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The Roles of Artificial Intelligence in Transforming Credit Risk Assessment in Modern Banking

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ABSTRACT: This article takes into account the implementation of artificial intelligence in credit risk assessment as main objectives and tries to explore the potential benefits from such implementation. It also tries to identify the challenges of its implementation in the banking sector of Bangladesh. To fulfill these objectives the research adopted focus group discussion for finding important data and insights. As AI is not widely used in credit risk assessment in Bangladesh the researcher cannot get sufficient secondary data for analysis. The participants of the discussion agreed that there are huge potential of application of AI in credit risk assessment especially for micro small and Medium enterprises where traditional method not that much applicable. But there are a number of challenges prevailing in Bangladesh that is responsible for poor utilization of such advanced technology in the banking system of Bangladesh. The industry needs to be ready to accept disruptive technology keeping pace international banks.

KEYWORDS: Artificial intelligence, credit risk assessment, machine learning,

1. INTRODUCTION

A well-structured financial system is characterized as efficient channeling of funds from surplus unit to deficit unit of the economy (Mishkin & Eakins, 2024). Banks are the most important financial institution in any financial system which collects deposit from savers and channel those for productive uses as credit. The financial health of an economy depends largely on the proper functioning of banking system. Whereas, soundness of a bank depends on the proper and efficient distribution of credit. The financial crisis of 2008 exposed fundamental weaknesses in credit assessment of a bank (Temelkov & Svrtinov 2024). Traditional credit scoring systems, based largely on static historical data and linear assumptions, were unable to adequately represent the complexity of contemporary borrower activity (Li & Zhong 2012). But cut to the present, and oh, how things have changed. Today, banks record millions of transactions every day. Both borrowers and lenders leave digital footprints across multiple platforms and the need to make instant credit decisions is increasingly becoming more of a rule than an exception.

Artificial intelligence is not an incremental change to existing systems (Păvăloaia & Necula 2023) but an entirely new way of doing business for financial institutions to conceptualize and measure risk. Experimenting with machine learning algorithms has grown into a set of advanced systems that can analyze alternative data, identify misinformation and disinformation which is not possible for human analysts. It is able to react quickly to changing economic conditions.

The purpose of this article is to investigate how AI is transforming credit risk assessment in banking sector of Bangladesh. The research aims to explore the technical breakthroughs behind the transformation and what this means in practice for lenders, borrowers and regulators.

The article starts with a description of the topics followed by literature review and the methodology followed for conducting the research. After that the finding and the discussion of the research are discussed in detail. At the end, the article concludes with direction for future research and suggestions for borrowers, lenders and policy makers.

2. LITERATURE REVIEW

The assessment of credit risk is one of the most important and primary functions of banking business which indicates whether customers will be able to repay loan. Conventional methods of credit evaluation mainly depend on financial ratios, past repayment patterns and judgment of the credit officer. But these methods have their own limitations. They are subjective and slow in arriving at a concrete decision. On the wave of Artificial Intelligence (AI), in particular machine learning (ML) and deep learning (DL), credit scoring has been greatly impacted. And researchers continue to emphasize AI's capacity to make lending more accurate, faster and fairer.

2.1 Evolution of Credit Risk Assessment

Earlier credit scoring used statistical techniques like Logistic Regression and Discriminant Analysis (Thomas et al., 2002). While these models are structured with neutrality, they were unable to handle big data volumes and complex borrower habits. Traditional

models, such as credit scoring and financial ratio analysis, often lack the predictive accuracy needed in volatile economic environments. These models are typically based on historical data, which may not accurately reflect future credit risk, especially during economic downturns or market shifts("Recent Development in Credit Risk Measur...", 2024) (Nwachukwu et al., 2025).
Classical models (Hand and Henley 1997) assume linearity and are more sensitive to the presence of noise. The classical credit scoring methods are very much rigid and are unable to incorporate diverse data sources, such as behavioral data or alternative credit information, which can provide a more comprehensive view of a borrower's creditworthiness(K & S, 2025) (Nwachukwu et al., 2025). These models lack flexibility and adaptability (Konno & Itoh, 2014), so they are not easy to adapt. As a result, they are unable to address the current evolving situation occurring due to emergence of Big data, crypto currency, Fintech, sustainable finance and artificial intelligence (AI).

2.2 AI and Machine Learning in Predicting Credit Risk

Machine learning (ML) algorithms including Random Forests (RF), Gradient Boosting (GB), Support Vector Machines (SVM) and Neural Networks outperformed conventional statistical models in predicting outcome. According to Khandani, Kim, and Lo (2010), ML models perform far better than traditional ones in credit default prediction as the novelty of these approaches accounts for non-linear relationships and interaction effects among variables. Similarly, Lessmann et al. (2015) evaluated 41 credit scoring methods and found that ML techniques offer optimal prediction accuracy on profusion datasets.
AI enables banks to tap into alternate sources of data (for example, mobile phone usage, online transaction patterns, social media activities and digital footprint). "Alternative data helps credit scoring that's faced with scarce credit history: This can benefit less established borrowers such as the younger generation or informal workers, in particular." (Bazarbash 2019) By using AI and big data, fintech lenders are able to score "thin-file" customers, addressing the financial exclusion that has been entrenched in traditional banking (Jagtiani & Lemieux, 2019).

2.3 AI in Automating and Streamlining the Credit Assessment Process

AI systems can evaluate thousands of variables within seconds. According to Moro et al. (2015), banks using ML models for loan underwriting reduce processing time by more than 50%, allowing quicker and more consistent decisions. Human judgment in credit evaluation can introduce bias.
AI reduces human intervention and brings consistency, although researchers caution that AI can also replicate existing bias if trained on biased data (Bose & Mahapatra, 2021). Banks increasingly rely on AI-driven scoring models to enhance objectivity and transparency in approvals.

2.4 Explainability and Transparency of AI Models

A major challenge in AI-driven credit assessment is the "black-box" nature of some models. Regulators expect banks to justify credit decisions. Ribeiro, Singh, and Guestrin (2016) introduced LIME, which helps explain complex model predictions.
Similarly, Shapley Additive Explanations (SHAP) are used in banking to interpret how each variable influences a customer's risk score. Omar et al. (2022) argue that explainable AI (XAI) is essential for ethical and regulatory compliance in banking.

2.5 AI for Early Warning Systems and Risk Monitoring

AI is not limited to initial credit approvals; it also improves post-lending monitoring. According to Bellotti and Crook (2013), ML models can effectively predict early signs of borrower distress, allowing banks to intervene before default occurs. Real-time monitoring using AI helps banks detect unusual spending, cash flow problems, and behavioral changes, strengthening overall credit portfolio management.

2.6 Conclusion

The reviewed literature shows that AI is transforming credit risk assessment by improving predictive accuracy, enabling the use of alternative data, enhancing decision-making speed, and supporting real-time monitoring. While challenges remain—such as explainability, data privacy, and regulatory uncertainties—the overall direction suggests that AI will become a central tool in modern banking's credit risk management strategies.

3. METHODOLOGY OF THE STUDY

The purposes of the study are to identify the Prospects of AI application in credit risk assessment and to find out the problems and challenges of such uses. We also tried to find the probable solutions for those problems. Our study is designed based on the objectives of the study.

3.1 Research Design

The study adopts an exploratory qualitative research design using Focus Group Discussions (FGDs) as the primary method of data collection. This design is chosen as it is the most suitable study design for collecting data on a topic like this one. Being an emerging economy in the south Asia, Bangladesh has potential of Ai revolution. But it lacks the degree of development in this sector so that a huge number of professionals will be available with ample experience in this field. That is why seems most suitable. FGDs enable the researcher to capture collective insights, shared experiences, and interactive discussions among participants with relevant expertise. The purpose of the design is not to test hypotheses but to explore perceptions, identify themes, understand practical challenges, and uncover patterns in how AI may influence credit risk practices.

3.2 Rationale for Using Focus Group Discussions

Several factors contribute to choose focus group discussion as the basis of this research. Some of the factors are discussed in the following paragraphs.

One of the most important factors is very low artificial intelligence adoption in the banking sector of Bangladesh. As artificial intelligence is not heavily used in the banking sector specially in credit risk assessment, we did not get sufficient number of employees and regulators who are very much well conversant with application of artificial intelligence in credit risk assessment. That is why we were forced by the situation to choose focus group to find out insights of the topic. Another reason is the nature of the study is exploratory we want to find out prospects for use of AI in credit risk assessment.

3.3 Participant Selection and Sampling

Participants were recruited through purposive sampling, a non-probability sampling technique that allows researchers to select individuals based on specific characteristics relevant to the research objectives. The participants were chosen based on their background and experience. They were chosen for their past experience and also their familiarity with AI driven packages so that they can contribute to AI application in banking sector especially in credit risk assessment. The researcher tried to take participants from different background and professional experience for this purpose. At least one from each of following categories:

1. IT expert working at a bankers
2. Professional working in the credit department of a bank or non-bank financial institutions
3. Software developers
4. Regulators &
5. Academician

While choosing banks we considered both state-owned banks and private commercial banks. As NBFIs play an important role in Bangladesh economy. We also considered professionals from these NBFIs. The participants were diverse in terms of their level of experiences. It was followed that younger professionals have different perception regarding AI application than their matured peer. There were three FGD sessions each lasting for ninety to a hundred minutes. All the sessions were moderated by the researcher but supported by a professional moderator. The sessions were arranged during later part of 2025.

3.4 Data Collection Procedures

All participants were informed about the purposes of the research, procedure and their rights as research participant. Participants were assured of confidentiality and informed that their responses would be anonymized in all research outputs. A written copy of detailed guidelines governing the FGD were provided to the participants prior to each session.

All the sessions were conducted in a neutral and comfortable settings suitable for open discussion. There were open ended discussion within some specific research areas. The moderator facilitated the discussion to specific direction to get maximum out of the discussion. The Whole thing was organized two hours some specific thematic areas to get desired information from the participants. The thematic areas include Current state of artificial intelligence utilization in credit risk assessment, perceived benefits and challenges related with its application and future expectations regarding AI application in banking.

The moderator actively involved in encouraging the participants to express their opinion regarding the topic so that maximum information can be obtained. He was also involved in balancing the time given to each of the participants so that one do not take much time and others are deprived from expressing their opinion.

All focus group sessions were audio-recorded with participants' permission, and comprehensive field notes were maintained throughout each session. These field notes captured non-verbal communications, group dynamics, and contextual observations that might not be evident from audio recordings alone. After each meeting or the session there were internal discussion among the person involved so that the researcher do not miss any important insight from the discussion.

3.5 Data Analysis

All focus group discussions were audio-recorded and subsequently transcribed verbatim by a professional transcription service, as well as reviewed by the research team to confirm with original recordings. These transcriptions, along with field notes and observation data, constituted the body of data we analyzed.

The analysis was conducted using the principles of thematic analysis, a flexible approach to identifying, analyzing and reporting patterns in qualitative data. Familiarization was the first step of the analysis process, and involved members of the research team reading and re-reading transcripts to gain a sense of ownership for what the data were about. Primary codes were then developed through the systematic analysis of the data by annotating text passages in terms of their semantic content and in relation to research questions.

Coding was conducted both inductively, allowing themes to emerge from the data itself, and deductively, applying theoretical concepts from existing literature on artificial intelligence and credit risk assessment. This inclusive methodology allowed our study to be both rooted in the lived experiences of participants, whilst remaining linked with larger theoretical frameworks.

After coding, codes were collated into potential themes that captured an ordered pattern of response or meaning (a theme) pertinent to the overall dataset. The research team, as part of the back-and-forth process, repeatedly reviewed and refined the themes in such a way that each theme was internally consistent, distinctive from other themes. Relationship between themes and sub-themes was represented on thematic maps. The research team also kept journals to document and ledger analytical decisions, as well as reflect on possible traps of their own view-points (reflexive notes).

Several validation method were used to increase the credibility of findings. These included investigator triangulation, where multiple members of the research team analysed extracts of data independently and then cross-compared interpretations; member checking whereby early interpretations were discussed with a sample of participants to ascertain whether they accurately represented their experience; and maintaining an audit trail detailing all analytical decisions and processes.

4. RESULT AND DISCUSSION

The different sessions of FGD on AI application in credit risk assessment depicted different aspects of the topic. As per the pre-determined research objectives the following sections discusses the outcome of the sessions.

4.1 The Persistence of Traditional Assessment Paradigms

A noteworthy finding which came out from the interviews was that traditional, manual methods of credit risk assessment persist being used in all Bangladeshi banks. The participants also expressed their reliance on traditional documentation such as financial statements, bank statement, Credit Information Bureau reports and collateral valuations. Even some participants honestly expressed that credit decisions are predominantly "based on officers' judgment and subjective interpretation". Two officers rating similar borrower profiles were prone to reach different opinions, as bluntly put by one senior credit risk officer.

This insight reveals a fundamental paradox in today's banking practice. Despite the existence of well-defined methodologies for formal risk analysis, it is ultimately applied through human judgment that may be influenced by organizational culture, professional experience and contextual knowledge. One participant from a bank commented that risk assessment becomes about hedging our position rather than actually measuring risk. This defensive stance is arguably reasonable in bureaucratic environments where audit and accountability controls are tight.

The challenges are more pronounced in small SME borrowing. The small entrepreneur's lack of rigorous financial reporting requires alternative evaluation techniques to payment that can include site visit, observation of the business, and reputation in the community. Behind this fact, there is an important need where AI can potentially provide significant value by analyzing secondary data sources not conveniently covered by traditional means of assessment.

4.2 Current State of AI Adoption

AI adoption in the banking sector of Bangladesh for credit assessment is very limited and uneven. Even after having huge potential, the technology is not that much prevalent in Bangladesh. There are several reasons behind this tendency. One of the most important reason is lack of confidence on the success of AI technology in this sectors. The top management is ready to use AI for routine works but not for decision making purposes. The second reason is lack of readiness to adopt technological changes in this sector. Most of the participants agree that we are not sufficiently equipped to adopt AI technology for credit risk assessment. Most of the participant are good corporate lending is entirely untouched and supposed to be so for a long. Because top managements are not ready to accept AI technology as a game changer for credit risk assessment. As in the corporate lending, the amount is huge so is he risk.

As per the opinion most of the participant, there are huge potential of AI application in Micro and small lending where traditional risk assessment is not appropriate. As there are not sufficient data of micro, small and medium enterprises, it becomes very difficult for the bank or any financial institution to assess credit worthiness of a micro or a small borrower. For this situation a separate ecosystem can be developed for Micro small and medium enterprises based on artificial intelligence which is able to skip the limitation traditional credit assessment.

4.3 Perceived Benefits and Strategic Opportunities

All the participants unanimously agreed about the fact that AI can be fruitfully applied for credit risk assessment by non-traditional financial system.

There is ample potential Mobile financial services (MFS) providers for applying Artificial intelligence and big data analysis for credit risk assessment of micro and small borrowers. As MFS possesses huge data of their client, they can apply AI in assessing them based on these data using AI and assess them and decide on whether to extend credit to them.

One of the participants talked about potential social media in assessing credit worthiness of the borrowers. Now a days almost all have social media presence that represents their activities. These data from social media can be used to decide on whether the person is worth giving credit.

4.4 Implementation Barriers and Organizational Challenges

In spite of having huge benefit, there are a number of challenges that make it difficult to implement artificial intelligence in credit risk assessment. To implement AI models we need huge amount of quality and authentic data. Data is one of the major impediment in implementing AI models in credit risk. If sufficient and quality data in not available AI cannot give quality output.

Financial constraints represent another significant barrier. It implement this model huge investment is needed. If the bank is a small one, it cannot afford those huge investments.

Human factor is also an important barrier in such projects. Participant agreed that employees are anxious of being irrelevant, just like any other technological disruption.

5. CONCLUSION

This paper investigated the perception of AI approach on bank credit risk assessment in Bangladesh. The study investigated awareness, perceived benefits, barriers and readiness for adoption of AI-based models. The research is based on FGD. The findings show that there are significant interest about AI based model among young banker, but the actual adoption is very limited. Most of the participants agreed that AI based model have potential to do better in terms of accuracy and efficiency in assessing credit risk. These models, if applied appropriately, can detect risk in advance and save a lot for the institutions. The Takeaways indicate an interest that continues to grow as well as dismal use-case details. But most remain stuck with manual processes and are not yet technically equipped to efficiently deploy AI systems.

Based on the findings of the research, it can be said that Banks should start investing development of their data system and artificial intelligence ecosystem. Most of the participants agree to the fact that in the coming is a bank cannot survive with if it does not adopt artificial intelligence and all technological advancements. Machine Learning, Big data, artificial intelligence and blockchain are no more buzz words. These are current reality of modern banking system. So if does not embrace this change It will lag behind and cannot compete in the changing global scenario. To adopt these disruptive technologies, banks and other financial institutions must assess current level of artificial intelligence literacy and if it is not sufficient they have to take necessary action to increase it sharply. The current research is based on focus group discussion of some selected personnel working in banks and other financial institutions and information technology experts. As focus group discussions are conducted with an expert group of people who have ample knowledge of the subject matter, the outcomes of such discussion bear significant implication for the industry. However it cannot be generalized as it is an outcome of a small group of people. So there are opportunities for working with secondary data of banks working with artificial intelligence.

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