



AI-Driven Credit Risk Assessment in Indian Banking: Opportunities and Ethical Concerns

Author: Sohan Kumar Jha¹

Research Scholar, University Department of Commerce and Business Administration,
LNMU, Darbhanga, Bihar

Co-Author: Nirmala Kushwah²

Assistant Professor, University Department of Commerce and Business Administration,
LNMU, Darbhanga, Bihar

Abstract

Artificial intelligence is steadily emerging as a key component in modern banking activities, including digital banking, CRM systems, payment gateways, and compliance, particularly when it comes to evaluating credit risk. Traditionally, banks in India have relied on formal financial records and credit histories to evaluate borrowers. However, such methods often leave out a large section of the population, particularly those working in the informal sector, cottage industry. With the increasing availability of digital data, AI-based models are now being used to assess creditworthiness using alternative sources such as transaction patterns and behavioural indicators.

This paper examines how AI is leveraged in credit risk assessment in the Indian banking system, its challenges that come with it. The study is based on secondary data collected from RBI reports, industry publications, and existing research. The findings indicate that AI helps banks make quicker and more informed lending decisions, improves the accuracy of risk prediction, and supports financial inclusion.

At the same time, some practical concerns start to appear, such as handling personal data, and who is responsible if something goes wrong when AI is used in this way. AI is not just a tool for efficiency, but also something that needs careful use and proper oversight in the banking system.

Keywords: Artificial Intelligence, Credit Risk Assessment, Indian Banking, Ethical AI, Financial Inclusion, Machine Learning

1. Introduction

In recent years, the Indian banking sector has been going through a lot of changes. Earlier, most



of the work depended on traditional systems, but now digital platforms and data-based processes are becoming more common. Among these changes, the use of Artificial Intelligence (AI) has also started picking up, though not in a very uniform way. Some banks are experimenting with it more actively, while others are still in the early stages. It seems to be more useful in areas where a lot of data needs to be looked at together, which is otherwise difficult to handle manually. A common example is credit risk assessment. This is basically the process banks follow before giving a loan. Earlier, they mostly depended on documents such as income details, past borrowing records, or collateral. That approach still continues, but it does not always cover everyone equally. Many people do not have complete records, so their ability to repay is not always reflected properly through these documents. In India, many individuals, especially those in small businesses or informal work, do not have detailed records. Because of this, even capable borrowers may not get access to credit.

Now, with more people using digital payments and online banking, a different kind of data is available. Banks have started using AI-based systems to look at this data and understand borrower behaviour in a different way. Instead of only checking formal documents, they also look at patterns in transactions or usage. This does not completely replace the old system, but it adds another layer to it. It can also make the process faster, which is useful from the bank's side. At the same time, this shift is not entirely straightforward. The results depend a lot on the data type being used, and that data may not always be correct. In some situations, even bank officials may find it difficult to clearly explain how a decision was made by the system. There are also concerns about how personal data is handled and whether it is being used carefully. Another issue that comes up is responsibility, because when decisions are taken by systems, it is not always clear who should answer for them.

Keeping this in view, the present study looks at how AI is being used in credit risk assessment in Indian banking. It focuses on understanding both the advantages and the practical issues that are coming up along with its use.

2. Literature Review

In recent years, Artificial Intelligence has received increasing attention in the banking sector, but its adoption and application in India differ somewhat from those in other countries. This difference is partly because the Indian banking system deals with a mix of borrowers, some with proper records and others without. Because of this, many studies do not look at AI only as a technical change, but also try to understand how it works within the existing system.

If we look at some Indian reports, it becomes clear that adoption is still uneven. The Reserve Bank of India (RBI, 2023) mentions that banks have started using data-based tools in areas like loan processing, but it does not suggest that these tools are being used independently. These are often used along with human judgment rather than replacing it completely. A similar point comes up in IDRBT (2022), where it has been observed that machine learning models can give better predictions in some cases, but much depends on how stable the data is and how the models are designed. It is also not clearly established that these systems will fully replace human involvement. When the data is not consistent, the outcomes may not improve in a noticeable way.

A few studies try to connect this with financial inclusion, which is an important issue in India. Some research reflects this idea, such as Bansal and Kumar (2022), who indicate that AI-based approaches allow banks to consider borrowers who may not have detailed credit records. This



becomes relevant for first-time borrowers who are otherwise left out. Sharma and Singh (2021) look at this from the fintech side and mention that transaction patterns are sometimes used to get a basic idea about borrower behaviour. It does help in some cases, but the results are not always equally clear in every situation.

There are also some concerns that come up in Indian research. Dvara Research (2024) points out that if the data used in these systems is not balanced, the outcomes may differ across groups. This becomes important in a country where financial behaviour varies widely. In recent policy discussions as well, there seems to be more attention on how these systems are being used, not just how efficient they are. The RBI's approach towards responsible AI reflects this shift.

Data-related problems are also mentioned in a number of studies. Gupta (2020) discusses how digital lending platforms rely on collecting large volumes of user information. This can support better decision-making in some cases, but at the same time it raises concerns about how safely that information is handled. This becomes easier to notice in AI-based systems, mainly since they rely quite heavily on such inputs.

Industry reports also give a more practical picture. NASSCOM (2023) mentions that AI adoption is increasing, but many banks are still dealing with basic issues like data quality or shortage of trained staff. So, there is some progress in this direction, but it does not happen in the same way across all institutions.

If we look outside India, a few studies help in adding perspective. Jagtiani and Lemieux (2019) indicate that AI-based credit models may perform better in certain situations, particularly in predicting defaults, although this is not always consistent across all cases. They also suggest that such systems need regular monitoring rather than being left on their own. Bazarbash (2019) makes a related point and notes that changes in technology are happening quite quickly, which can make it difficult for regulatory systems to adjust in time.

There are also broader concerns that are discussed at a general level. O'Neil (2016) explains that algorithms can reflect patterns present in the data, and those patterns may not always be neutral. Even though this discussion is not specific to India, the idea still applies in situations where data varies across different groups.

If all these studies are looked at together, it seems that AI can improve credit risk assessment in several ways, especially in terms of speed and wider coverage. Even after all this, AI is not usually seen as something that can solve everything on its own. In many discussions, there is still some caution, especially when these systems are used in real situations rather than controlled settings.

3. Research Questions

The study looks at a few basic questions related to the use of AI in credit risk assessment in Banks and financial institutions:

- In what ways are banks in India currently using AI while assessing credit risk?
- Does the use of AI actually make the process quicker or more reliable when compared to traditional methods?
- Can these systems help in giving access to credit to people who do not have a proper credit history?



- What kind of issues or concerns come up when decisions are taken using AI instead of human judgment?
- How far are banks and regulators prepared to deal with these changes in practice?

4. Objectives of the Study

Keeping the above questions in mind, the study tries to focus on the following:

- To understand how AI is being used in credit risk assessment in the Indian banking system.
- To look at whether AI helps in improving the speed and accuracy of lending decisions.
- To examine whether AI-based methods are helping in expanding credit access for new or underserved borrowers.
- To identify some of the concerns that come up, particularly in areas like bias, data use, and decision transparency.

To get an idea of how ready banks and regulators are in handling these changes.

5. Statement of Hypotheses

To understand the possible impact of Artificial Intelligence in credit risk assessment, the study considers both expected outcomes and alternative possibilities. While earlier discussions suggest that AI may improve efficiency and inclusion, it is also important to examine whether these effects are actually significant in practice.

H01: The use of Artificial Intelligence does not significantly improve the efficiency or accuracy of credit risk assessment.

H02: The use of Artificial Intelligence does not have a significant impact on financial inclusion or raise major ethical concerns in credit assessment.

6. Research Methodology

6.1 Research Design and Data Approach

This study is based on an analytical approach. It uses data. The reason for choosing this method is that Artificial Intelligence is still developing in India. Most insights come from reports and existing research.

The data for this study comes from sources like Reserve Bank of India reports and NASSCOM reports. These sources provide trends and insights. They help us understand how Artificial Intelligence is being used.

This study does not just focus on theory. It looks at trends like lending growth and the use of data-based decision systems. These trends support the arguments.

6.2 Variables, Hypotheses, and Analytical Framework

To make the analysis more structured this study considers a key variables. The main variable is the use of Artificial Intelligence in credit risk assessment. This includes machine learning models and automated decision systems. The outcomes are looked at in three areas. First



efficiency, which includes loan processing. Second financial inclusion, which means access to credit for borrowers. Third risk-related aspects, like identification of defaults.

This study also considers concerns like bias in data and issues with data handling.

The study is guided by two hypotheses. The first hypothesis is that Artificial Intelligence improves efficiency and accuracy in credit assessment. The second hypothesis looks at the effect of Artificial Intelligence on access to credit and concerns.

To understand these relationships this study follows a framework:

Artificial Intelligence use leads to efficiency and inclusion which leads to concerns, which leads to the need for monitoring.

6.3 Method of Analysis and Limitations

The analysis is carried out by observing trends and comparing information. This study looks at how Artificial Intelligence-based systems differ from methods. Some data trends are used to support the discussion. For example the increase in lending is looked at to understand if it is connected to improved risk assessment practices.

This study does not use testing. It uses interpretation instead.

There are limitations. Since this study depends on sources it may not capture recent changes. Ethical concerns like bias are difficult to measure and it is discussed in a descriptive manner.

With these limitations, the approach helps in understanding how Artificial Intelligence is being used in credit risk assessment, in Indian banking.

7. Data Analysis

7.1 Analysis of Efficiency and Accuracy (H01)

Table 1: Trend in Gross NPAs in Indian Banking

Year	Gross NPA Ratio (%)
2021	7.3
2022	5.8
2023	3.9
2024	2.6
2025	2.1 – 2.2

Source: RBI Reports; Ministry of Finance (2025–26); CEIC Data

Table 1 shows that the Gross NPA ratio has gone down steadily from 7.3% in 2021 to around 2.1–2.2% in 2025. This means the Gross NPA ratio has decreased a lot over the four to five years. The Gross NPA ratio is the proportion of loans in the banking system.

If we look at the numbers closely, we can see that the Gross NPA ratio drops sharply between 2021 and 2023. The Gross NPA ratio falls from 7.3% to 3.9%. Then it keeps going down. This shows that banks have got better at checking who they lend money to and keeping an eye on



them. One reason for this could be that banks are using systems that look at data and use intelligence to understand how borrowers behave before they get a loan.

Another thing to notice is that the Gross NPA ratio keeps going down in a way. It does not go up and down. This steady fall means that the improvements are not just temporary. The artificial intelligence systems that banks use to keep an eye on borrowers all the time may have helped with this. These systems can spot problems early.

At the time we cannot say that the improvement is only because of artificial intelligence. Other things, like rules from the RBI and better ways of getting money back from borrowers, have also played a role. So while the numbers show that things have got better, it is because of a lot of things working together. The Gross NPA ratio has gone down because of all these things.

7.2 Analysis of Financial Inclusion (H02)

Table 2: Growth in Credit and Borrower Access

Indicator	Recent Trend
MSME Credit Growth (FY2025)	~14–14.1% YoY
Overall Bank Credit Growth	~11–13%
Retail Loan Growth	~11–15% (moderating trend)
Digital Lending Expansion	~25–35% growth (fintech-led)

Source: RBI Data; IBEF (2026); Economic Times; TransUnion CIBIL Reports

Table 2 presents an overview of the expansion of credit across various sectors in recent years. The growth of credit to Micro, Small, and Medium Enterprises (MSMEs) appears to be approximately 14%, a rate that slightly exceeds the overall credit growth, which fluctuates between 11% and 13%. This trend may indicate a heightened focus on small businesses relative to previous periods.

At the same time, overall credit growth staying in a similar range suggests that lending activity is continuing steadily. It does not show any sudden jump, but there is a gradual expansion.

Retail loans are also growing, somewhere between 11–15%, although this growth does not look as aggressive as it was in earlier years. It feels like banks are still expanding in this area but with a bit more caution now.

Digital lending is becoming increasingly prominent.

The growth of this sector, now pegged at 25–35%, is outstripping expansion in other areas. This surge likely comes from the increasing adoption of online platforms and data-driven systems within the lending industry.

It also points to a trend: more borrowers are now using these newer methods to access loans.

If we look at all this together, it gives the impression that access to credit is widening. MSMEs, retail borrowers, and especially those using digital platforms seem to be getting more opportunities than before. At the same time, it is difficult to say that this is only because of AI. Other factors like economic conditions, demand for loans, and policy support, the growth of industries also plays a big role.



7.3 Analysis of Ethical Concerns

Table 3: Reported Issues in AI-Based Credit Systems

Concern Type	Observation
Data Bias	Uneven data affects decisions
Transparency	AI decisions not easily explainable
Data Privacy	Risk of misuse of personal data
Regulatory Issues	Need for stronger AI governance

Source: RBI Discussion Papers; Industry Reports; Policy Observations

Table 3 highlights Four main issues: Data Bias, Transparency Data Privacy, and Regulatory Issues

Data bias, a lack of transparency, and concerns about data privacy. Although these issues aren't always measured, they frequently appear in reports and academic studies. Data bias occurs when artificial intelligence systems are trained on datasets that don't fairly represent all types of borrowers. This can lead to unfair outcomes, where some groups are either helped or hurt by the system.

Another important issue is Data transparency. Unlike traditional methods, which allow for clear explanations of decisions through documents and rules, Artificial Intelligence systems often use complex models in their machine Learning and other as a result, it can be difficult to clearly explain why a loan was approved or denied, as there is not a single criterion, but multiple at the same time.

The third issue is Data privacy, which is very significant. Because artificial intelligence systems depend on large amounts of personal and behavioral data, there's always a risk of misuse or inadequate protection. Although these issues aren't quantified with numbers or percentages, their repeated appearance in various sources suggests they are real and important.

The fourth is Regulations. When AI is used in credit assessment, one issue that comes up is related to regulation. The use of these systems is increasing quite fast, but the rules around them are still not fully settled. Because of this, there is sometimes a gap between how banks are using technology and how it is being monitored. In traditional lending, decisions are usually based on clear documents and rules, so it is easier to understand how a decision is made. With AI systems, this is not always the case. Sometimes the decision comes from a model, and it is not very easy to explain it step by step. This makes things a bit difficult from a regulatory side. There is also some confusion about responsibility. If a decision is taken using an AI system, it is not always clear who should be held accountable for it. This can create uncertainty, especially when something goes wrong. Another point is related to data. These systems use a large amount of personal and behavioural information. Regulators need to ensure that such data is used properly, but clear rules for this are still developing. The Reserve Bank of India is very active on all fronts to see the impact of AI on consumer approval, and time to time, it advises making changes in regulations by issuing guidelines on digital lending and engaging in discussions about AI applications. However, the broader regulatory landscape remains a work in progress, and a more defined and robust framework is likely still some distance away.



8. Result and Discussion

The results of the study give a general idea of how Artificial Intelligence is being used in credit risk assessment in Indian banks. From the data and reports considered, it can be seen that AI is gradually becoming part of the lending process, although its use is not the same across all banks.

One thing that becomes noticeable is the change in efficiency. The decline in NPAs over the years and the faster loan processing suggest that banks are handling credit decisions in a better way than before. The use of data-based algorithms seems to be helping in sorting and analysing the information more quickly and easily. However, it's important to recognize that this improvement isn't solely due to AI. Other factors, like changes in regulations and recovery efforts, also play a role.

There is also some indication that access to credit has increased. It has been observed that the rise in MSME lending for all types of loans, whether it is retail loans like Consumer loan especially digital lending suggests that more borrowers are entering the formal system. This is important in the Indian context, where many people do not have proper credit records. Systems that use alternative data appear to be helping in such cases, even though the extent may differ across situations.

At the same time, a few concerns keep coming up. Issues related to data privacy and the way decisions are made are still being discussed. In some cases, it is not very clear how a decision has been reached, which can create doubt. There is also the possibility that the data used may not always represent all groups equally.

Considering these factors, the impact of artificial intelligence appears to be beneficial in certain domains, particularly in terms of accelerating processes and broadening accessibility. Nevertheless, the consequences are not entirely unambiguous, and specific areas warrant further scrutiny. Consequently, the observed results seem to be a blend of both positive and negative aspects, rather than exclusively favorable or unfavorable.

9. Conclusion

This study tried to understand how Artificial Intelligence is being used in credit risk assessment in Indian banking and what kind of changes are becoming visible because of it. Based on the trends and observations discussed earlier, it appears that the impact is there, but it is not exactly the same in every area. One of the clearer changes can be seen in the decline of NPAs over the years. This suggests that banks are becoming more careful while giving loans and advances and possibly better at identifying risky borrowers. It may not be only because of AI, but the use of data-based systems seems to be helping in improving the process. Simply, it can be said that NPAs declining leads to improved risk assessment (also efficiency).

There are also signs that access to credit has increased. Lending to MSMEs and retail borrowers, along with the rise of digital platforms, shows that more people are now part of the formal credit system. This is important in India, where many borrowers earlier did not have proper credit history. The use of different types of data appears to be making some difference here. So, it can be understood that credit growth increases the financial inclusion. At the same time, everything is not completely smooth. Some concerns are still being discussed, especially related to how data is used and how decisions are made. In many cases, it is not very clear how an AI system arrives at a decision. There are also worries about bias and privacy. Because of



this, it can be said that ethical concerns present in the making governance challenges. Looking at all of this together, the role of AI does not seem entirely positive or negative. It is helping in some ways, but it is also creating new issues that need attention. Further, it may be more important to use these systems carefully, along with transparency, rather than just expanding their use without proper checks.

References:

1. Bazarbash, M. (2019). *FinTech in financial inclusion: Machine learning applications in assessing credit risk* (IMF Working Paper No. 2019/109). International Monetary Fund. <https://doi.org/10.5089/9781498314428.001>
2. Dvara Research. (2024). *Responsible AI in financial inclusion*. <https://dvararesearch.com>
3. India Brand Equity Foundation. (2026). *Banking in India: Growth, trends, and opportunities*. <https://www.ibef.org/industry/banking-india>
4. Jagtiani, J., & Lemieux, C. (2019). The roles of alternative data and machine learning in fintech lending: Evidence from the LendingClub consumer platform. *Financial Management*, 48(4), 1009–1029. <https://doi.org/10.1111/fima.12295>
5. National Association of Software and Service Companies. (2022). *Artificial intelligence for banking, financial services & insurance*. <https://nasscom.in/product/114>
6. O'Neil, C. (2016). *Weapons of math destruction: How big data increases inequality and threatens democracy*. Crown.
7. Press Information Bureau. (2025, December 9). *Gross NPA ratio declines to 2.79% as of March 31, 2025* [Press release]. Government of India. <https://www.pib.gov.in/PressNoteDetails.aspx?NoteId=156404>
8. Reserve Bank of India. (2025). *Report on trend and progress of banking in India 2024–25*. <https://www.newsonair.gov.in/rbi-releases-its-report-on-trend-and-progress-of-banking-in-india-2024-25/>
9. Small Industries Development Bank of India. (2026). *MSME Pulse*.
10. The Economic Times. (2025, July 1). Loans flow at a faster clip into MSMEs; asset quality up, too. <https://economictimes.indiatimes.com/industry/banking/finance/banking/loans-flow-at-a-faster-clip-into-msmes-asset-quality-up-too/articleshow/>
11. TransUnion CIBIL. (2024). *Credit market indicator report*.
World Bank. (2022). *Financial inclusion*. <https://ieg.worldbankgroup.org/evaluations/financial-inclusion>