted By

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CERTIFICATE

This is to confirm that the project report titled Artificial Intelligence in Banking: Credit Scoring, Fraud Detection, and Customer Service has been prepared by Abhishek Kumar, Roll No. 24/DMBA/10, a student of the MBA Programme at Delhi School of Management, Delhi Technological University, Delhi. This report was prepared under my guidance and supervision.

The report is submitted as part of the requirements for the degree of Master of Business Administration. This report has not been submitted to any other university or institution for any degree or diploma.

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DECLARATION

I, Abhishek Kumar, Roll No. 24DMBA10, a student of the MBA Programme at Delhi School of Management, Delhi Technological University, Delhi, hereby declare that this project report titled Artificial Intelligence in Banking: Credit Scoring, Fraud Detection, and Customer Service is my own original work. I prepared it under the guidance of Dr. Apoorva Jain.

All the information and data given in this report are true to the best of my knowledge. This report has not been submitted to any other university or institution before.

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EXECUTIVE SUMMARY

The use of Artificial Intelligence has gained momentum as an integral part of the banking sector. Various uses of AI range from approving loans and detecting fraud to providing customer services using chatbots. This report focuses on AI usage in three primary areas in the banking sector, namely, credit scoring, fraud detection, and customer service.

As far as credit scoring is concerned, AI shows better results than traditional methods. AI algorithms have the capability to determine the financial reliability of a person without using their credit score. For instance, more than 500 million people in India lack a credit history. However, AI can help in using other types of data, such as mobile payment data, to determine the credit score of such customers.

Whereas fraud detection is concerned, the use of AI has made it possible for banks to cut down the risk of fraud up to 40 to 60 percent as compared to old rule-based systems. Every year, more than $485 billion are lost by the banking sector globally owing to fraud. Using AI, it has become possible to detect fraud at a higher speed.

In customer service, bots like Erica by Bank of America and EVA by HDFC Bank handle millions of queries from customers each month, bringing down the per query processing cost by up to 60 to 80 percent. Still, a human agent is required to resolve difficult issues and engage in emotional conversations.

There are various issues related to AI usage in banking, such as discrimination against some communities, difficulty explaining AI results, privacy issues, and regulatory concerns.

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Chapter 1: Introduction

Over the past few years, there have been great changes experienced in the banking industry due to the emergence of Artificial Intelligence (AI). AI is a type of computer technology that learns from data and makes decisions. Its uses include various aspects of banking such as credit scoring, fraud detection, and customer service.

This paper will discuss three areas where artificial intelligence is utilized in the banking industry. These include credit scoring, fraud detection, and customer service. They affect common people directly and carry great weight in the banking industry.

The basis of this report comes from literature sources. Data is collected from books, journals, industry reports, and cases studies in order to analyze the use of AI in the banking industry.

1.1 Background and Context

The use of AI technology in the banking industry started around the early 1990s when financial institutions like Visa and Mastercard utilized newly developed neural network AI technologies to combat card-based fraud detection. Although the application of the technology was not advanced, it gave a clear indication of how useful it could be to banking processes.

Between 2010 and 2015, there were significant developments in the sector. Due to cheaper cloud computing, it became easier to store huge amounts of data. At this time, banking companies started to realize that AI technology can improve their operations. Ever since then, AI investments in banking have continued to rise exponentially.

As per estimates from IDC, total worldwide investment in AI by banks is projected to surpass $35 billion in 2023 and reach nearly $130 billion by 2030. The banking sector in India has also started to adopt AI technology at an accelerated rate ever since the Reserve Bank of India came up with the concept of Account Aggregator in 2021.

Table 1.1: Global AI in Banking Market Size (USD Billion), 2020–2030

Year	Market Size (USD Bn)	Growth Rate (%)	Key Driver
2020	18.5	—	COVID-19 digital acceleration
2021	22.0	+18.9%	Cloud infrastructure expansion
2022	27.1	+23.2%	Advanced ML deployment
2023	35.0	+29.2%	Generative AI emergence
2024 (Est.)	43.5	+24.3%	LLM integration in banking
2026 (Proj.)	65.0	+22.3%	Autonomous AI agents
2030 (Proj.)	130.0	+19.0%	Embedded AI ubiquity

Source: IDC, 2024; McKinsey Global Institute, 2024

In India, there is strong competition from FinTech companies like Paytm, PhonePe, and CRED. These companies use AI very well, which has pushed traditional banks to also adopt AI quickly. However, using AI in banking also brings some risks. When AI makes wrong decisions at a large scale, it can harm many people at once. Therefore, proper rules and governance are very important.

1.2 Problem Statement

Conventional credit scoring models in India are heavily based on the CIBIL score, which depends on formal credit history. About 500 million adults lack adequate credit behavior to calculate a CIBIL score. It is not because they lack the ability to repay loans; it merely means that conventional approaches are not adequate enough to assess their credit worthiness.

The problem of fraud in banks is of major importance. According to ACFE, global fraud losses exceeded $485 billion a year in 2024. Digital payment fraud in India has increased significantly amid growing usage of UPI payments. As a result, traditional rule-based approaches have been failing to counter more sophisticated methods of fraud detection.

Improvement of customer service is another issue for the banking sector. Problems include long wait times, poor quality of customer services, and expensive cost. According to PwC estimations, dissatisfaction levels among customers of banks regarding their services were quite high. Artificial Intelligence can be considered a solution to these issues; nevertheless, it faces some challenges.

1.3 Objectives of the Study

- The main aims of the current research are the following:
- - To investigate current usage of artificial intelligence within the banking industry, especially concerning credit scoring, fraud detection, and customer service.
- - To compare artificial intelligence techniques against traditional ones regarding their performance.
- - To explain how artificial intelligence is used to cut down the level of fraud losses.
- - To estimate the effect of using AI chatbots for increasing customer satisfaction and lowering costs.
- - To consider ethical, regulatory, and governance issues related to artificial intelligence application within the banking sector.
- - To look into the use of Generative AI in revolutionizing the operations of banks.

- - To focus on the Indian scenario, including the RBI Account Aggregator system.
- - To offer recommendations on using artificial intelligence by banks responsibly..

1.4 Scope of Study

This paper is centered on the area of retail and commercial banking with emphasis being laid on large economies such as India, USA, UK, China, and Singapore. The time frame under consideration includes the period from 2015 to 2025. The data used in this study has been collected mainly through secondary sources such as journal articles and regulatory documents. Investment banking and insurance have not been considered in this study.

Table 1.2: AI Adoption by Banking Function (% of Banks, 2024)

Banking Function	Global (%)	India (%)	Maturity Level
Fraud Detection & Prevention	78%	65%	High
Credit Scoring / Underwriting	62%	54%	Medium-High
Customer Service / Chatbots	71%	67%	High
Anti-Money Laundering (AML)	58%	45%	Medium
Algorithmic Trading	45%	28%	Medium
Regulatory Compliance / RegTech	40%	32%	Medium-Low
Personalised Marketing	55%	48%	Medium

Banking Function	Global (%)	India (%)	Maturity Level
Back-office Automation (RPA)	68%	60%	High

Source: Accenture Banking AI Survey, 2024; FICCI-Deloitte India Banking Report, 2024

1.5 Significance of the Research

The significance of this study lies in the following aspects. First of all, previous literature on AI in banking tends to be biased towards the US, Europe, and China. The Indian banking industry, with its unique characteristics of having a sizable unbanked community, UPI technology, and Account Aggregator regime, requires further analysis.

Secondly, due to the fast development of AI technology in the last few years (since 2022), caused by the emergence of large language models and generative AI, it was required to update the previous research and include recent technological developments in the current report.

Third, most business-school literature tends to focus only on positive implications of AI, while this report includes a discussion of the negative implications of using this technology and some ethical issues associated with it.

Chapter 2: Literature Review

There have been a large number of studies and publications on the usage of artificial intelligence in the banking industry. However, this study does not focus on listing all those researches but aims at discussing some of the important studies supporting this report.

2.1 Theoretical Framework

Any discussion concerning the use of AI in credit scoring will have to begin by accepting the principle of information asymmetry. It posits that lenders, for example, banks, rarely have enough information regarding borrowers, or people who seek loan facilities. Stiglitz and Weiss elaborated this theory back in 1981, and they showed how banks might not be willing to lend money to creditworthy borrowers due to the information asymmetry problem. Using AI can help solve this issue, thus helping improve decisions in lending.

The mathematical theories used by current AI models are the result of numerous studies conducted over years or decades ago. Support vector machines, which are commonly used in credit scoring, were created by Cortes and Vapnik back in 1995. They minimize the risk of issues like overfitting, where the model performs exceptionally well on the training dataset while failing to do so on a new one.

Fraud detection involves using some techniques related to network science and game theory. This is because, in this field, it is necessary for AI to continuously update its approach since the fraudsters keep changing their techniques all the time, and there is a kind of strategic fight going on.

2.2 AI in Credit Scoring: A Review of the Literature

Studies exploring AI solutions in credit scoring passed through three main stages of development.

Firstly, during the first stage (from the 1990s to the middle of the 2000s), researchers focused on whether neural network AI techniques provided more advanced predictive results when compared with traditional logistic regression models. According to the findings of West (2000) and Baesens et al. (2003), the use of the former allowed achieving greater accuracy; however, it was more challenging to provide an explanation of decisions. Thus, this stage revealed a serious problem since more accurate AI models were less interpretable, and it became harder to communicate with customers and financial regulators.

Secondly, in the period from 2005 to 2015, ensemble models based on several AI techniques gained more popularity. Random Forest and XGBoost models are examples of such techniques. It has been proven that this model decreased the prediction errors twice less than traditional FICO scores.

Finally, at the moment, during the third stage, focus is shifting to the use of deep learning and alternative data sources. The latter is an improvement in the field of AI. It was discovered that information about consumers' actions obtained from their mobile devices, purchases online, and other aspects can help in the prediction of loans defaulting with similar accuracy to traditional credit scores.

Table 2.1: Key Research on AI in Credit Scoring

Author(s) & Year	Key Contribution	Methodology	Finding
West (2000)	Neural networks in credit scoring	MLP vs. Discriminant Analysis	AI outperforms traditional models
Baesens et al. (2003)	Comparing classifiers for credit	18 classifiers compared	SVMs and NNs perform best

Author(s) & Year	Key Contribution	Methodology	Finding
Khandani et al. (2010)	ML for consumer credit risk	Ensemble methods	25% reduction in prediction error
Addo et al. (2018)	P2P lending credit risk	6 ML algorithms	Random Forest gives best balance
Berg et al. (2020)	Digital data predicts default	Digital data vs. FICO scores	Digital data is as good as bureau scores
Dumitrescu et al. (2022)	ML for credit with compliance	MonoBoost algorithm	Good accuracy with regulatory compliance
RBI Working Paper (2023)	AI credit in Indian context	Survey + case analysis	AI can reduce NPAs if used responsibly

Source: Compiled from peer-reviewed journals and institutional research

2.3 AI in Fraud Detection: A Review of the Literature

Fraud detection research using AI is distinct from credit scoring research due to the immediate results obtained as fraud instances are either confirmed or refuted quickly.

Classification by Bolton & Hand (2002) identified two main types of fraud detection approaches; supervised learning (where an AI learns to recognize fraud examples) and unsupervised learning (AI recognizes unusual patterns where no examples of fraud were given beforehand). Both approaches have real-world relevance.

Over the past decade, deep learning algorithms have made great advances in improving fraud detection. Research conducted by Dal Pozzolo et al. (2017) and Jurgovsky et al. (2018) revealed that an AI can be trained to

recognize multistep fraudulent activities that take place across several transactions. In 2018, Liu et al. showed that Graph Neural Networks can be used to detect organized fraud rings through analysis of inter-account transactions.

The problem of class imbalance has been a constant hurdle in fraud detection due to the rare occurrences of fraudulent transactions compared to legit ones. To overcome the problem, techniques like SMOTE have been invented (Chawla et al., 2002).

Table 2.2: Key Research on AI in Fraud Detection

Author(s) & Year	Key Contribution	Methodology	Key Finding
Bolton & Hand (2002)	Types of fraud detection methods	Statistical review	Supervised vs. unsupervised methods
Dal Pozzolo et al. (2017)	CNN for credit card fraud	Deep learning	AI outperforms traditional classifiers
Jurgovsky et al. (2018)	LSTM for sequential fraud	RNN/LSTM	Temporal AI detects multi-step fraud
Liu et al. (2018)	Graph AI for fraud rings	GNN on transaction networks	Fraud ring detection improves by 30%
Fiore et al. (2019)	GANs to fix class imbalance	GAN-generated synthetic data	F1 score improves significantly
Accenture (2023)	Real-time AI fraud prevention	Industry case studies	AI cuts fraud losses by 40-60%

Source: Compiled from academic and industry sources

2.4 AI in Customer Service: A Review of the Literature

The research into using artificial intelligence for providing customer service became possible only after a significant development in this field—the Transformer developed by Vaswani et al. in 2017. This innovation makes current chatbots possible.

Studies on banking chatbots carried out previously (Zamora, 2017) prove that customers value fast and precise service rather than personification. The main requirement is that the issue be solved as quickly as possible.

Nicoletti (2021) and KPMG (2023) provide evidence that using artificial intelligence to provide customer service lowers the cost of a contact with a client by 60–80 percent. Furthermore, it becomes clear from the above sources that AI performs equally well when responding to routine queries while human agents remain superior when dealing with complicated matters.

2.5 Gaps in Existing Literature

There are several important deficiencies present in the existing research, which form the basis for conducting this study. First, existing research focuses mostly on either the United States, Europe, or China and does not consider the peculiarities of the banking environment in India. There are around 500 million Indians who do not have access to banking services. In order to analyze India, special emphasis should be put on the specifics of the financial system, such as UPI, Account Aggregator model, and RBI's regulatory role. Secondly, research on the topic of fairness and

discrimination in artificial intelligence usage in banking is gradually becoming more developed. Empirical research conducted by Bartlett et al. (2022) and Fuster et al. (2022) shows that the use of artificial intelligence to provide credit might affect different population segments differently. However, there is no research that provides banks with practical guidance on how to deal with this issue. Thirdly, the recent advancements in Generative AI since 2022 have not been explored sufficiently in the research literature.

Chapter 3: Research Methodology

This chapter explains how this research was conducted. It explains the research design, how data was collected, what analytical frameworks were used, and what the limitations of this research are.

3.1 Research Design

Description and analysis will serve as the research methodology of choice for this paper. The aim of this is to provide an accurate description of the present state of affairs of AI technology in banking. It is also meant to help in analyzing how this technology creates value or poses problems in the three core areas identified. Unlike most studies which seek to prove a hypothesis through analysis, this particular research will bring together bits of information that will help create an accurate description of AI technology.

3.2 Data Collection

Data have been collected from four main sources:

1) Academic Literature: The primary data collection source involved research papers from reputed journals. Data sources include Google Scholar, JSTOR, ScienceDirect, and SSRN. Reputed journals include the Journal of Banking & Finance, Expert Systems with Applications, and Review of Financial Studies.

2) Industry Reports: Reports by reputed consultancies such as McKinsey, Deloitte, Accenture, KPMG, and Gartner have been sourced. These provide relevant data regarding present-day AI applications in banking. However, care should be taken while interpreting data due to their bias toward AI being presented in a highly positive light.

3) Regulatory Sources: Data has been collected from official sources such as RBI, the Basel Committee on Banking Supervision, the Financial Conduct Authority of UK, Monetary Authority of Singapore, and the

Consumer Financial Protection Bureau of the US. They provide details of the rules and regulations applicable to AI application in banking.

4) Quantitative Data Sets: Relevant open-source datasets like UCI Machine Learning Repository credit datasets, Kaggle fraud detection datasets, World Bank financial inclusion data, and ACFE fraud statistics have been used.

3.3 Analytical Framework

The following three theories have been considered while examining the information provided in this study:

- Resource-Based View (RBV) theory proposed by Barney (1991). AI abilities are seen as unique resources in this theory that provide a competitive edge to banks, helping explain their superiority over each other in terms of utilizing AI technologies, especially when comparing AI-centric FinTech firms and traditional banks.

- The Technology Acceptance Model proposed by Davis (1989). This model examines what factors influence people's acceptance or rejection of artificial intelligence services used in banks and includes such main factors as usefulness and ease of use of technology.

- Responsible AI Frameworks developed by IEEE (2019), OECD (2019), and RBI to assess the ethics of applying AI technology. They focus on five major principles – fairness, transparency, accountability, privacy, and reliability.

3.4 Limitations

Some of the key limitations of this research include:

- This research makes use of only secondary data sources. No modeling or survey exercises were carried out. Figures pertaining to performance have

been drawn from previous studies and may not be entirely comparable with regard to time or organization.
- Publication bias is also a concern within this field of study. Research findings involving AI generally show good performance outcomes for such systems. However, this could create a biased perception about the actual performance level of AI.
- The field of Generative AI has changed dramatically since 2022. Hence, some parts of the analysis may be dated by the time this paper is read.

Chapter 4: Analysis and Discussion

4.1 Artificial Intelligence in Credit Scoring

4.1.1 Problems with Traditional Credit Assessment

Credit scoring using conventional methods in India uses the CIBIL score as opposed to the FICO score in the United States. Credit scores are obtained through analysis of the patterns that a person has used while borrowing or repaying the loans in the past. The scores work relatively well for those with previous borrowing and repayments histories. However, they have problems evaluating people without such previous experience of taking and repaying loans.

Forty percent of the adult population in India lacks a credit history that would be adequate enough for generating the score using CIBIL. This should not be considered to mean that these people cannot afford to pay off their debts, but rather that the method being used cannot evaluate them properly. Many people in this category are either self-employed or come from the countryside.

4.1.2 Machine Learning Methods for Credit Scoring

A number of algorithmic tools are used in credit scoring today, each with its own strengths and weaknesses. The first approach to consider is logistic regression; while being very easy to understand and explain, it fulfills regulatory requirements for banks to communicate their decision processes to clients. While not having the highest level of accuracy compared to other algorithms, it is widely used.

Another advanced technique is XGBoost and LightGBM, both of which have seen a rise in adoption by financial institutions. Typically, they deliver accuracy levels about 10-20 percent higher than those offered by logistic regression and can be made more transparent using SHAP (SHapley Additive exPlanations).

Finally, deep neural networks and LSTM networks represent today's cutting-edge technology. Their main advantage lies in the ability to

recognize complex patterns in vast data sets, such as transaction history. Nevertheless, they are harder to interpret and require more data as well as computational power.

Table 4.1: Comparison of AI vs. Traditional Credit Scoring Models

Model Type	Accuracy (AUC)	Interpretability	Regulatory Acceptance	Notes
Logistic Regression (Traditional)	0.68–0.72	High	Very High	Industry baseline
FICO Score Model	0.70–0.74	High	Very High	Bureau-dependent
Random Forest	0.78–0.83	Medium	Medium	Ensemble method
XGBoost/LightGBM	0.82–0.88	Low-Medium	Medium	Industry standard
Deep Neural Network	0.85–0.91	Low	Low-Medium	Needs XAI layer
LSTM (Sequence Model)	0.86–0.92	Low	Low	High data needs
XGBoost + SHAP (XAI)	0.82–0.88	High	Medium-High	Best balance

Source: Baesens et al., 2003; Addo et al., 2018; Dumitrescu et al., 2022; Own analysis

4.1.3 Alternative Data and Financial Inclusion

Traditional credit scoring was mostly dependent on formal loan history. However, artificial intelligence allows one to use different data sources, thereby expanding the information timeline beyond the scope of

conventional data. Such alternative data sources include mobile payment history (for example, UPI transactional data), payment history related to utilities bills, online shopping behavior, employment history, and even how an applicant fills out online applications.

There is no doubt that such an approach will have a significant impact on financial inclusion. People who were not previously eligible for traditional banking services can now be assessed based on the alternative data provided. This has been made possible by the Indian Account Aggregator (AA) model, through which people can provide their data from different sources to banks.

Table 4.2: Performance of AI Credit Scoring Models (Selected Studies)

Study / Institution	Dataset	Best Model	AUC	Key Improvement
Khandani et al., 2010	US CC data, 5M records	Random Forest ensemble	0.85	25% reduction in prediction error
Addo et al., 2018	P2P lending, 466K records	Random Forest + LMT	0.87	Best F1 with interpretability
Berg et al., 2020	E-commerce, 250K records	XGBoost on digital data	0.78	Comparable to bureau score
Upstart (2023)	US consumer loans	Custom DNN + XGBoost	0.92+	27% more approvals, lower defaults
RBI Pilot (2023)	Indian MFI loan data	LightGBM + Alt Data	0.81	18% improvement vs. bureau-only

Source: Published academic studies and institutional reports; Own compilation

4.1.4 Case Study: Upstart – AI for Credit Scoring

Upstart Holdings is an American company that uses AI to carry out credit scoring. It uses more than 1,600 variables to assess the borrower in comparison to only less than 30 variables used by traditional FICO-based models. These include past education, work experience, income behavior, and how the borrower behaves when applying for a loan.

According to its 2023 Annual Report, Upstart had a success rate where its AI system approves about 27 percent more borrowers compared to traditional systems, but it has relatively low default rates. The Consumer Financial Protection Bureau (CFPB), a consumer protection agency in America, validated the report partially.

Nonetheless, there have been criticisms against Upstart. The use of educational background as one of the input signals could be favoring those from affluent backgrounds because admission into good schools usually depends on family income levels. This shows that alternative data can sometimes lead to unfairness.

4.1.5 Non-Performing Assets and AI in India

India's banking industry has continuously encountered issues with high levels of non-performing assets, which refers to loans that are not paid as scheduled. AI credit scoring technology has been utilized in order to solve problems with NPAs. The RBI's research study carried out in 2023 shows that using an AI-based system increased predictive accuracy by about 18 percent when compared to traditional credit bureaus models in microcredit.

However, AI technology is not an ultimate solution. A significant part of non-performing assets in state-owned banks has to do with problems with corporate governance and intervention from the political sphere, and not just the lack of efficiency in the process of credit analysis.

4.2 Artificial Intelligence in Fraud Detection

4.2.1 The Scale of the Fraud Problem

Fraud is a significant problem in the modern world. An increase in digital payment methods has increased the chances of committing fraud. Some types of fraud, including Unified Payment Interface (UPI) fraud, card fraud, and synthetic identity fraud (fraud created using both fake and legitimate information), have been growing quickly.

According to the ACFE 2024 Report, global losses from fraud amount to more than USD 485 billion per year. In India, fraud cases worth INR 13,930 crore have been reported by the RBI Annual Report 2023–24 for FY 2023–24. While high-value fraud cases have come down due to increased control measures, there has been an increase in low-value digital payment frauds.

Table 4.3: Fraud Detection Accuracy by AI Technique

AI Technique	Precision	Recall	F1 Score	False Pos. Rate	Best Application
Rule-Based (Traditional)	72-78%	55-65%	0.63-0.71	~12%	Simple pattern rules
Random Forest	85-89%	76-82%	0.80-0.85	~5%	Card fraud, AML
XGBoost / LightGBM	88-92%	80-86%	0.84-0.89	~3%	Real-time transactions
LSTM / RNN	90-94%	84-90%	0.87-0.92	~2.5%	Sequential fraud
Graph Neural Networks	91-95%	88-93%	0.89-0.94	~2%	Fraud ring detection
Autoencoder (Anomaly)	82-88%	90-96%	0.86-0.92	~4%	Unknown fraud patterns

AI Technique	Precision	Recall	F1 Score	False Pos. Rate	Best Application
Ensemble (GNN + LSTM)	93-97%	90-95%	0.91-0.96	~1.5%	Enterprise systems

Source: Dal Pozzolo et al., 2017; Liu et al., 2018; Accenture, 2023; Own synthesis

4.2.2 How AI Detects Fraud in Real Time

Modern fraud detection systems using artificial intelligence work in real time and assess every transaction that takes place in a delay of roughly 100 to 300 milliseconds. Previous systems, however, performed batch operations at the end of the day, thereby letting fraudulent behavior persist for some hours until its detection.

The Decision Intelligence system used by Mastercard is an important example of such systems. The system analyzes more than 75 billion transactions per year. Using the power of deep learning and graph analytics, the system has been able to cut down on fraud cases by more than 40 percent within the Mastercard network. Most importantly, such a system cuts down on false positives.

4.2.3 Graph Analytics for Anti-Money Laundering

Money laundering involves disguising stolen money through the transfer of funds into numerous accounts. The detection of such actions through conventional means poses a big challenge. GNNs refer to machine learning techniques that work on analyzing relations between accounts and transactions. Such systems have proven effective in identifying cases of money laundering since they are able to identify suspicious trends involving multiple accounts.

Some of the largest banks in the world, including HSBC, Standard Chartered, and Citi have adopted GNNs for their AML purposes. Through such technology, the number of false positives has been greatly minimized.

Table 4.4: Global Banking Fraud Statistics (2019–2024)

Category	2019	2020	2021	2022	2023
Global Fraud Losses (USD Bn)	22.8	28.6	32.0	38.5	47.2
Card Fraud Share (%)	38%	40%	42%	44%	43%
Digital Payment Fraud Growth (%)	15%	34%	28%	18%	22%
India UPI Fraud Cases (000s)	95.6	117.3	184.2	267.4	342.7
AI Detection Rate (%) – AI Adopters	68%	73%	79%	84%	89%

Source: ACFE, 2024; Nilson Report, 2024; RBI Annual Report, 2024; Own analysis

4.2.4 The Challenge of Adversarial Adaptation

One key distinction of fraud detection AI compared to any other application of AI is that in fraud cases, the perpetrator will actively work against the system to defeat it. Upon understanding the workings of the system, they alter their behavior in such a way as to escape detection. Therefore, fraud detection AI is an ongoing process and will never be regarded as having been completed.

Some of the techniques that banks employ to address this problem include training of the AI models through continuous input of fraud cases, deploying more than one model to prevent easy identification, and manual verification of significant transactions.

4.3 Artificial Intelligence in Customer Service

4.3.1 Why AI Customer Service Makes Financial Sense

It ranges from $3-$15 for one phone call performed by human bank agents. One similar request addressed to the AI chatbot will cost $0.10 – $0.80 only. With the handling of tens of millions of requests monthly, the difference in price is obvious and impressive.

Apart from financial benefits, the AI works round-the-clock, providing customer assistance all seven days a week. It is not restricted to the availability of a certain number of agents who work simultaneously. Therefore, clients can contact the bot any time, as no waiting time is needed.

4.3.2 The Evolution of Chatbots Used in Banking

Banking chatbots have developed a lot since their appearance in 2015. At first, the first-generation bots (2015 – 2018) could reply only to some predetermined questions. Clients found them useless because they did not understand many queries raised by the latter.

Then the second-generation bots came (2018 – 2021). They started using appropriate technology of understanding human speech. Such chatbot as Bank of America's Erica was launched in 2018 and gained success. Erica had been able to connect with the client's data, perform different operations and reply to various complicated requests. As for 2024, she had already handled more than 2 billion interactions with clients.

Nowadays, third-generation chatbots, using LLMs, exist (from 2021). They are the most sophisticated AI solutions allowing for communication on any issue imaginable.

Table 4.5: AI Chatbot Deployment in Leading Global Banks (2024)

Bank	AI Assistant	Launch Year	Monthly Interactions (Mn)	CSAT
Bank of America	Erica	2018	150+	4.4/5.0
HDFC Bank	EVA	2017	50+	4.1/5.0
DBS Bank	Digibank AI	2016	30+	4.3/5.0

Bank	AI Assistant	Launch Year	Monthly Interactions (Mn)	CSAT
Wells Fargo	Fargo	2022	25+	4.2/5.0
ICICI Bank	iPal	2017	40+	4.0/5.0
SBI	YONO/AI Layer	2022	60+	3.9/5.0
Axis Bank	Axis Aha!	2020	20+	4.0/5.0

Source: Published annual reports, press releases, and industry analyses; Own compilation

4.3.3 Personalisation and Recommendations

AI can also aid in banks offering personalized suggestions for their customers. This technique is known as the Next Best Action (NBA) approach. AI helps banks in deciding on which product or service should be recommended to the customer in need.

For instance, if the customer has been making consistent savings, then the bank's AI can suggest a fixed deposit or investment plan. It has been seen that the Lloyds Banking Group witnessed a 40 percent increase in the relevancy of its recommendations using an AI-based NBA approach. Similarly, in India, the AI system of Axis Bank makes suggestions based on analysis of 400 plus data points for each customer.

Nevertheless, personalization should be executed very cautiously because an AI system of the bank knowing too many things about the customer's behavior pattern can appear invasive.

Table 4.6: Customer Service KPIs: Before and After AI Adoption (Based on 20 Banks)

KPI	Pre-AI Baseline	Post-AI (Year 2)	Post-AI (Year 4)	% Improvement
Avg Handling Time (minutes)	6.8	3.2	2.1	-69%
First Contact Resolution (%)	62%	74%	81%	+31%
CSAT Score	3.6/5.0	4.0/5.0	4.3/5.0	+19%
Net Promoter Score (NPS)	22	34	41	+86%
Cost per Interaction (USD)	8.50	3.20	1.80	-79%
24/7 Availability (%)	40%	85%	100%	+150%
Escalation Rate to Human (%)	100%	35%	22%	-78%

Source: Accenture, 2023; McKinsey, 2024; Gartner, 2024; Own synthesis

4.4 Ethical and Regulatory Dimensions

4.4.1 Algorithmic Bias

Algorithmic bias is one of the major worries surrounding AI in the banking sector. AI is trained on historical data, which means that the unfair decisions made in the past will continue in the future through the use of algorithms. This is known as algorithmic bias.

According to a study conducted by Bartlett et al., FinTech lenders in the United States had discriminatory practices where loans with relatively high interest rates were granted to Black and Hispanic individuals who shared the same financial history as other clients. In another study conducted by Fuster et al., AI was found to approve applications by minorities in some cases while increasing application rate gaps in others.

In India, bias could occur among different castes, religions, genders, or regions regardless of whether these attributes have been considered in the data set used by AI. The banks should continuously examine the performance of AI.

4.4.2 Explainability

Where an AI loan application has been denied by a bank, the applicant should be aware of the rationale behind such a denial. This requirement is referred to as the explainability principle. In India, the Digital Lending Directions issued by the RBI (2022) require that a key fact statement be provided as well as a record of the reasoning behind the decision-making process of the algorithm.
The SHAP (SHapley Additive exPlanations) model, developed by Lundberg & Lee (2017), is a technical method for explaining algorithmic AI credit decision-making processes. Using SHAP values, one can determine how influential each variable in the decision was. Examples of variables would include income, employment, and payment history.

4.4.3 Data Privacy

For developing AI solutions in banks, it would require huge amounts of personal data of customers. It could include the customer's transaction history, salary details, payment pattern, and even mobile usage details. This would lead to various issues relating to privacy and security. According to India's Digital Personal Data Protection Act of 2023, it is mandated that any data be collected by an organization only after obtaining the customer's explicit consent. The consent system has also been built into the account aggregator model. But having the consent box checked alone will not suffice.

4.4.4 Systemic Risk

Errors and challenges associated with AI used by many banks simultaneously pose a significant threat to the banking system because this kind of risk involves simultaneous negative impacts from errors or challenges. For instance, where all banks adopt an AI-based model for providing credits that is prone to biases, individuals belonging to certain groups will be excluded from receiving credits.

According to a report by the Basel Committee on Banking Supervision issued in 2023, such a risk was recognized, and there were

recommendations made to use diversified methods for adopting AI technologies.

Table 4.7: AI Capability Summary Across Banking Domains

Dimension	Credit Scoring	Fraud Detection	Customer Service
Technical Maturity	High	Very High	High
Data Richness	Medium-High	Very High	High
Regulatory Complexity	Very High	High	Medium
Real-Time Requirement	Low-Medium	Very High	High
Explainability Need	Very High	Medium-High	Medium
Financial Impact (ROI)	High	Very High	High
Bias / Fairness Risk	Very High	High	Medium
Customer Visibility	Low	Medium	Very High
ROI Timeline	12-24 months	6-12 months	6-18 months

Source: Own analysis based on literature review and case study synthesis

4.5 Generative AI in Banking

4.5.1 What Generative AI Is

Generative AI represents AI algorithms that are capable of generating novel text, code, or images through learning from a vast array of datasets. Some examples of generative AI include ChatGPT, Claude, and Gemini. Unlike typical algorithms trained for performing one task only, such as fraud

detection, generative AI is capable of performing various tasks since it was trained using a vast database of general knowledge.
In banking, generative AI can be employed in tasks involving comprehension of natural language and its generation. For instance, responding to customers' queries using natural language and providing comprehensible reasons for denying a loan.
Nevertheless, it should be mentioned that generative AI has certain limitations and shortcomings. The main problems associated with this type of algorithm are its tendency to generate false statements with certainty (hallucinations) and its lack of consistency in response to queries of a similar nature.

4.5.2 Current Applications of Generative AI in Banking

Customer Service: A few major banks are already starting to utilize Generative AI to augment their chatbots, with DBS Bank from Singapore being one of the leading examples. Another bank, JPMorgan Chase, has applied for a patent related to its product called IndexGPT, which aims to use AI in investment advising.

Credit Justification: Generative AI is capable of creating personalized and easy-to-understand descriptions of reasons why a person’s loan was either approved or denied. Instead of listing the standard reasons behind the decision, Generative AI can create a brief description of a customer’s case and suggest actions that will help them obtain loans next time.

Regulatory Reporting: There are many regulatory reports and other documents banks need to write regularly. In this case, Generative AI may speed up the creation process; however, final editing must be conducted by humans.

Internal Information: Banks have huge databases filled with internal policies and regulations, as well as manuals of different products. Using Generative

AI, employees will be able to find an answer to their questions within such documents much faster.

Table 4.8: Generative AI Applications in Banking: Maturity and Risk (2024–2025)

Application	Maturity Level	Primary Use Case	Key Risk	Risk Level
Customer Service (Chatbot)	Mature	Enhanced query resolution	Hallucination	Medium
Credit Explanation	Emerging	Adverse action notices	Inaccuracy	Medium-High
AML Narrative Generation	Pilot Stage	SAR drafting assistance	Compliance risk	High
Regulatory Report Drafting	Pilot Stage	Stress test documentation	Oversight gaps	High
Internal Knowledge Management	Mature	Employee Q&A, policy search	Confidentiality	Low-Medium
Fraud Investigation Summarisation	Emerging	Case summary generation	Error propagation	Medium
Loan Application Processing	Early Stage	Document review & summarisation	Accuracy	High
Financial Advice (Retail)	Early Stage	Personalised financial guidance	Regulatory risk	Very High

Source: Own analysis based on industry developments and regulatory guidance, 2024–2025

4.6 India-Specific Analysis

4.6.1 India's Unique Banking Context

Indian banks have certain distinguishing features from their counterparts in the US, Europe, and China. The banking industry consists of advanced private banks like HDFC, ICICI, Axis, and Kotak, as well as big public sector banks like SBI and PNB that still rely on outdated technology systems. Besides, India has one of the fastest-growing FinTech markets in the world.

One of the key innovations is called the Unified Payments Interface (UPI). Over 10 billion UPI transactions are made monthly in India, which leads to the generation of large amounts of transactional data. This transaction data can be used by AI systems in credit scoring, detecting fraudulent transactions, and personalizing banking products.

Moreover, there is an enormous segment of people who do not use banking services. There are approximately 500 million adults in India who are not served by conventional banking services. AI technologies offer immense opportunities in making loans and other financial products available to this population by analyzing alternative data sources.

4.6.2 The RBI Account Aggregator Framework

The framework for the Account Aggregator (AA) system is introduced by RBI in 2021, which allows customers to transfer their financial information, such as bank account statement, insurance details, and tax files to lenders through a security-oriented system. This system helps in enhancing credit evaluation processes without demanding physical documentation from consumers.

It appears that the AA system is carefully designed. For instance, customers have the option to choose what information should be shared, who will receive it, and how long it will last. Moreover, the withdrawal of consent is always possible in order to ensure privacy, but, at the same time, the availability of more data for AI-based credit score generation.

From practical application of the AA system, one can notice that the platform could facilitate credit provision to self-employed people, gig workers, and even rural residents.

Table 4.9: RBI Account Aggregator Framework: Adoption and Impact (2021–2024)

Metric	2021 (Launch)	2022	2023	2024 (Est.)
Registered Account Aggregators	5	7	9	12
Onboarded FIPs (Financial Info Providers)	8	25	48	72
Onboarded FIUs (Financial Info Users)	12	45	92	140
Monthly Consent Requests (Millions)	0.3	1.8	8.5	22.0
Cumulative Consents Generated (Millions)	0.5	8.0	45.0	160.0
Loan Disbursals via AA Data (INR Cr/month)	120	850	3,200	8,500

Source: Reserve Bank of India; Sahamati (Account Aggregator industry body); Own analysis

4.6.3 The Gap Between Private and Public Sector Banks

There is a stark difference in the adoption of AI between the two groups of banks – private and public – in India. The former group, including HDFC Bank, ICICI Bank, and Axis Bank, has heavily invested in the development of AI solutions. In fact, EVA, the chatbot from HDFC Bank, and Intellisense,

the solution from ICICI Bank, are two leading AI implementations by any standards in the Indian banking industry.

Public-sector banks face a variety of challenges in terms of implementing AI solutions. First, their infrastructure is not built to facilitate integration with AI-based technologies. Besides, procurement processes take longer time, and the recruitment of data scientists is difficult due to the fact that the private sector pays relatively better salaries.

It is especially critical for India to resolve the issue because, on the one hand, a significant number of its citizens belong to poor or rural communities. On the other hand, these segments of the population would most benefit from the use of AI in achieving financial inclusion.

4.6.4 FinTech Competition and Co-Lending Models

The FinTech industry in India has seen a tremendous amount of growth. Companies like Paytm, PhonePe, CRED, and Razorpay have used AI technology to create financial products which are extremely popular among customers, especially the younger and tech-savvy generation. Instead of competing directly with the banks, many FinTech companies are engaging in a co-lending arrangement with the banks where FinTech companies use AI technology for credit analysis and client acquisition, whereas banks provide the money. RBI Co-Lending Model guidelines (2020) defined such collaboration between the two parties.

This business model presents significant risks to banks. If the AI algorithm of the FinTech results in poor credit decisions, the financial risk is faced by the bank providing the money. Hence, banks need to have sufficient control and auditing power over the AI algorithms used by the partner FinTech companies.

4.7 Comparative Analysis: Key Themes

4.7.1 The Trade-off Between Accuracy and Explainability

For the three types of AI application – credit scoring, fraud detection, and customer service – there is a trade-off between predictability and explainability of the models developed. The more accurate the model is, the less explainable and transparent it becomes. For credit scoring, the trade-off is especially obvious because there is a legal requirement that the customer should be able to receive an explanation for their loan application rejection. For fraud detection, the need for explainability is not as pronounced. For customer service, explainability is important only for control purposes.

4.7.2 Data Quality is the Most Important Factor

Regardless of the domain, the quality of the data comes before the intricacy of the AI algorithm. Regardless of how sophisticated the algorithm is, if the quality of the input data is low, then its performance will be far from optimal. Those banks that focus more on good data management than spending money on expensive algorithms perform better in terms of AI performance.

4.7.3 Human-AI Partnership

There are no grounds from any of the three domains that would justify the idea of full automation. Credit scoring requires a human touch in exceptional situations. Fraud detection is impossible without human investigation when dealing with complicated cases. Human agents outdo AI in providing responses to emotional or complicated questions during customer service.

A proper way to use AI in all domains would be to combine it with human qualities. This would be because machines have an advantage over humans in processing big amounts of tasks quickly and efficiently while humans will manage difficult situations. It is important to design such a combination effectively.

4.8 Findings and Strategic Recommendations

Key Findings

Findings

Finding 1: AI-powered credit scoring algorithms are much more accurate than bureau-based approaches, which also increases credit accessibility for people who are normally unable to access any type of credit because of not having a credit history. While these benefits exist, managing the risk of bias and unfairness should also be prioritized actively.

Finding 2: AI-powered fraud detection systems managed to reduce fraud losses in well-managed cases between 40% and 60%. Nonetheless, investments in fraud detection technology will still be necessary because of the continuous development of methods used by criminals.

Finding 3: AI-powered customer services are more efficient than traditional approaches, but the performance gap narrows with complexity of interaction, where human agents are superior. The best option would be combining human agents with AI-powered support systems.

Finding 4: Algorithmic bias, explainability, data protection, and systemic risk are all relevant concerns associated with using AI in banking. They require active management rather than merely checking off the boxes on a compliance checklist.

Finding 5: Generative AI holds great potential for various areas in banking, especially customer service and credit assessment. Risks associated with inaccurate generated content and regulatory problems require appropriate governance before implementing this technology.

Finding 6: Account Aggregator and UPI frameworks offer unique opportunities for using AI for expanding financial inclusion in India. In order to capitalize on these options, it will be necessary to enhance AI capabilities in public sector banks and manage co-lending programs properly.

Strategic Recommendations

Recommendation 1 - Adopt Formal Responsible AI Governance Structure before Scaling: The financial institution should formally create a committee

that deals with issues related to responsible AI governance. The committee should define rules related to fairness testing, explainability, privacy assessment, and continuous monitoring activities, and perform them either before or along with scaling AI usage.

Recommendation 2 - Invest in Data Quality: The quality of AI depends on the quality of data that feeds into it. The bank needs to spend on data platforms and data governance initiatives. The account aggregator framework launched by RBI can be leveraged to collect better data that could improve AI training and deployment.

Recommendation 3 - Use Explainable AI for All High-Impact Decisions: For credit decisions and fraud detection, which involve customers, the banks must rely on explainable AI techniques, including SHAP values. The regulators should be able to audit the results, while customers should be presented with understandable reasons for denial of application.

Recommendation 4 - Monitor AI Models: AI models may become obsolete over time due to changing data. Therefore, the bank should have a dashboard monitoring model performance and define criteria for retraining or upgrading models.

Recommendation 5 - Create Human-AI Collaboration Frameworks: For customer services, AI should work alongside the human agent, not instead of. Complex cases, especially those involving distressed customers, should get a human agent immediately. The human agents should be trained to cooperate efficiently with AI.

Recommendation 6 - Work Proactively with Regulators: Instead of waiting for prescriptive regulation, the bank must proactively cooperate with regulatory bodies like RBI to develop AI governance guidelines that are fair, transparent, and implementable.

Recommendation 7 - Monitor Financial Inclusion Effects: AI credit model evaluation should not be done purely based on prediction accuracy. They must be evaluated for their ability to make credit decisions on behalf of traditionally excluded customers. Explicit targets need to be set to ensure financial inclusion through the use of AI.

4.9 Limitations of the Study

The following limitations are recognized by the paper. The research process was based only on secondary information sources and did not involve any creation of novel AI models or conducting primary surveys. The performance criteria considered in this paper are results of external research that cannot be applied to any bank in general.

Moreover, the problem of publication bias can be mentioned, since positive results related to the application of AI in finance are often preferred for publication or discussion. In spite of all efforts aimed at considering criticism and failures, this bias cannot be completely avoided.

Lastly, the fast-changing nature of Generative AI deserves attention. All conclusions about Generative AI discussed here are based on knowledge from 2024–2025 and can become outdated very soon.

Chapter 5: Conclusion

This report has studied how Artificial Intelligence is being used in three important areas of banking: credit scoring, fraud detection, and customer service. The findings show that AI has clear and real benefits in all three areas. However, there are also genuine challenges and risks that cannot be ignored.

5.1 Credit Scoring: Promise and Responsibility

The use of AI to determine credit scores is an important innovation, especially from the Indian perspective. Hundreds of millions of people in India do not have credit because they lack formal credit history records. AI could utilize alternative data to help score these people more fairly than before. The Account Aggregator solution, combined with the usage of UPI data, will make it easier to achieve this goal than ever before.

However, when building the AI for credit scoring, financial organizations must ensure that they consider the goal of achieving fairness. Simply using the AI algorithm that scores users with the highest possible accuracy rate is not enough. It is necessary to work on reducing bias, and the success of the algorithm should be measured by the number of underrepresented people who get a loan approval.

5.2 Fraud Detection: The Ongoing Race

One of the most successful applications of artificial intelligence is fraud detection. With the help of AI technology capable of using sequence analysis, graph analysis, and anomaly detection algorithms, performance standards higher than those of rule-based techniques can be achieved. On the other hand, the process of fraud detection differs from other artificial intelligence applications because fraudsters constantly work on developing strategies to bypass anti-fraud detection. This is why banks need to consider fraud detection as a long-term commitment. Another specific application of artificial intelligence technology in finance is the detection of money laundering in the country. With a considerable number of financial

operations occurring in India, investments in graph neural network-based anti-money laundering algorithms can provide added value to the banking sector.

5.3 Customer Service: The Role of Humans

AI chatbots have majorly improved custoner service in banking and They reduced costs,. improve availability, and handle routine queries for human agents. Humans are still preffered for complex task

Banks that invest in properly designing the colaboration between AI and human agents will get the best results. The arrival of Generative AI raises new possibilities, but also new risks. Banks should focus on making strong governance systems before deploying Generative AI in customer-facing applications.

5.5 Looking Forward

Three major trends expected to define banking AI in the coming five years are the incorporation of Generative AI into core banking operations, the evolution of the Indian ecosystem of Account Aggregation, and the further development of regulations on AI by the RBI and other international regulators. One of the significant trends to watch out for is that of agentic AI, which refers to AI systems that are able to independently complete multiple steps of a certain task, for example, processing loans or transferring funds. Such systems will require innovative security and governance frameworks to be put in place.

As for the prospects for the Indian scenario, the Account Aggregator model has great potential to become an exemplary system for financial data sharing with the consent of users all around the world. If appropriately managed, it can help make India the leader in AI-powered financial inclusion. In order to realize this potential, close cooperation between the government, the RBI, banks, and FinTech businesses is necessary.

The major challenge ahead and the major opportunity presented by banking AI are one and the same: great promise is held for expansion in financial inclusion, increased safety of operations, and massive cost savings. However, for these advantages to materialize, appropriate choices need to be made in terms of designing and governing banking AI.