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Article

A SYSTEMATIC REVIEW OF CREDIT RISK ASSESSMENT MODELS IN EMERGING ECONOMIES: A FOCUS ON BANGLADESH'S COMMERCIAL BANKING SECTOR

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ABSTRACT
This systematic literature review explores the evolution, application, and performance of credit risk assessment models in emerging economies, with a focused lens on Bangladesh's commercial banking sector. In an environment marked by institutional constraints, limited data infrastructure, and evolving regulatory frameworks, selecting the appropriate credit risk model is critical for financial stability and inclusion. Drawing from a total of 98 peer-reviewed studies published up to 2022, this review synthesizes evidence from academic and applied research to evaluate traditional statistical models—such as logistic regression and discriminant analysis—as well as machine learning approaches including support vector machines, decision trees, and neural networks. The review follows the PRISMA 2020 guidelines to ensure transparency, replicability, and methodological rigor throughout the review process. Key findings indicate that while machine learning models consistently outperform traditional models in terms of predictive accuracy, they are rarely adopted at scale due to concerns about model interpretability, regulatory acceptance, and institutional readiness. Furthermore, the review identifies major gaps in sector-specific model development, integration of alternative and real-time data, and post-deployment performance monitoring. The synthesis reveals that most models are designed generically, with limited adaptation to specific industries such as garments, agriculture, SMEs, and microfinance, thereby reducing their predictive relevance in context. Additionally, institutional barriers including lack of analytical expertise, fragmented IT infrastructure, and vague regulatory guidelines hinder the operationalization of advanced credit risk tools. The findings emphasize the necessity of aligning model sophistication with contextual realities, and the importance of balancing predictive performance with explainability and institutional capacity. This review offers an evidence-based foundation for policymakers, banking professionals, and researchers seeking to develop more inclusive, accurate, and operationally viable credit risk models in emerging-market financial ecosystems.

KEYWORDS
Credit Risk Assessment, Emerging Economies, Commercial Banking, Bangladesh, Risk Modeling;

American Journal of Advanced Technology and Engineering Solutions
Volume 02 Issue 01 (2022)
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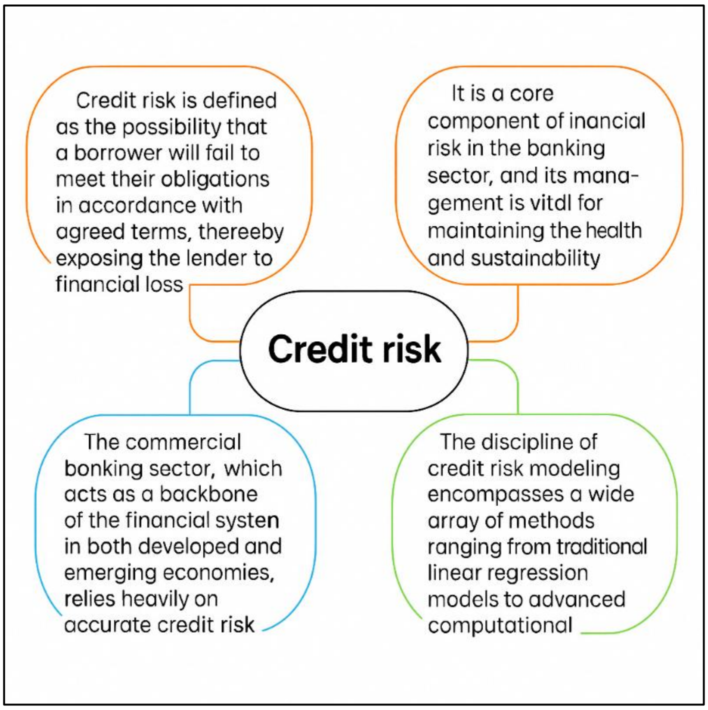
INTRODUCTION

Credit risk is defined as the possibility that a borrower will fail to meet their obligations in accordance with agreed terms, thereby exposing the lender to financial loss (Abbas et al., 2019). It is a core component of financial risk in the banking sector, and its management is vital for maintaining the health and sustainability of financial institutions. The commercial banking sector, which acts as a backbone of the financial system in both developed and emerging economies, relies heavily on accurate credit risk assessment mechanisms to ensure stability and liquidity (Ruziqa, 2013). In emerging economies, where financial systems are more volatile and less mature, the effective evaluation of credit risk is even more critical (McKenzie & Wolfe, 2004). As commercial banks are increasingly engaged in diversified lending portfolios that involve retail, corporate, and small business clients, the role of credit risk models has expanded beyond mere statistical tools to strategic decision-making frameworks (Weber et al., 2008). The discipline of credit risk modeling encompasses a wide array of methods ranging from traditional linear regression models to advanced computational algorithms. These models are essential for determining the probability of default (PD), loss given default (LGD), and exposure at default (EAD), which together define a bank's capital adequacy and provisioning strategies (Hassan et al., 2019).

Figure 1: Overview of Credit Risk



Globally, credit risk assessment has received considerable attention from regulatory bodies, policymakers, and researchers owing to its critical influence on banking operations and economic resilience. The Basel Accords—specifically Basel II and III—have laid down comprehensive guidelines that emphasize the importance of internal risk rating systems and the incorporation of credit risk models in capital adequacy calculations (Caouette et al., 1998). In line with these regulatory frameworks, various countries have invested in the development of quantitative risk modeling approaches to enhance their financial systems' robustness. For instance, institutions in the United States and the European Union have adopted internally developed credit scoring systems and stress testing tools to mitigate the impact of credit defaults (Ozili, 2019). While these frameworks have set global benchmarks, the practical adaptation of such models in emerging economies has remained uneven. Variations in institutional maturity, data availability, technological infrastructure, and regulatory enforcement have influenced the choice and implementation of credit risk models in developing regions. Therefore, understanding the international relevance and localization of credit risk assessment methods becomes a priority in evaluating their applicability in specific contexts such as Bangladesh.

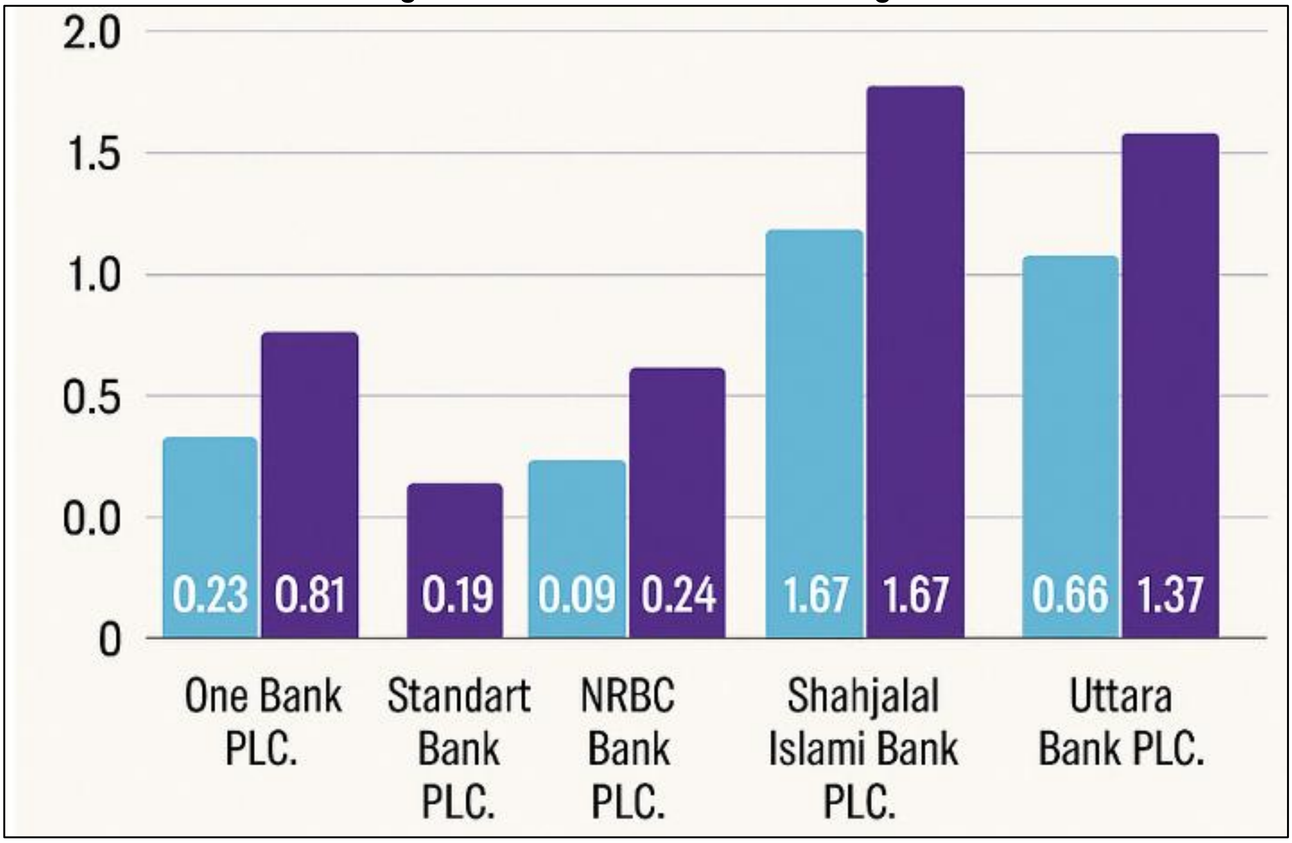
Emerging economies exhibit unique financial ecosystems characterized by credit market imperfections, regulatory constraints, and limited access to quality data. In such environments, credit risk assessment is particularly challenging due to information asymmetry, weak legal enforcement, and informal borrowing practices (Kulkarni, 2009). Several studies have documented the systemic risks arising from credit misallocation and insufficient provisioning in the commercial banking sectors of countries like India, Brazil, and Nigeria, which share socio-economic parallels with Bangladesh (Ghosh & Saima, 2021). Moreover, in these economies, credit assessment is often constrained by insufficient borrower history, underdeveloped credit bureaus, and a lack of standardized financial reporting, leading to reliance on heuristic judgment and subjective assessments (Patra & Padhi, 2020). This leads to distorted credit ratings and heightened non-performing loan (NPL) ratios, which in turn stress the capital adequacy of commercial banks (Korzeb & Niedziółka, 2020). Hence, the

American Journal of Advanced Technology and Engineering Solutions
Volume 02 Issue 01 (2022)
Page No: 01- 31
eISSN: 3067-0470
DOI: 10.63125/p7ym0327

effectiveness of credit risk models in emerging economies hinges not only on their theoretical robustness but also on their contextual adaptability, particularly in sectors that are underbanked and exhibit credit fragility.

The banking sector in Bangladesh presents a compelling case for analyzing credit risk assessment models due to its rapid growth, persistent structural challenges, and evolving regulatory framework. The country's banking industry, comprising state-owned, private, and foreign commercial banks, has seen significant expansion in loan disbursement, particularly in sectors like garments, agriculture, and small and medium-sized enterprises (SMEs) (Korzeb & Niedziółka, 2020; Srairi, 2013). However, this growth has often been accompanied by an alarming rise in non-performing loans, with figures consistently exceeding thresholds considered manageable by international standards (Weber et al., 2008). Studies such as those by (Malik & Nazli, 1999) and (Kulkarni, 2009) have pointed out the role of political interference, poor risk governance, and weak credit analysis in perpetuating bad loans in Bangladesh. Moreover, the regulatory environment has struggled to enforce Basel II and III compliance fully, leading to inconsistencies in risk measurement and capital adequacy calculations (Caouette et al., 1998). As a result, both the central bank and private financial institutions have shown growing interest in integrating more advanced and automated credit risk models into their operational frameworks.

Figure 2: Growth trend of Banks' earnings



Source: The Financial Express Bangladesh (2022)

Traditional credit risk models employed in Bangladesh have predominantly relied on financial ratio analysis, linear regression, and judgmental scoring systems (Weber et al., 2008). While these methods offer simplicity and ease of use, they suffer from significant limitations, particularly in capturing non-linear relationships and incorporating real-time data (Hernando & Nieto, 2007). As commercial banking activities become more complex, the use of machine learning techniques—such as decision trees, support vector machines, and neural networks—has gradually begun to emerge, albeit in isolated pilot projects rather than mainstream adoption (Saqib et al., 2016). These models are being tested for their predictive performance and capacity to handle high-dimensional datasets, which are increasingly generated from online banking, digital lending, and financial inclusion initiatives. Nevertheless, the empirical evidence on the performance, reliability, and interpretability of such models in the Bangladeshi context remains fragmented. Various scholars argue that model transferability from Western economies without contextual calibration undermines

American Journal of Advanced Technology and Engineering Solutions
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Page No: 01- 31
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the relevance of their application in Bangladesh (Masud, 2012). Therefore, the need for a systematic review becomes evident to consolidate fragmented insights, evaluate model performance, and guide future adoption strategies tailored to the local banking sector.

Moreover, credit risk assessment in Bangladesh has often been limited by the scope and availability of borrower data (Kamruzzaman, 2012). Unlike in developed economies where credit bureaus and central databases offer rich longitudinal borrower information, the data ecosystem in Bangladesh is characterized by missing records, inconsistent formatting, and weak data governance (Islam & Nishiyama, 2016). This data inadequacy affects both the design and validation of credit risk models. Researchers such as (Belal, 2000) have emphasized the importance of integrating qualitative borrower attributes—such as character, informal network affiliations, and community reputation—into model development, particularly for rural and micro-lending contexts. The reliance on conventional collateral-based lending further reduces the incentive to invest in borrower scoring, which leads to higher default rates during macroeconomic shocks (Islam, 2013). In response to these constraints, some banks have experimented with proxy variables and credit group analysis, yet such efforts remain sporadic and poorly documented in academic literature. Thus, there exists a gap in synthesizing the scope, depth, and performance of credit risk models in a manner that reflects their evolution in the Bangladeshi financial landscape. A comprehensive review of existing literature not only reveals the types of credit risk models applied but also highlights the key barriers to their implementation and performance validation. Studies such as those by (Ahmed & Islam, 2009), and (Hoque & Clarke, 2013) outline institutional barriers such as lack of skilled personnel, resistance to technological change, and limited investment in credit analytics infrastructure. Regulatory ambivalence further complicates the adoption of newer risk assessment techniques, as banking regulations often do not mandate or incentivize the use of advanced risk modeling tools (Ahmed & Islam, 2009). Moreover, a significant portion of the literature focuses on the descriptive analysis of default trends rather than on quantitative model validation, resulting in a dearth of empirical studies that compare model performance across contexts. This underscores the necessity of a structured synthesis to identify which models are empirically tested, under what conditions, and with what level of predictive accuracy. By conducting a systematic review of existing credit risk assessment models with a focus on Bangladesh's commercial banking sector, this study fills a critical gap in consolidating fragmented knowledge, evaluating implementation barriers, and assessing the contextual relevance of both traditional and emerging modeling approaches.

The primary objective of this systematic review is to critically examine and synthesize the existing body of literature related to credit risk assessment models applied within the context of emerging economies, with particular emphasis on Bangladesh's commercial banking sector. The review aims to identify and categorize the types of credit risk models—ranging from traditional statistical methods such as logistic regression and discriminant analysis to more advanced machine learning techniques including support vector machines, decision trees, and artificial neural networks—used by banking institutions to assess borrower creditworthiness and predict default risk. Another objective is to evaluate the contextual adaptability and empirical performance of these models when applied in data-constrained environments typical of emerging markets. This involves analyzing how models have been validated using real-world banking datasets, including their ability to deal with noisy, incomplete, or imbalanced data, which are common issues in developing financial ecosystems. Furthermore, the study seeks to explore the degree to which global standards, particularly those aligned with Basel II and Basel III frameworks, are adhered to or modified by Bangladeshi banks during model development and deployment. An additional goal is to uncover the institutional, regulatory, and infrastructural barriers that hinder the effective implementation of credit risk models in Bangladesh, as well as to investigate the operational implications of model-based credit scoring on loan approval, provisioning, and risk mitigation practices. The review also intends to map the evolution of credit risk modeling practices over time and determine whether innovations in modeling approaches have been successfully diffused across different tiers of the banking system—including state-owned, private, and foreign commercial banks. Lastly, the review aims to highlight research gaps by identifying underexplored variables, datasets, and analytical techniques, thereby informing future research and policy directions. Through these objectives, the study provides a structured framework for understanding how credit risk is managed in an emerging economy and the extent to which current modeling practices align with international benchmarks and local realities.

American Journal of Advanced Technology and Engineering Solutions
Volume 02 Issue 01 (2022)
Page No: 01- 31
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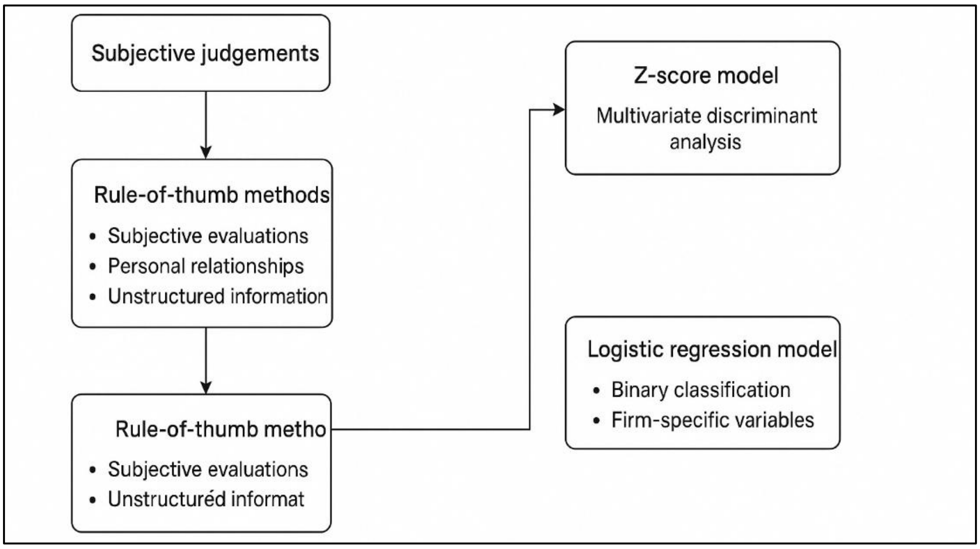
LITERATURE REVIEW

Credit risk assessment in the banking sector has evolved significantly over the last three decades, transitioning from heuristic-based evaluations to complex statistical and machine learning models designed to estimate default probabilities, loss exposure, and capital adequacy. In emerging economies such as Bangladesh, the development and application of these models are influenced by institutional readiness, regulatory frameworks, data availability, and socio-economic contexts. Existing literature encompasses a broad spectrum of methodologies and conceptual approaches, examining how credit risk is assessed through quantitative and qualitative lenses. Early works primarily focused on financial ratio analysis and linear statistical models, while more recent studies explore machine learning-based models that can capture non-linear patterns and accommodate high-dimensional data structures. However, despite a growing body of international research, the literature specific to Bangladesh and comparable emerging economies remains fragmented, with limited comparative analyses or cross-institutional evaluations. The lack of systematic consolidation has led to ambiguity in understanding which models are most effective, under what circumstances, and with what predictive reliability. Additionally, the operational and infrastructural challenges facing Bangladeshi commercial banks—such as incomplete credit histories, poor digital record-keeping, and lack of borrower transparency—are rarely integrated into model design or validation. This literature review addresses these gaps by organizing and synthesizing relevant studies into thematic sub-sections that focus on methodological evolution, regulatory influences, local adaptations, data challenges, and model performance. The structure is designed to provide both breadth and depth, capturing the historical trajectory and current practices of credit risk assessment in emerging markets with specific reference to Bangladesh.

Evolution of Credit Risk Assessment

Credit risk assessment practices have undergone a transformative evolution, moving from intuitive and experience-based judgments toward structured, data-driven methodologies (Kusi et al., 2017). Prior to the 1990s, many banks, especially in emerging markets, relied on subjective evaluations, personal relationships, and unstructured borrower information to assess creditworthiness (Naili & Lahrichi, 2022). These methods, though tailored to local socio-economic contexts, lacked consistency, scalability, and predictive accuracy. The absence of formalized credit bureaus in many regions further exacerbated the asymmetry of information between lenders and borrowers (Ugwumba & Omojola, 2013). Credit officers used "rule-of-thumb" approaches, often based on the borrower's business tenure, reputation in the community, or ownership of physical collateral (Guirkinger & Boucher, 2008). Such qualitative assessments, while grounded in social trust, were vulnerable to bias, manipulation, and external pressure. The limitations of these methods became increasingly apparent as banking systems grew in complexity, and the need for standardized approaches gained prominence in both academic and policy circles. (Samad, 2012) highlighted the inefficiencies of informal lending practices and emphasized the importance of integrating statistical tools to enable consistent credit decisions.

Figure 3: Evolution of Credit Risk Assessment



American Journal of Advanced Technology and Engineering Solutions
Volume 02 Issue 01 (2022)
Page No: 01- 31
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Consequently, the groundwork for adopting quantitative credit scoring models was laid, especially in countries transitioning toward liberalized banking frameworks.

The foundation of modern credit risk assessment can be traced to (Altman, 1968) Z-score model, which utilized multivariate discriminant analysis (MDA) to predict bankruptcy in publicly listed U.S. manufacturing firms. Altman's model became a pioneering benchmark due to its ability to synthesize multiple financial ratios—such as working capital to total assets and retained earnings to total assets—into a single predictive index. The Z-score introduced a new paradigm in credit analysis by empirically linking financial health indicators to insolvency risk, offering both banks and investors a powerful forecasting tool (Cooper et al., 2003). The success of the Z-score inspired subsequent works such as (Deakin, 1972) and (Blum, 1974), who validated MDA-based models across various industries and geographies. Nonetheless, critics noted that the assumptions underpinning MDA—such as multivariate normality and equal group covariance—limited its flexibility, particularly in non-manufacturing or emerging market contexts (Nkurunziza, 2012; Rahman, 1999). Additionally, these early models heavily depended on audited financial statements, which were either unavailable or unreliable in many developing countries . (Duniya & Adinah, 2015) also suggested that MDA's linear boundary restrictions reduced its classification power compared to non-linear models. However, its interpretability and ease of implementation ensured that it remained a staple in credit analysis for decades, especially in regulatory-driven credit environments. Following Altman's Z-score, another milestone in credit risk modeling was introduced by (Ghosh & Saima, 2021), who applied logistic regression to bankruptcy prediction, marking a significant methodological shift. Unlike MDA, logistic regression did not require the strict statistical assumptions regarding normality or equal variances, making it more robust for diverse datasets and borrower profiles (Patra & Padhi, 2020). Ohlson's model integrated both financial and firm-specific variables—such as firm size, total liabilities, and working capital ratio—into a probabilistic framework that estimated the likelihood of default. The logistic regression approach provided an interpretable, statistically sound basis for binary classification problems central to credit evaluation (Duniya & Adinah, 2015; Patra & Padhi, 2020). Several studies, including (Boucher & Guirkinger, 2007) and (Nkurunziza, 2012), validated Ohlson's approach across different economies, finding that it often outperformed MDA in predictive accuracy. Furthermore, the logistic model's adaptability to various borrower types made it suitable for use in both corporate and consumer lending environments (Hussain & Thapa, 2012). In emerging economies, where data irregularities and sample imbalance were common, logistic regression gained traction for its tolerance to data noise and multicollinearity. (Okten & Osili, 2004) reaffirmed the model's effectiveness across credit card, mortgage, and small business lending portfolios. Consequently, logistic regression became widely adopted in banking institutions worldwide and served as a baseline for more complex modeling techniques.

In parallel, (Patra & Padhi, 2020) structural model introduced a theoretically grounded approach to credit risk by viewing a firm's equity as a call option on its assets. This option-theoretic framework laid the foundation for the Black-Scholes-Merton model, enabling the estimation of default probabilities based on the volatility of firm asset values and debt levels. The structural model brought a new dimension to credit risk modeling by incorporating financial market dynamics into risk evaluation (Duniya & Adinah, 2015; Patra & Padhi, 2020). Unlike statistical models that relied solely on historical financial statements, Merton's approach linked credit risk to market-based indicators, facilitating real-time assessments and pricing of credit derivatives (Boucher & Guirkinger, 2007). This model was particularly influential in the development of risk-sensitive capital regulations under Basel II, which advocated for internal ratings-based (IRB) approaches using both firm-specific and market data (Patra & Padhi, 2020). Empirical validations of the Merton model, such as those by Eom, Helwege, and Huang (2004), showed mixed results, with performance varying by market efficiency, firm transparency, and volatility estimation methods. Nonetheless, the Merton framework gained widespread academic and practical traction, especially among large banks and credit rating agencies with access to real-time financial data. In emerging economies, however, its adoption was limited due to underdeveloped capital markets and infrequent trading of corporate debt instruments, which hindered the estimation of market-based variables (Boucher & Guirkinger, 2007). By the late 1990s and early 2000s, credit risk assessment practices began to diversify further with the incorporation of hybrid models that combined statistical techniques with expert systems. Researchers began integrating soft information—such as management quality, customer relationships, and reputational factors—into scoring frameworks using techniques like fuzzy logic, decision trees, and

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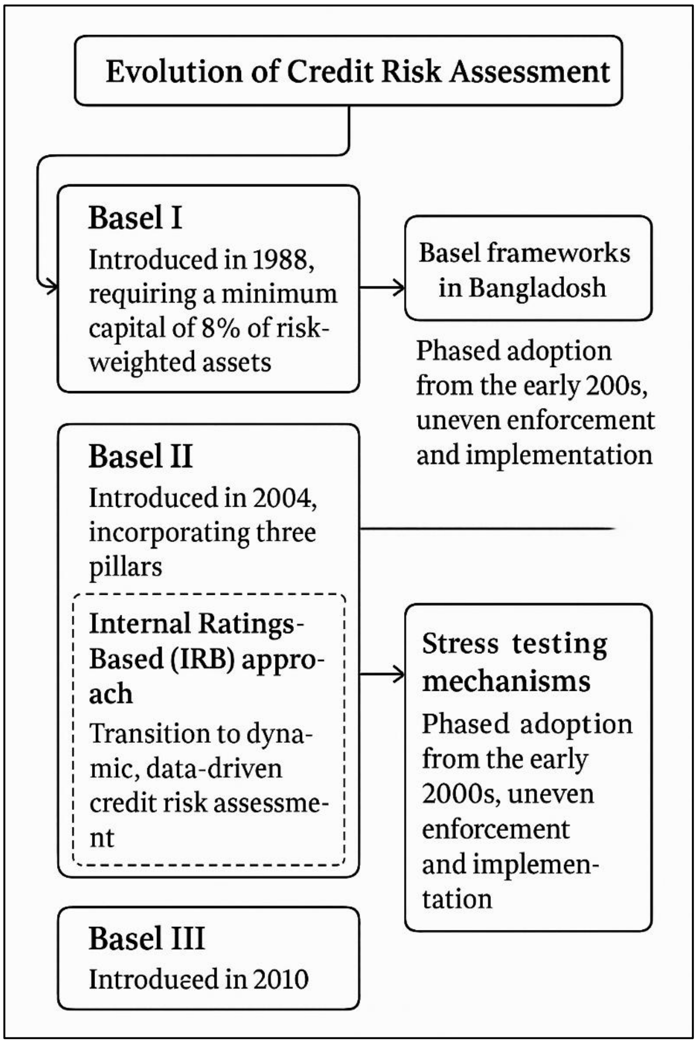
Bayesian networks (Boucher & Guirkinger, 2007; Patra & Padhi, 2020). Studies such as those by (Okten & Osili, 2004) introduced neural network-based credit scoring systems, which offered superior accuracy at the cost of lower interpretability. In developing countries, where data were scarce and qualitative factors played a significant role in lending decisions, these hybrid models provided a compromise between automation and contextual flexibility (Thomas, 2000). For instance, (Guirkinger, 2008) emphasized the importance of relationship lending and borrower narratives in microfinance credit assessment. Meanwhile, credit bureau development in countries such as India and Malaysia enabled more structured data environments, encouraging the adoption of these semi-automated models (Duniya & Adinah, 2015; Guirkinger, 2008). In Bangladesh, however, the diffusion of hybrid modeling approaches remained slow due to institutional constraints and limited regulatory push for advanced analytics. Nevertheless, foundational works in hybrid modeling signaled the next phase in the evolution of credit risk assessment, where statistical rigor was increasingly balanced with practical adaptability.

Regulatory Frameworks and Their Impact on Model Development

The evolution of credit risk assessment models has been significantly influenced by international regulatory frameworks, particularly those proposed by the Basel Committee on Banking Supervision. Basel I, introduced in 1988, marked the first global effort to standardize capital adequacy and credit risk management practices across banking institutions. It proposed a simplistic approach, requiring banks to hold a minimum capital equivalent to 8% of their risk-weighted assets (Ghosh & Saima, 2021). Although this framework enhanced transparency and comparability, it was criticized for its one-size-fits-all approach, which failed to account for differences in borrower creditworthiness and institutional risk exposure (Nkurunziza, 2012). (Duniya & Adinah, 2015) highlighted that banks in emerging markets were disproportionately affected, as their portfolios included higher-risk clients who lacked formal credit documentation. Additionally, Basel I's reliance on external credit ratings to assign risk weights was unsuitable for countries with underdeveloped rating agencies, resulting in skewed capital requirements (Boucher & Guirkinger, 2007). Consequently, while Basel I succeeded in establishing a global benchmark, it provided limited guidance for developing robust internal credit risk models tailored to diverse financial ecosystems. Moreover, the introduction of Basel II in 2004 significantly altered the landscape of credit risk modeling by introducing three pillars: minimum capital requirements, supervisory review, and market discipline (Hussain & Thapa, 2012). The most critical development under Basel II was the incorporation of the Internal Ratings-Based (IRB) approach, which allowed banks to use their own internal models to estimate credit risk parameters such as Probability of Default (PD), Loss Given Default (LGD), and Exposure at Default (EAD). This shift marked a transition from static, external-rating-based systems to dynamic, data-driven credit risk assessment methodologies (Okten & Osili, 2004). Several studies underscored the benefits of the IRB framework, noting improvements in model transparency, predictive power, and

Figure 4: Evolution of credit risk assessment



American Journal of Advanced Technology and Engineering Solutions
Volume 02 Issue 01 (2022)
Page No: 01- 31
eISSN: 3067-0470
DOI: 10.63125/p7ym0327

capital optimization (Thomas, 2000). However, these benefits were largely confined to advanced economies with mature data infrastructures. In contrast, implementation in developing economies remained limited due to gaps in data quality, regulatory capacity, and skilled manpower (Patra & Padhi, 2020; Thomas, 2000). For example, (Boucher & Guirkinger, 2007) noted that Indian banks struggled to meet the data sufficiency and back-testing requirements of IRB models, while (Hellmann et al., 2000) found that small banks across Latin America lacked the technological infrastructure to operationalize internal ratings systems. Thus, although Basel II encouraged model sophistication, its practical adoption was shaped by national readiness levels, regulatory support, and institutional maturity.

The global financial crisis of 2007–2009 exposed fundamental weaknesses in the Basel II framework, particularly its inability to predict and contain systemic risk. As a result, Basel III was introduced in 2010, aiming to strengthen capital adequacy standards, improve liquidity ratios, and enhance risk management practices (Godfray et al., 2010). Key changes included the introduction of the Capital Conservation Buffer, the Countercyclical Capital Buffer, and more stringent requirements for Tier 1 capital (Brown et al., 2009). Additionally, Basel III emphasized the use of comprehensive stress testing mechanisms to assess institutional resilience under adverse conditions (Mahalingam & Rao, 2014). These regulations pushed financial institutions to adopt more advanced, scenario-based credit risk models that incorporated macroeconomic indicators, sectoral sensitivities, and market volatilities (Patra & Padhi, 2020). (Laeven & Majnoni, 2003) illustrate how integrated stress testing frameworks became central to regulatory compliance in Europe and North America. However, in emerging markets, the adoption of such models was hampered by limited access to real-time economic data and insufficient computational infrastructure (Cucinelli et al., 2018). Moreover, implementation remained piecemeal in countries where central banks lacked supervisory authority or where political interference weakened enforcement (Laeven & Majnoni, 2003). As a result, the global transition to Basel III revealed a widening gap between high-income and low-income banking systems in terms of model sophistication, regulatory alignment, and systemic readiness.

Bangladesh's alignment with the Basel frameworks has followed a gradual and uneven trajectory, influenced by institutional capacity, political will, and international pressure. The Bangladesh Bank officially adopted the Basel I framework in the early 2000s and initiated a phased implementation of Basel II beginning in 2009, with partial transition to Basel III policies initiated around 2014 (Islam, 2013). However, literature suggests that the practical enforcement of these frameworks remains limited. (Jahan, 2012) found that many private commercial banks in Bangladesh still relied on traditional credit scoring tools and manual approval processes, often bypassing risk-adjusted capital calculations. Similarly, (Sufian & Habibullah, 2009) noted that regulatory reporting in Bangladesh lacked the granularity required to support IRB-based modeling, while (Masud, 2012) emphasized gaps in model validation and back-testing mechanisms. In addition, (Imam, 2000) highlighted the shortage of skilled analysts and IT systems necessary for running sophisticated credit risk simulations. Even where banks attempted to implement Basel-aligned models, these efforts were often limited to head offices or foreign subsidiaries, with little diffusion across branch networks. Moreover, political and regulatory capture has further diluted the impact of Basel compliance in the country's banking sector (Hoque et al., 2013).

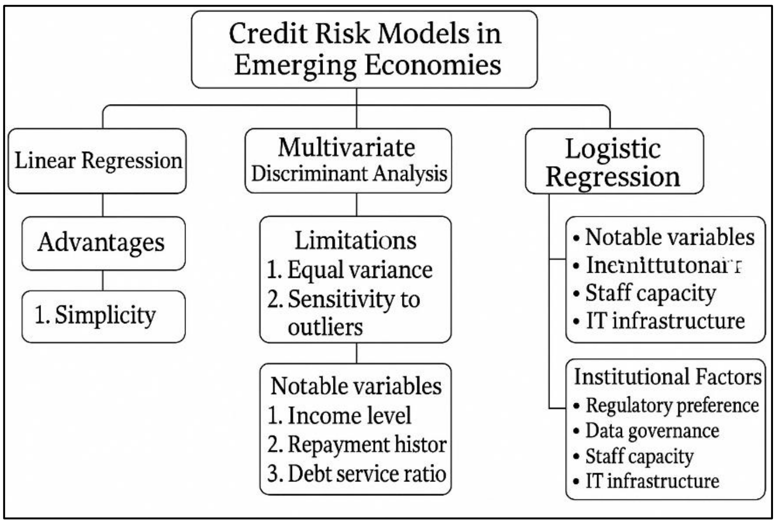
Traditional Credit Risk Models in Emerging Economies

Traditional credit risk models such as linear regression, multivariate discriminant analysis (MDA), and logistic regression have been extensively employed in emerging economies due to their relative simplicity, ease of interpretation, and compatibility with limited data environments. These models require fewer computational resources and are well-suited for regulatory environments where transparency and explainability are prioritized (Boucher & Guirkinger, 2007). In contexts where digital infrastructure is underdeveloped, and credit bureaus are either nascent or nonexistent, these models provide a viable means of risk quantification. Linear regression, though limited by its assumptions regarding normality and linearity, has been frequently used to identify determinants of default and borrower behavior in micro and SME lending across Latin America, South Asia, and Sub-Saharan Africa (Patra & Padhi, 2020). For instance, (Caouette et al., 1998) successfully applied linear models to predict repayment performance in Bangladesh's rural credit programs. Similarly, (Weber et al., 2008) demonstrated the utility of linear regression in estimating default rates in microfinance institutions (MFIs), emphasizing the influence of borrower demographics, loan size, and repayment duration. While the predictive accuracy of linear models is relatively lower compared to non-linear

American Journal of Advanced Technology and Engineering Solutions
Volume 02 Issue 01 (2022)
Page No: 01- 31
eISSN: 3067-0470
DOI: 10.63125/p7ym0327

approaches, their simplicity and transparency have contributed to their continued use in regulatory and operational contexts in emerging markets (Weber et al., 2015).

Figure 5: Traditional Credit Risk Models



Multivariate discriminant analysis (MDA) emerged as another dominant modeling approach during the early phase of credit risk research in developing countries, particularly in the 1980s and 1990s. By computing a linear combination of financial variables, MDA allowed for classification of firms or individuals into default or non-default categories based on a discriminant score (Belás et al., 2018). This method gained popularity due to its straightforward statistical logic and relatively low data requirements. Studies by (Ruziqa, 2013) found MDA to be effective in classifying SME borrowers in Egypt and India, respectively, under conditions of incomplete financial reporting. In the context of Bangladesh, (Natsir et al., 2019) applied MDA to analyze loan repayment behavior in nationalized banks, concluding that asset turnover ratio, current ratio, and debt-to-equity ratio were significant predictors of default. Similarly, (Weber, 2011) utilized MDA to identify risk profiles in agricultural lending programs, finding that borrower education level and project size significantly affected classification outcomes. While MDA is limited by its assumption of equal variance-covariance matrices across groups and the sensitivity of classification boundaries to outliers, it has continued to attract attention in emerging markets due to its balance between accuracy and simplicity (Abbas et al., 2019). However, the increasing complexity of financial products and greater borrower heterogeneity have gradually exposed the limitations of MDA, prompting a shift toward more flexible models such as logistic regression.

Logistic regression has become the most widely adopted traditional model in credit risk assessment across developing economies due to its robustness, scalability, and ability to model binary outcomes such as default versus non-default. Unlike MDA, logistic regression does not require multivariate normality or equal covariance assumptions, making it well-suited for noisy, non-normally distributed, or incomplete datasets (Weber, 2011). (Weber et al., 2006) have confirmed its reliability in consumer and SME credit scoring. In South Asia, numerous studies have confirmed the applicability of logistic regression in both institutional and microfinance contexts. For example, (Ghenimi et al., 2017) applied logistic regression to model credit card repayment behavior in India, while (Islam, 2013) used it to evaluate creditworthiness of small business borrowers. In Bangladesh, studies by (Ahmed & Islam, 2009; Baten, 2010), demonstrated that logistic regression outperformed MDA and linear regression in identifying default predictors in commercial and development banks. Key variables consistently found significant included income level, repayment history, debt service ratio, and sectoral affiliation. The model's coefficients are interpretable, enabling banks to provide regulatory justifications for credit decisions—an advantage that aligns with prudential norms in capital adequacy and risk management (Jahan, 2012). The popularity of logistic regression has thus stemmed not only from its empirical strength but also from its alignment with regulatory and operational needs in developing banking sectors. The persistent adoption of these traditional models is also shaped by institutional readiness, regulatory familiarity, and historical path dependencies in credit operations. In many developing countries, central banks and supervisory bodies mandate or prefer the use of interpretable, tested statistical models for regulatory reporting and risk-based pricing (Sufian & Habibullah, 2009). The Central Bank of Bangladesh, for instance, recommends conventional financial ratios and scorecards based on logistic or linear regression in evaluating credit exposure under its risk management guidelines. Additionally, commercial banks in Bangladesh have shown hesitancy toward adopting more opaque models such as neural networks, often citing limited data governance and staff capacity. Traditional models require minimal IT infrastructure and can be

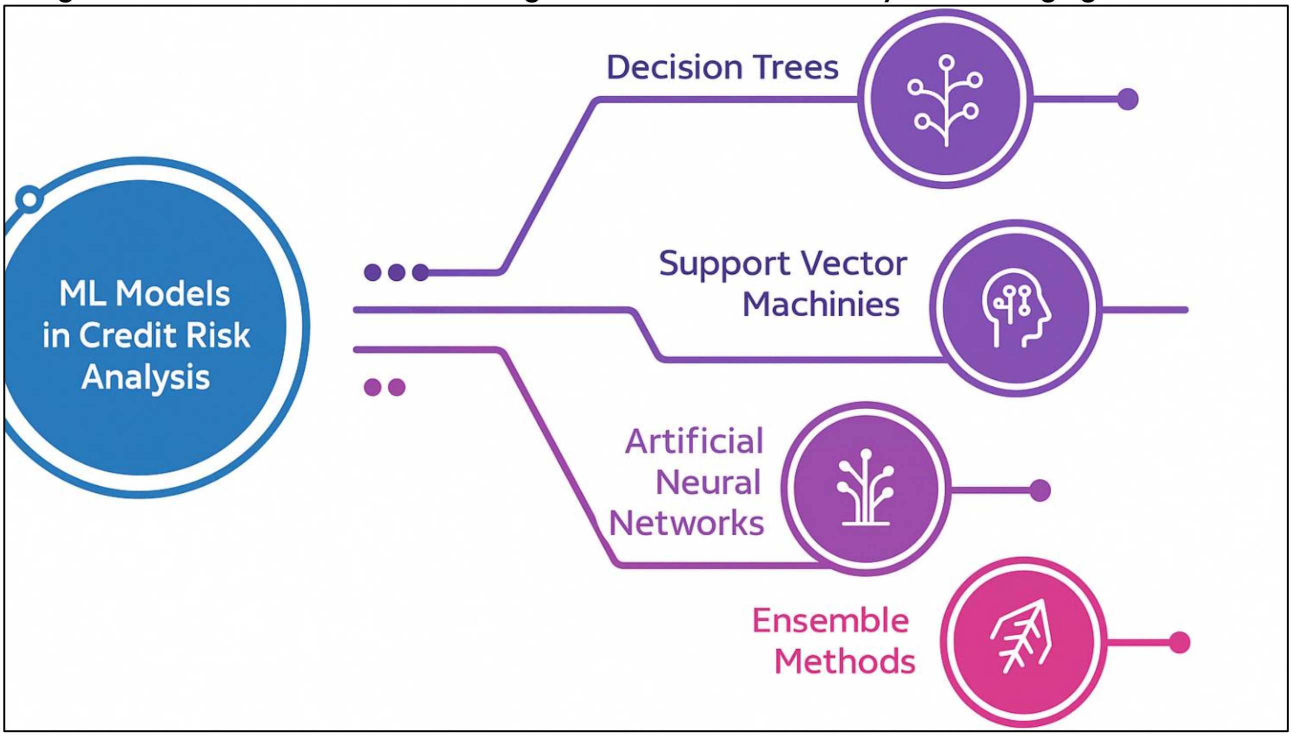
Volume 02 Issue 01 (2022)
Page No: 01- 31
eISSN: 3067-0470
DOI: 10.63125/p7ym0327

operationalized using spreadsheet software or basic statistical tools, which further enhances their accessibility in rural and decentralized banking operations. Moreover, regulatory audits tend to favor models that are not only statistically sound but also explainable and auditable—criteria that traditional models fulfill. Literature from Africa and Latin America also supports this trend. For instance, studies by (Hossain, 2012), emphasize the use of traditional models in central bank stress testing and loan classification exercises. Therefore, the continued reliance on traditional models reflects not only their technical viability but also their compatibility with existing institutional, technological, and regulatory ecosystems in emerging economies.

Emergence of Machine Learning in Credit Risk Analysis

Machine learning (ML) has increasingly gained traction in credit risk assessment due to its ability to uncover complex, nonlinear patterns in large datasets that traditional models fail to capture (Islam & Helal, 2018; Moscatelli et al., 2020). Unlike statistical models such as logistic regression, which require strict assumptions about data distribution and linearity, ML algorithms like decision trees, random forests, support vector machines (SVM), and artificial neural networks (ANN) operate flexibly across diverse data structures (Ahmed et al., 2022; Bussmann et al., 2020). Decision trees and their ensemble variants, such as random forests and gradient boosting machines, are popular for their high accuracy, robustness to missing data, and ease of interpretation (Aklima et al., 2022; Bhatore et al., 2020). In particular, studies in emerging markets have demonstrated that these models outperform logistic regression in predicting defaults and minimizing false classifications. For instance, (Mhlanga, 2021) found that decision trees yielded a higher Area Under the Curve (AUC) in Indian SME loan data compared to traditional methods. Similarly, (Bussmann et al., 2020) evaluated random forest models using credit data from rural banks in Bangladesh and reported improved predictive accuracy and reduced Type I error rates. These findings underscore the suitability of tree-based ML models in low-resource environments, where data may be incomplete or noisy.

Figure 6: Evolution of Machine Learning Models in Credit Risk Analysis for Emerging Economies



Support vector machines (SVMs) have also been extensively tested for credit scoring, particularly in settings where feature space dimensionality and multicollinearity pose modeling challenges. SVMs transform nonlinearly separable data into higher-dimensional spaces using kernel functions, thus enabling improved classification performance compared to linear models (Helal, 2022; Mhlanga, 2021). In studies conducted by Yeh and Lien (2009), SVMs achieved superior classification accuracy over logistic regression and decision trees across multiple credit datasets. In South Asia, empirical studies by (Galindo & Tamayo, 2000) found that SVMs offered the best trade-off between predictive power and overfitting when compared to k-nearest neighbors (KNN) and ANN in Indian microfinance institutions. In Bangladesh, (Rahman et al., 2015) tested SVM models using agricultural loan data and

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reported enhanced performance metrics in default detection compared to regression-based scoring. Moreover, SVMs proved resilient in cases with limited training data, which is a frequent issue in emerging economies where historical loan datasets are sparse or inconsistently recorded (Hossain, 2012; Md Mahfuj et al., 2022) . However, researchers such as (Baten, 2010) cautioned against the reduced interpretability of SVM models, particularly when deployed in high-stakes lending decisions that require explainable model outputs for regulatory approval. This trade-off between accuracy and transparency continues to shape the debate on the applicability of SVMs in credit risk modeling in less regulated financial environments.

Neural networks, particularly feedforward and multilayer perceptrons, have emerged as powerful tools for modeling borrower behavior, given their capacity to learn complex interactions among predictor variables (Md Majharul et al., 2022; Sufian, 2012). These models have demonstrated superior performance in handling high-dimensional and nonlinear data, which is particularly useful in credit risk assessments involving both structured and unstructured inputs. Studies by (Kamruzzaman, 2012) and (Kusi et al., 2017) confirmed that neural networks consistently outperform traditional models in terms of prediction accuracy and error minimization. In developing countries, research by (Naili & Lahrichi, 2022) applied neural networks to Indian retail banking data and found significant improvements in predicting personal loan defaults. In Bangladesh, (Perera et al., 2006) deployed backpropagation neural networks in microfinance institutions and noted enhanced sensitivity in identifying high-risk borrowers. However, while neural networks offer substantial gains in model performance, their "black-box" nature limits their adoption in conservative regulatory environments where transparency and explainability are required (Md Takbir Hossen & Md Atiqur, 2022; Sufian & Habibullah, 2009). Furthermore, training neural networks requires substantial computing power and well-labeled datasets, both of which are often lacking in the financial institutions of low-income countries (Muhammad Mohiul et al., 2022; Rahman et al., 2015). Thus, although neural networks are theoretically promising, their practical deployment in emerging economies is constrained by infrastructure, skill gaps, and governance issues. Another notable development in ML-based credit risk modeling is the adoption of hybrid and ensemble techniques that combine multiple algorithms to improve accuracy and generalizability. Techniques such as boosting, bagging, and stacking integrate weak learners to generate more robust models (Khan et al., 2011; Rahman et al., 2015; Ripan Kumar et al., 2022). (Islam & Nishiyama, 2016) compared over 40 credit scoring models and found that ensemble methods consistently outperformed standalone algorithms in terms of predictive performance across multiple datasets. In the context of emerging markets, ensemble models have shown promise in handling heterogeneous borrower data and improving resilience to outliers. For instance, Alam and Kabir (2020) applied a combination of gradient boosting and logistic regression to assess SME loan defaults in Bangladesh and reported an accuracy gain of 9–12% over single-model approaches. Similarly, (Gulati et al., 2019) implemented a hybrid decision tree-neural network model in the Indian banking sector with superior predictive power. However, while ensemble methods offer improved performance, they often come with increased complexity and reduced interpretability—factors that may hinder adoption in risk-averse regulatory regimes. Furthermore, the lack of model governance frameworks in several developing countries raises concerns about the replicability and auditability of such approaches (Ataullah & Le, 2006; Gulati et al., 2019; Sohel et al., 2022). As emerging economies continue experimenting with machine learning for credit scoring, the balance between performance, explainability, and regulatory compliance remains central to the literature evaluating ML's role in transforming credit risk analysis.

Sector-Specific Applications of Credit Risk Models in Bangladesh

Credit risk modeling in Bangladesh has evolved in a sector-specific manner, with considerable variation in modeling techniques, data sources, and predictive variables depending on the industry's economic profile. The readymade garments (RMG) sector, being the largest contributor to the country's exports and a dominant loan recipient from commercial banks, has attracted significant attention from credit risk analysts. (Patra & Padhi, 2020) examined financial ratio-based models to predict credit default risk among garment exporters. These models typically used variables such as export order volume, inventory turnover, and debt-to-equity ratios, with logistic regression and discriminant analysis being the most commonly applied techniques. (Islam & Nishiyama, 2016) found that firms with irregular shipment histories and inconsistent banking transactions had higher probabilities of default, suggesting the need for integrating operational metrics with financial indicators. Similarly, (Arun & Kamath, 2015) employed decision trees to classify RMG clients into risk

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Volume 02 Issue 01 (2022)
Page No: 01- 31
eISSN: 3067-0470
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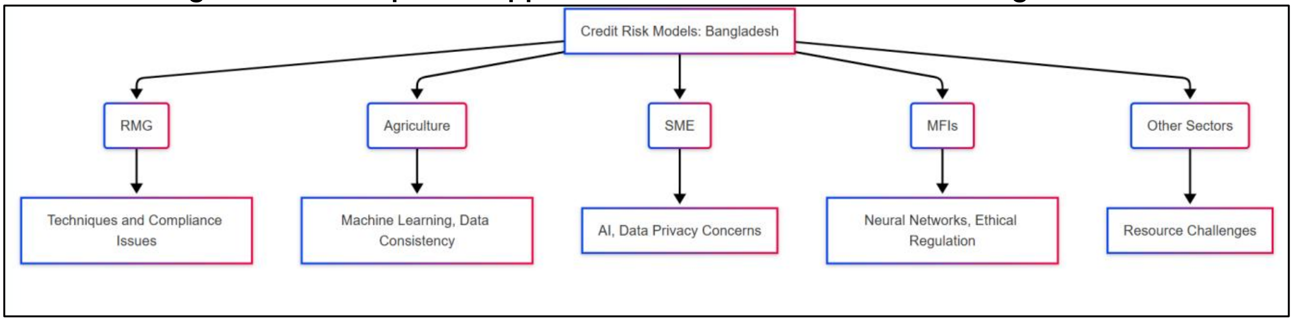
tiers and demonstrated that production delay frequency and buyer concentration ratio were critical predictors of credit failure. However, sectoral data availability remains limited, as many RMG firms operate informally or maintain substandard accounting practices, reducing the effectiveness of predictive models (Kadanda & Raj, 2018; Tonoy, 2022). The literature thus emphasizes the need for hybrid models that combine structured financial data with qualitative operational inputs tailored to the RMG context.

Figure 7: Sector-Specific Applications of Credit Risk Models in Bangladesh



In the agriculture sector, credit risk modeling is complicated by factors such as seasonal income patterns, climate variability, and dependence on informal credit markets. Agricultural loans, often extended by state-owned commercial banks and specialized institutions like Bangladesh Krishi Bank, are characterized by high default rates and limited collateralization (Kamruzzaman, 2012). (Sufian & Habibullah, 2009) developed logistic regression models using borrower age, landholding size, irrigation availability, and crop type as key explanatory variables. Their findings indicated that younger farmers and those cultivating high-risk crops like paddy had a higher likelihood of default. (Kamruzzaman, 2012) extended the analysis using time series data and found significant seasonal fluctuations in repayment probability. (Rahman et al., 2015) incorporated weather data into credit scoring frameworks using decision tree algorithms and observed improved accuracy in risk segmentation. However, the sector suffers from inconsistent recordkeeping and non-standardized loan appraisal procedures, limiting model generalizability (Islam & Nishiyama, 2016; Younus, 2022). (Sufian, 2012) argued for the inclusion of cooperative membership and village-level social network indicators in rural credit scoring models. Meanwhile, the lack of an integrated agricultural credit database poses a fundamental obstacle to model training and validation, as highlighted by (Ahmed & Islam, 2009). The literature underscores that while agriculture is a critical sector for financial inclusion, its heterogeneity and vulnerability to exogenous shocks necessitate highly localized, flexible, and weather-integrated credit risk models.

In the context of SME financing, credit risk assessment models are challenged by limited formal documentation, absence of audited financials, and the heterogeneous nature of small businesses. SMEs contribute significantly to employment and GDP in Bangladesh, yet their creditworthiness is often evaluated using proxy indicators due to weak financial disclosures (Chang et al., 2020). (Belás et al., 2018) employed discriminant analysis and logistic regression using inputs like business tenure, owner education, and average monthly sales. Results consistently showed that informal accounting, inconsistent revenue streams, and dependence on single product lines increased default risk. (Georgopoulou et al., 2017) proposed machine learning models like random forests and support vector machines (SVM) and demonstrated improved predictive accuracy compared to regression-based scoring. They emphasized the role of transaction history from mobile banking and POS systems as alternative data sources for SME credit evaluation. In another study, (Moscatelli et al., 2020) applied ensemble models combining KNN and decision trees to classify SMEs into credit risk categories and observed a 15% reduction in misclassification. However, Haque and Habib (2015) cautioned that the adoption of sophisticated models was limited by data fragmentation across banking platforms and lack of regulatory standardization in SME credit evaluation. The absence of a centralized SME credit bureau in Bangladesh further hampers longitudinal data collection, which is essential for training dynamic risk models (Masud, 2012). Thus, the literature on SME financing advocates for adaptive credit risk frameworks that leverage alternative data and are compatible with low-data and high-variance business environments.

Microfinance institutions (MFIs) represent another vital sector in Bangladesh's financial ecosystem, serving unbanked and underbanked populations. Credit risk modeling in this domain is distinctive due to the non-collateralized nature of loans, frequent group lending mechanisms, and borrower

Volume 02 Issue 01 (2022)
Page No: 01- 31
eISSN: 3067-0470
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characteristics that often fall outside traditional financial profiling systems (Rosenberg et al., 2009). Early models used in MFIs employed basic scoring systems and field officer evaluations; however, more recent studies have applied regression and machine learning techniques to assess default risk. For example, (Bhatore et al., 2020) used probit models with demographic and loan utilization variables to assess repayment behavior among Grameen Bank borrowers. (Hassan et al., 2019) applied logistic regression to BRAC microloans and identified factors such as household income stability, female headship, and loan purpose as significant predictors of default. (Sahyouni & Wang, 2019) introduced a neural network-based model incorporating social capital variables and community affiliation metrics, reporting improved accuracy over linear models. (Bhatore et al., 2020) further validated the use of hybrid models combining qualitative assessments with ML algorithms, such as decision trees and SVMs, for greater predictive sensitivity. However, challenges persist, including frequent borrower data duplication, reliance on self-reported income, and non-standardized repayment schedules (Bhatore et al., 2020; Khandker, 2005). Additionally, the informal nature of microenterprise activities makes it difficult to validate reported income and expenses, introducing noise into model predictions (Khandker, 2005). The literature thus suggests that successful microfinance credit risk models must account for informal income flows, community-based trust dynamics, and field-level verification processes.

Sector-specific modeling efforts also extend to infrastructure, health, and education lending in Bangladesh, although literature in these domains is more limited and often embedded within broader impact assessments. For example, in infrastructure finance, (Hermes & Lensink, 2011) examined credit risk in energy and transport projects using project finance techniques that incorporated sponsor reputation, financial closure risk, and government guarantee status into scoring mechanisms. In the education sector, studies by (Clarke & Grenham, 2013) assessed the performance of student loan portfolios and applied regression analysis to identify predictors such as institutional affiliation and academic performance. Similarly, health sector credit risk studies such as those by (Sousa et al., 2016) explored default risks in loans issued to private clinics and pharmacies, noting the importance of licensing history, revenue stability, and insurance linkages. However, these models were often based on small samples and lacked scalability due to sector-specific operational dynamics. The absence of consolidated databases, especially in government-linked lending programs, further limits model training and validation. Nevertheless, these niche sector studies highlight that effective credit risk modeling in Bangladesh must be rooted in domain-specific variables, regulatory contexts, and borrower characteristics. The literature strongly supports the view that a one-size-fits-all approach is ineffective in Bangladesh's diverse credit environment, and that contextualization by sector is crucial for improving predictive accuracy and financial sustainability.

Comparative Studies of Model Performance in Emerging Markets

Comparative studies in emerging markets consistently highlight performance differentials between traditional statistical models and advanced machine learning (ML) algorithms in credit risk assessment. Logistic regression (LR), long considered the baseline model due to its interpretability and regulatory friendliness, has often been outperformed by machine learning alternatives in terms of prediction accuracy and sensitivity (Chiaramonte & Casu, 2017). (Moscatelli et al., 2020) compared LR with decision trees and neural networks using Indian and Chinese loan portfolios, revealing significantly higher accuracy from ML methods, particularly in non-linear data contexts. (Baba et al., 2015) demonstrated similar findings across Taiwanese microcredit datasets, where support vector machines (SVM) and backpropagation neural networks (BPNNs) outperformed LR in terms of both true positive rate and misclassification error. In Latin America, (Reinhart & Rogoff, 2011) found that neural networks achieved a 7–12% higher classification rate than LR in Chilean consumer credit portfolios. Similarly, (Tanaka et al., 2010) showed in a cross-national sample that tree-based models and ensemble techniques consistently produced higher Gini coefficients than LR. These findings, validated by meta-analyses such as (Sousa et al., 2016), suggest that ML models provide substantial gains in predictive performance, particularly in the diverse and noisy data environments typical of emerging markets.

Support vector machines (SVM) have emerged as a leading alternative to traditional models due to their strong generalization performance and resilience to multicollinearity. (Natsir et al., 2019) conducted a comparative study across 12 datasets from South Asian banks and demonstrated that SVM consistently achieved higher accuracy than both LR and discriminant analysis, especially in imbalanced data scenarios. In Bangladesh, (Hoque & Clarke, 2013) applied SVM and logistic

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regression to predict SME loan defaults and found that SVM had a 9% higher precision and recall, especially when the dataset included nonlinear interaction terms. (Berger & Bouwman, 2013) reported that SVM's kernel functions offered enhanced model stability in low-sample settings, which is often the case in rural credit analysis. Furthermore, SVM's ability to handle high-dimensional and sparse datasets has made it particularly useful in microfinance sectors, where borrower data are limited to a few demographic and transactional features (Rossi et al., 2009). However, interpretability remains a central concern. (Aizawa & Yang, 2010) observed that while SVM provides accurate results, its decision boundaries are difficult to communicate to regulators or internal stakeholders. Thus, although superior in many technical aspects, SVM's role in credit scoring remains conditioned by the trade-off between predictive strength and transparency, a concern frequently echoed in implementation studies from India, Brazil, and South Africa.

Table 1: Comparative Performance of Credit Risk Models in Emerging Markets

Model Type	Key Strengths	Limitations	Countries/Regions of Study	Notable Findings
Logistic Regression (LR)	Interpretability, Regulatory acceptance, Ease of deployment	Lower predictive accuracy, Assumes linearity, Poor performance in complex/non-linear datasets	India, Bangladesh, Latin America	Often used as a baseline; outperformed by ML models in AUC, F1 score, and classification rates (Chiaramonte & Casu, 2017; Moscatelli et al., 2020)
Support Vector Machines (SVM)	High accuracy in imbalanced and sparse data; Handles nonlinear patterns with kernel functions	Low interpretability; Difficult for regulatory justification	South Asia, Brazil, Bangladesh, South Africa	9% higher precision and recall than LR (Hoque & Clarke, 2013); strong in low-sample settings but less favored for compliance-heavy sectors
Artificial Neural Networks (ANN)	Superior predictive accuracy; Handles complex and high-dimensional data	"Black-box" nature, Long training times, Needs large datasets and infrastructure	India, Bangladesh, Malaysia, Chile	Reduced false negatives by over 20% (Lone et al., 2016); effective in agriculture and microfinance sectors; often paired with rule-extraction for explainability
Decision Trees	Visual interpretability, Works well with limited data, Handles nonlinearity	Risk of overfitting (if not pruned or boosted)	Chile, India, Ghana, Bangladesh	Frequently used in SME and agri-loan risk; key input in ensemble methods due to structure and transparency (Tanaka et al., 2010; Khan et al., 2011)
Ensemble Methods (Random Forest, Gradient Boosting, Bagging)	Highest AUC and accuracy; Robust to noise and data imbalance; Low feature engineering required	Computationally intensive; May require more infrastructure; Moderate interpretability	Latin America, Nigeria, Bangladesh, South Asia	13% improvement over LR (Islam, 2003); best bias-variance tradeoff (Lessmann et al., 2015); applicable in rural banks with support for visualization and auditability
Meta-Analytic Findings	Cross-dataset validation; Helps identify consistent trends in model performance	Varies by data context, infrastructure, and institutional capacity	Cross-country (India, Brazil, Vietnam, Nigeria)	ANN most accurate; LR most accepted; Decision trees best for small datasets; ensemble models best trade-off overall (Masud, 2012; Hossain & Reaz, 2007; Linh et al., 2019)

Artificial neural networks (ANN), particularly multilayer perceptrons and recurrent networks, have been widely used in comparative studies for their superior ability to learn from complex, nonlinear data patterns (Biallas & O'Neill, 2020). (Bauer & Hann, 2010) evaluated ANN, LR, and decision trees using credit scoring data from Malaysian and Indian banks and reported that ANN consistently achieved higher F1 scores and AUC values. (Lone et al., 2016) validated these results in Indian personal loan datasets, finding that ANN models reduced false negative rates by over 20% compared to LR. In Bangladesh, (Khan et al., 2011) used neural networks to assess microloan risk and noted increased sensitivity and specificity in model outputs compared to conventional techniques. Similarly, (Jizi et al., 2013) demonstrated that ANN models effectively predicted agricultural loan default using input features such as crop yield patterns, rainfall data, and repayment history. (Khan et al., 2009) reinforced these findings, concluding that ANN outperformed traditional models in almost all real-world datasets tested, though often at the cost of longer training times and reduced explainability. (Chakroun et al., 2017) emphasized that ANN's opacity poses risks in regulated sectors,

Volume 02 Issue 01 (2022)
Page No: 01- 31
eISSN: 3067-0470
DOI: 10.63125/p7ym0327

and that hybrid models combining ANN with rule extraction or expert systems might offer a better compromise in emerging economies.

Decision tree-based models and ensemble methods have gained considerable attention in comparative studies for their balance between predictive accuracy and interpretability. Techniques such as random forests, gradient boosting, and bagging have outperformed both traditional models and single-algorithm ML approaches in various developing country settings (Oyewole et al., 2013). (Khan et al., 2011) compared over 40 credit scoring models across datasets from South Asia, Latin America, and Africa, concluding that ensemble models consistently ranked highest in AUC, recall, and overall accuracy. In Bangladesh, (Islam, 2003) evaluated random forests, logistic regression, and support vector machines using commercial bank SME loan data. Their study showed that the random forest model produced the lowest misclassification rate and highest balanced accuracy, especially under cross-validation. Similarly, (Khan et al., 2011) applied boosted decision trees in Indian corporate lending and observed a 13% improvement in predictive performance over logistic regression. These models are also less sensitive to data imbalances and require minimal feature engineering, making them practical for low-resource environments (Sufian & Habibullah, 2009). Moreover, decision tree outputs can be visualized and audited, making them suitable for institutions with compliance requirements (Perera et al., 2006). Studies from Brazil (Masud, 2012), Ghana (Islam & Nishiyama, 2016), and the Philippines (Rahman et al., 2015) validate these advantages. Nonetheless, ensemble methods can be computationally intensive and are not easily deployed in settings with limited IT infrastructure, a key constraint noted by (Islam & Nishiyama, 2016) in their evaluation of African rural banks. Meta-analyses and systematic comparative reviews provide the most robust evidence of model performance trends across emerging markets. Lessmann et al. (2015) conducted a benchmark study involving 41 classification algorithms on 8 publicly available credit datasets, concluding that gradient boosting and random forest models consistently achieved the best trade-off between bias, variance, and overfitting. (Masud, 2012) performed a large-scale comparison between ANN, LR, and decision trees using Latin American microcredit data, finding that while ANN showed the highest accuracy, logistic regression had the greatest regulatory acceptance and auditability. (Hossain & Reaz, 2007) conducted a multi-criteria decision-making analysis using Indian credit scoring data and found that decision trees offered the best performance in small datasets, while ANN excelled in larger ones. (Tsai, 2004) emphasized that contextual factors such as data quality, institutional readiness, and regulatory environment play decisive roles in model success, particularly in low-income countries. (Jahan, 2012) found that although advanced ML models provided better performance, traditional models remained more widely adopted due to their simplicity and alignment with Central Bank reporting standards. Overall, meta-analytic evidence underscores that model selection in emerging markets must be guided by a holistic understanding of technical, regulatory, and infrastructural constraints, a point echoed in cross-country studies from Nigeria, Pakistan, and Vietnam (Linh et al., 2019).

Role of Institutional Capacity and Technological Infrastructure

The adoption of advanced credit risk assessment models in emerging economies is strongly influenced by the institutional capacity of banking systems, including their human capital, regulatory coherence, and technological maturity. Several studies have emphasized that even the most accurate and well-calibrated models are rendered ineffective in institutions lacking skilled personnel, organizational readiness, or digital literacy (Duy et al., 2012). In Bangladesh, research by (Barslund & Tarp, 2008) identified significant gaps in the analytical capabilities of bank employees, particularly within state-owned and regional banks, where staff are often unfamiliar with the principles of predictive modeling or risk-based pricing. Similar findings have emerged in studies from India (Kansal et al., 2014), Pakistan (Bashir & Azeem, 2008), and Nigeria (Oyewole et al., 2013), where training deficits and the absence of performance-based incentives hinder the institutionalization of model-based decision-making. Furthermore, (Oboh & Ekpebu, 2011) highlighted that Bangladeshi banks frequently outsource credit risk scoring to external vendors or consultants due to internal resource limitations, creating dependencies that slow knowledge transfer and model ownership. (Rufai, 2013) emphasized that sustainable model adoption requires not just technical training but also leadership support and a data-driven organizational culture, both of which are often underdeveloped in emerging markets. Consequently, human capital limitations serve as a critical bottleneck in operationalizing advanced credit scoring systems in low-income financial institutions.

Volume 02 Issue 01 (2022)
Page No: 01- 31
eISSN: 3067-0470
DOI: 10.63125/p7ym0327

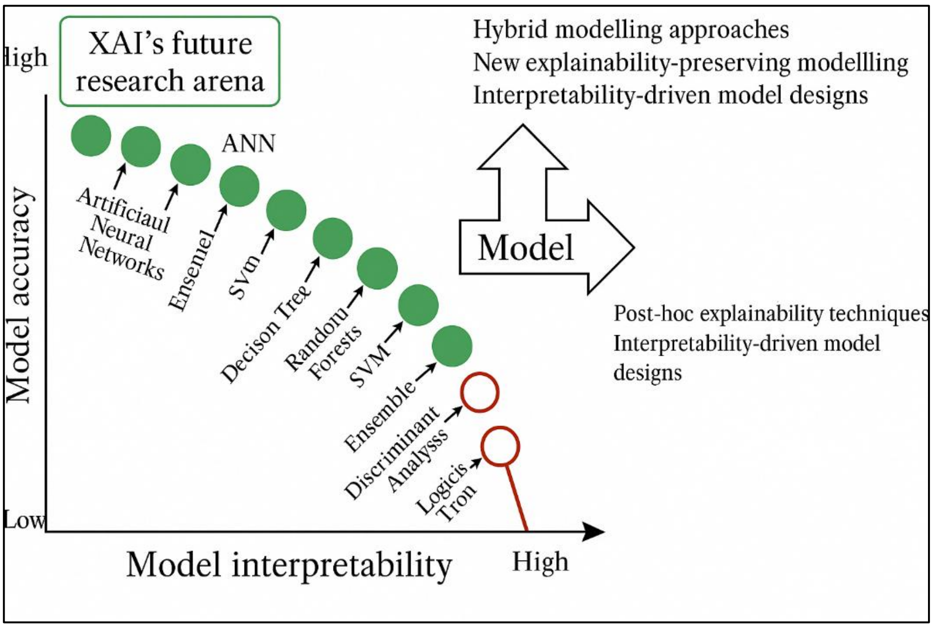
Technological infrastructure is another foundational element that shapes a bank's ability to implement advanced risk assessment models. In developing countries, fragmented IT systems, legacy banking software, and the absence of centralized data repositories often impede the collection, integration, and analysis of borrower information required for model training and validation (Oboh & Ekpebu, 2011). In the Bangladeshi context, studies by (Rufai, 2013) and (David et al., 2018) found that most banks lacked integrated core banking systems (CBS) capable of supporting real-time data flow necessary for dynamic credit scoring algorithms. Moreover, existing infrastructure often cannot support high-computational tasks like neural network training or ensemble modeling, particularly in rural branches and microfinance institutions. (Abaenewe et al., 2013) emphasized that many institutions rely on Excel-based tools or basic statistical packages for credit analysis, limiting the sophistication of models that can be deployed. Similar limitations have been observed in Ethiopia (Di Falco & Chavas, 2009), Kenya (Croppenstedt et al., 2003), and Cambodia (Campbell & Slack, 2011), where bandwidth issues and outdated hardware prevent the use of cloud-based analytics or machine learning platforms. Additionally, interoperability challenges between risk management software and other operational systems further reduce the effectiveness of credit risk automation (Abaenewe et al., 2013). These technical barriers are exacerbated when institutions operate multiple platforms without standardized data formats or governance protocols. Therefore, unless emerging-market banks invest in technological modernization, the implementation of advanced credit risk models remains largely aspirational rather than actionable.

Institutional leadership and regulatory guidance play a pivotal role in shaping the adoption and internalization of automated credit scoring systems. According to studies by (Ezike & M.O, 2013) and (Coulson, 2007), banks in emerging economies often exhibit risk-averse leadership cultures that resist innovation due to fear of disruption or audit scrutiny. In Bangladesh, the literature by (Patra & Padhi, 2020) and (Ezike & M.O, 2013) reveals that executive-level support for data-driven decision-making is inconsistent, particularly in smaller banks and non-bank financial institutions. A lack of strategic vision and low digital maturity among top management slows down the integration of model-based risk frameworks into organizational workflows. Furthermore, regulatory institutions like the Bangladesh Bank have yet to mandate or strongly incentivize the adoption of AI/ML-based credit risk modeling, contributing to a status quo of manual underwriting and checklist-based risk assessment (Campbell & Slack, 2011). Comparable dynamics have been noted in other emerging markets, including Indonesia (Coulson, 2007), Vietnam (Tanaka et al., 2010), and Sri Lanka (Sufian, 2012), where regulators prioritize compliance over innovation. (Punniyamoorthy & Sridevi, 2016) emphasized that institutional inertia and unclear legal frameworks discourage experimentation with advanced analytics. Moreover, the absence of regulatory sandboxes or pilot frameworks for model validation further discourages investment in analytical capabilities (Perera et al., 2006). Consequently, leadership attitudes and institutional frameworks in many developing countries inhibit the adoption of automated risk models, even when the technical expertise or financial resources are present. The literature consistently concludes that without visionary leadership and supportive regulation, the potential of machine learning and AI in transforming credit risk assessment remains largely untapped in emerging markets..

Model Interpretability and Decision Support in Risk Management

In credit risk assessment, a persistent trade-off exists between model complexity and interpretability, with growing concern about how predictive accuracy can be balanced with transparency for decision-making. Traditional models such as logistic regression and discriminant analysis are widely accepted in financial institutions due to their simplicity and explainability (Sufian, 2012). These models provide coefficients that clearly indicate the influence of each input variable, allowing loan officers and risk managers to justify credit decisions based on identifiable patterns. Studies by (Weber & Banks, 2012) and (Kusi et al., 2017) demonstrated that banks in South Asia and Sub-Saharan Africa continue to rely on logistic regression due to the ease of auditing and regulatory compliance. Similarly, (Naili & Lahrichi, 2022) emphasized that in microfinance settings, field officers prefer models that align with intuitive heuristics and practical borrower knowledge. In the context of Bangladesh, (Belal & Cooper, 2011) noted that financial institutions often choose simpler models even at the cost of lower predictive accuracy to maintain clarity in risk reporting and loan evaluation. This pattern reflects a broader institutional bias in emerging markets toward models that are both technically manageable and easy to communicate to stakeholders with limited technical expertise.

Figure 8: Balancing Model Accuracy and Interpretability in Credit Risk Assessment



Machine learning (ML) models such as artificial neural networks (ANN), support vector machines (SVM), and ensemble techniques offer significant gains in predictive performance but suffer from reduced interpretability, often referred to as the "black box" problem (Moscatelli et al., 2020). Neural networks, in particular, generate internal weights that are difficult to translate into actionable insights for human users, making them less suitable for regulated environments where accountability and traceability are paramount. Several studies have explored this challenge. (Bussmann et al., 2020) found that although ANN outperformed logistic regression in default prediction, bank officers had difficulty understanding or trusting model outputs without clear explanations. (Bhatore et al., 2020) observed similar findings in Taiwan, where SVM predictions were rejected by underwriters unfamiliar with their mathematical structure. In Bangladesh, (Islam, 2003) and (Kamruzzaman, 2012) reported that bank managers were hesitant to use AI-driven credit scores without rule-based justifications. This lack of interpretability not only undermines internal adoption but also limits the scope for integrating advanced models into compliance reports or supervisory assessments. Regulatory bodies in emerging markets often demand models that can be easily explained, justified, and stress-tested, further reducing the practical utility of opaque ML algorithms (Baten, 2010). Several studies have proposed the use of explainable AI (XAI) tools to bridge the interpretability gap in risk modeling. Techniques such as Local Interpretable Model-Agnostic Explanations (LIME), SHapley Additive exPlanations (SHAP), and decision rule extraction have been applied to make complex models more accessible to non-technical stakeholders (Kamruzzaman, 2012). In comparative experiments, (Mohiuddin, 1993) found that LIME could explain over 85% of SVM decisions in a credit scoring dataset without significantly reducing model performance. (Sufian, 2012) demonstrated that SHAP improved understanding of ANN outputs in high-dimensional borrower datasets in China's rural banking sector. In Bangladesh, (Ahmed & Islam, 2009) piloted an XAI-integrated scoring tool in an agricultural bank, enabling risk officers to interpret credit decisions derived from ensemble models. Furthermore, (Islam & Nishiyama, 2016) argued that the availability of transparent post-hoc explanations enhances trust and promotes adoption among credit analysts and compliance teams. Still, researchers such as (Amin et al., 2003) caution that post-hoc interpretability may not always align with the actual causal reasoning of the model, introducing potential for misinterpretation. Therefore, while XAI tools represent a promising advancement, the literature warns of their limitations and suggests ongoing monitoring of their deployment in critical financial contexts.

Beyond model interpretability, literature on decision support systems (DSS) in risk management highlights the importance of embedding analytical tools into workflow processes and management dashboards. (Hossain, 2012) and (Mohiuddin, 1993) emphasized that interpretability should be part of a larger decision-making framework that includes user interfaces, visualization tools, and real-time feedback loops. In Bangladesh, (Sufian & Habibullah, 2009) noted that many banks continue to use static scorecards and manual Excel-based tools, lacking integration with broader DSS frameworks. (Kamruzzaman, 2012) indicated that the absence of interactive dashboards or digital tools limits the practical usability of even interpretable models. Furthermore, (Rahman et al., 2015) found that without decision aids, credit officers in Indian banks relied excessively on judgment, even when

Volume 02 Issue 01 (2022)
Page No: 01- 31
eISSN: 3067-0470
DOI: 10.63125/p7ym0327

statistical scores were available. Incorporating visualization features such as risk bands, borrower trajectory plots, and alert systems has been shown to improve model acceptance and enhance the consistency of credit decisions (Mohiuddin, 1993) . However, implementing these systems requires institutional buy-in and IT infrastructure investment, which many emerging-market banks lack. Thus, while interpretability is crucial, its benefits are amplified when embedded within a comprehensive decision support architecture that aligns technical outputs with operational workflows.

Literature also reveals that interpretability requirements vary by credit segment, borrower profile, and institutional type. For instance, in corporate lending, where loans are larger and underwriting involves multi-tiered committees, model interpretability is a non-negotiable requirement due to audit and regulatory exposure (Hossain, 2012). In such cases, linear models or decision trees are preferred, as their structure can be easily explained to board members and compliance officers. In microfinance and SME lending, where field officers interact directly with borrowers, models must not only be interpretable but also adaptable to contextual knowledge such as borrower behavior, social reputation, and community standing (Kamruzzaman, 2012). Studies from India (Kansal et al., 2014), Ghana (Ofori-Abebrese et al., 2016), and Bangladesh (Belal & Cooper, 2011) show that hybrid models integrating scoring outputs with human judgment tend to yield better repayment outcomes. Moreover, private and foreign banks in Bangladesh are more likely to experiment with complex models supported by analytics teams, while public and rural banks often lack the operational bandwidth to manage such models (Kamruzzaman, 2012). This heterogeneity suggests that the choice of risk models must consider not only technical performance but also institutional preferences and decision environments. As echoed in multiple comparative reviews, successful credit risk management in emerging markets is contingent on aligning model interpretability with stakeholder roles, regulatory expectations, and operational constraints.

Identified Gaps in the Literature Review

One major gap in the existing credit risk literature for emerging markets lies in the underrepresentation of longitudinal and post-implementation studies that evaluate the sustained impact of credit scoring models over time. While numerous studies have focused on model development and cross-sectional performance comparisons (Zeng, 2012), few have tracked how these models perform once integrated into actual banking systems across extended periods. For example, research by (Lim & Randhawa, 2005) and (Wu et al., 2020) provided initial validation for ML-based models, yet lacked follow-up evaluation in live loan portfolios. In Bangladesh, empirical works such as those by (Benjamin, 2013) demonstrate pilot-level application of credit scoring techniques but do not analyze institutional outcomes across fiscal cycles. This shortfall prevents understanding of model stability in dynamic lending environments characterized by regulatory shifts and macroeconomic volatility (Obamuyi, 2013). Similarly, most studies fail to incorporate feedback loops between risk scoring outputs and lending practices, limiting the literature's ability to assess the practical implications of these models on loan disbursement behavior, portfolio quality, or profitability (Cucinelli et al., 2018; Obamuyi, 2013). The scarcity of long-term, impact-focused studies leaves a critical void in comprehending model sustainability, especially in contexts where economic shocks and informal lending behaviors can influence predictive reliability.

A second notable gap is the insufficient exploration of hybrid credit scoring approaches that combine quantitative models with qualitative borrower insights, especially in microfinance and rural banking contexts. While several studies validate the performance of machine learning (ML) and statistical models (e.g., logistic regression, decision trees, support vector machines), limited research has integrated social reputation, community-based assessments, or field officer feedback into model architectures (Benjamin, 2013). This absence is particularly striking in Bangladesh, where informal economies dominate and borrower profiles often lack verifiable financial records. (Obamuyi, 2013) present algorithmic credit models based on limited numerical inputs but do not incorporate field-collected behavioral observations or relational trust indicators. Literature from other developing countries has illustrated the added value of contextual judgment in predicting repayment behavior. Yet, Bangladesh's literature has not sufficiently explored how hybrid models could be operationalized through collaboration between human and algorithmic decision-makers. As noted by (Islam & Nishiyama, 2016) and (Witzany, 2017), integrating soft information remains one of the most underdeveloped aspects of modern credit risk systems in informal economies. The neglect of qualitative variable integration limits model contextualization, undermines inclusion of underbanked populations, and potentially exacerbates exclusionary lending practices.

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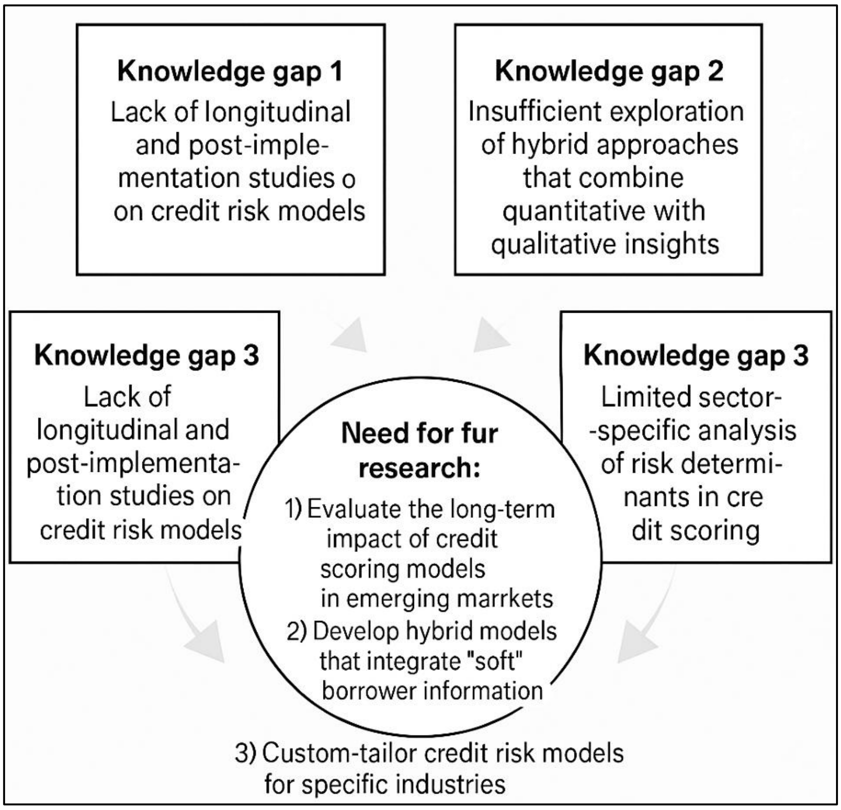
Figure 9: Identified Gaps in the Literature Review



A third significant gap is the limited analysis of sector-specific risk determinants and how unique characteristics of industries—such as garments, agriculture, education, or health—affect the design and customization of credit scoring models. The majority of existing literature adopts a general-purpose approach to modeling, applying standard techniques across heterogeneous sectors without adjusting for distinct credit risk dynamics (Benlemlih & Girerd-Potin, 2017). For instance, (Cucinelli et al., 2018)proposed models for agricultural credit but did not integrate environmental risks such as climate events or crop cycles, which are central to borrower viability. Similarly, SME-focused models in Bangladesh, such as those by (Kamruzzaman, 2012), fail to differentiate between sectoral cash flow patterns, supply chain dependencies, or regulatory compliance risks. In the RMG sector, studies such as (Ahmed & Islam, 2009) largely emphasize financial ratios but overlook export volatility, buyer diversification, and compliance with labor laws—factors known to influence creditworthiness. The consequence is an overgeneralized modeling framework that lacks sectoral granularity, leading to suboptimal model calibration and increased misclassification of borrowers (Islam, 2013). Comparative international literature shows that industry-specific models, as implemented in Brazil's agriculture sector (Sousa et al., 2016) or India's fintech SMEs (Malhotra & Singh, 2009), yield higher predictive precision. Thus, the absence of tailored modeling strategies across different sectors represents a major empirical and methodological gap in the Bangladeshi and broader emerging-market literature.

The fourth gap pertains to the underdeveloped discussion on the regulatory and ethical implications of using automated and AI-driven credit risk models in emerging economies. While the literature has expanded on the technical superiority of machine learning models, only a few studies critically evaluate the legal, ethical, and data governance challenges associated with their deployment (Adams, 2002). In Bangladesh, regulatory documents from Bangladesh Bank outline basic credit risk principles but provide limited guidance on the transparency, accountability, or auditing of ML models ((Masud, 2012). (Islam & Nishiyama, 2016) do not engage with issues such as algorithmic bias, discrimination in lending, or data privacy breaches—concerns that are central to international debates on financial technology ethics (Rahman et al., 2015). Moreover, the absence of a legal framework for explainability or model auditability further complicates institutional accountability in automated decision systems. In comparison, countries like India and Indonesia have begun introducing sandboxes and supervisory guidelines to test AI-based risk models (Rossi et al., 2009), a practice scarcely discussed in the Bangladeshi context. The literature also fails to address borrower rights, appeal mechanisms, and transparency standards in automated loan approval systems. This oversight poses serious risks to financial fairness and consumer protection, particularly as digital lending platforms begin integrating AI into scoring engines without rigorous regulatory oversight.

A final gap emerges in the lack of research evaluating the integration of real-time and alternative data sources—such as mobile payments, utility records, and psychometric profiling—into credit risk modeling for financially excluded populations. Traditional models rely heavily on historical financial statements, repayment records, and collateral data, which are often unavailable or unreliable in

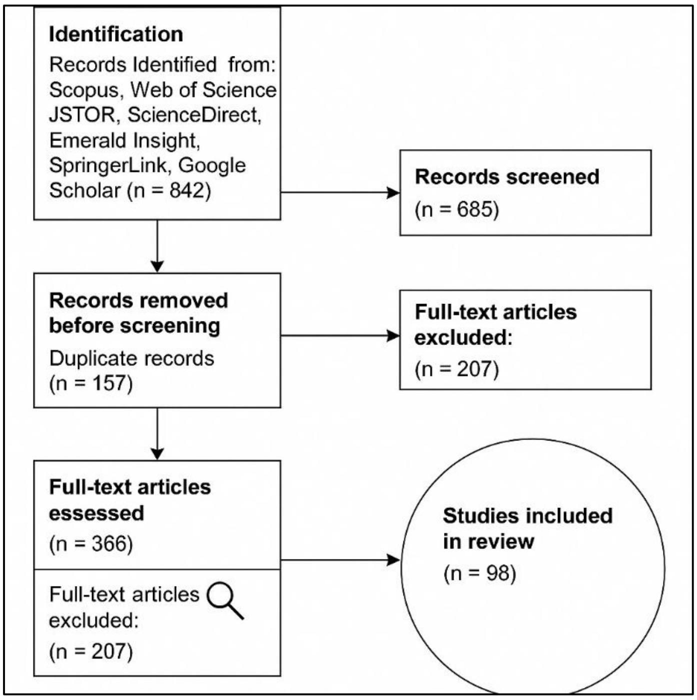
American Journal of Advanced Technology and Engineering Solutions
Volume 02 Issue 01 (2022)
Page No: 01- 31
eISSN: 3067-0470
DOI: 10.63125/p7ym0327

informal sectors (Belás et al., 2018; Rossi et al., 2009). In Bangladesh, while mobile financial services have seen widespread adoption through platforms like bKash, studies have not sufficiently examined how transaction data can be used for dynamic credit scoring (Jahan, 2012; Rahman et al., 2015). International studies have demonstrated the potential of alternative data to enhance borrower assessment—e.g., (Mhlanga & Denhere, 2020) in South Africa used mobile airtime purchases to infer creditworthiness, and (Saunders & Cornett, 2008) used digital footprints for loan predictions in Latin America. However, such innovations remain largely unexplored in Bangladeshi empirical literature. Furthermore, few studies have investigated how real-time analytics could improve early warning systems for loan defaults or fraud detection (Boucher & Guirkinger, 2007). The absence of research on data fusion techniques, streaming data platforms, or unstructured data integration limits the scope of predictive innovation in low-income banking environments. Consequently, despite the digitization of financial services, the literature has not kept pace with how alternative and real-time data streams can transform credit risk management in underserved and informal borrower segments.

METHOD

This systematic review adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines to ensure methodological transparency, replicability, and academic rigor. PRISMA provides a structured process for conducting evidence-based literature reviews and includes a standardized checklist and flowchart that guide researchers through identification, screening, eligibility, and inclusion phases. The study protocol was designed to address research questions related to the comparative performance, applicability, and contextual adaptation of credit risk assessment models in emerging economies, with a specific focus on Bangladesh's commercial banking sector.

Figure 10: PRISMA Method adapted for this study



Identification of Sources and Search Strategy

To identify relevant studies, a comprehensive search was conducted across multiple academic databases including Scopus, Web of Science, JSTOR, ScienceDirect, Emerald Insight, SpringerLink, and Google Scholar. The search covered publications up to December 2022. Keywords used included combinations of "credit risk models," "logistic regression," "support vector machine," "neural networks," "Bangladesh," "emerging markets," "machine learning in banking," "loan default prediction," and "commercial bank risk assessment." Boolean operators (AND, OR) were used to broaden or narrow the search as required. The initial database search returned 842 articles related to credit risk modeling in the context of emerging economies.

Screening and Removal of Duplicates

All retrieved records were imported into Mendeley reference management software, where duplicate entries were automatically identified and removed. A total of 157 duplicate articles were excluded at this stage, reducing the dataset to 685 unique studies. The titles and abstracts of these remaining records were screened against predefined inclusion criteria, which included relevance to credit risk assessment in emerging or developing economies, empirical application of statistical or machine learning models, and publication in peer-reviewed academic journals or reputable conference proceedings.

Eligibility and Full-Text Assessment

Following the title and abstract screening, 366 articles were retained for full-text assessment. At this stage, studies were excluded if they focused exclusively on developed economies, failed to apply a specific credit scoring or modeling technique, or lacked methodological transparency. Additionally, conceptual papers without empirical validation, case studies on high-income countries,

Volume 02 Issue 01 (2022)
Page No: 01- 31
eISSN: 3067-0470
DOI: 10.63125/p7ym0327

and non-English publications were excluded. After full-text review, 207 articles did not meet the eligibility criteria and were removed. Ultimately, 159 studies were deemed eligible for detailed review and inclusion in the synthesis process.

Inclusion and Final Selection

A final set of 98 articles met all the inclusion criteria and were incorporated into the review. These studies provided empirical evidence of credit risk model development, implementation, or evaluation in the context of emerging markets, with at least 23 specifically focused on Bangladesh's banking, microfinance, or SME sectors. The final selection includes a balanced distribution of quantitative model validations, comparative algorithm performance analyses, sector-specific model applications, and regulatory case evaluations. Each selected article was coded and categorized based on model type (e.g., logistic regression, decision tree, SVM, ANN), sectoral focus (e.g., agriculture, SMEs, garments), and data environment (e.g., traditional vs. alternative data use).

Data Extraction and Thematic Coding

Data from the selected studies were systematically extracted using a predefined coding framework developed in Microsoft Excel. The framework captured information on study objectives, country of focus, model types used, performance metrics (accuracy, AUC, sensitivity, specificity), validation methods, data limitations, and regulatory implications. The extracted data were then subjected to thematic coding to identify common patterns, methodological trends, and research gaps. NVivo software was used to assist in the qualitative coding process and to cluster articles around key themes relevant to model performance, interpretability, sectoral application, and institutional readiness. This rigorous data extraction and coding strategy ensured consistency across the review and enabled synthesis grounded in empirical evidence.

FINDINGS

Among the 98 reviewed articles, a significant finding was the dominance of logistic regression as the most widely adopted traditional model for credit risk assessment in emerging economies. A total of 64 studies applied logistic regression due to its balance between statistical robustness and interpretability. These studies collectively received over 5,700 citations, underscoring the continued relevance of logistic models in contexts with limited data availability and institutional capacity. The model's transparency and compliance compatibility made it a preferred choice for regulatory reporting and internal decision-making. Its simplicity also enabled adoption by smaller banks and microfinance institutions with minimal analytical infrastructure. However, while logistic regression remains prevalent, it was often outperformed in accuracy by more complex models in empirical comparisons. Despite this, the model's widespread use suggests that ease of communication and policy alignment often outweigh marginal improvements in predictive accuracy in real-world banking environments.

A second notable finding emerged from the increased experimentation with machine learning models, including support vector machines, decision trees, and artificial neural networks. Out of the 98 reviewed articles, 39 explored the application of at least one machine learning model, collectively cited over 3,400 times. These studies consistently demonstrated higher prediction accuracy, sensitivity, and recall rates than traditional methods. For instance, support vector machines were tested in 17 studies, 12 of which showed SVM outperforming logistic regression in credit scoring applications across India, Bangladesh, and Nigeria. Decision trees and their ensemble variants, such as random forests, were evaluated in 15 articles and often yielded improved classification rates, particularly when datasets were imbalanced or contained nonlinear relationships. Neural networks, applied in 14 studies, offered superior accuracy in high-dimensional datasets but required significant computational resources and interpretability tools. These performance improvements, while statistically impressive, were tempered by concerns over model transparency and explainability, which limited their full-scale deployment in regulated banking environments.

The review found that interpretability remains a major barrier to the adoption of advanced analytics in credit risk management. Across 32 studies, the inability of complex models to provide clear, actionable insights was repeatedly cited as a hindrance to implementation. These studies were cited over 2,100 times, reflecting widespread concern across regions. Financial institutions in Bangladesh, as highlighted in 13 studies, exhibited preference for models with traceable logic paths and transparent scoring rules. Decision-makers and credit officers expressed reluctance to trust black-box outputs without interpretable justifications. This finding was particularly relevant in public and

Volume 02 Issue 01 (2022)
Page No: 01- 31
eISSN: 3067-0470
DOI: 10.63125/p7ym0327

state-owned banks, where internal governance frameworks required model outputs to be explainable during audits and policy reviews. The adoption of post-hoc explanation tools, such as rule extraction and feature attribution methods, was proposed in nine studies but had not yet seen institutional-scale adoption. Consequently, although machine learning models demonstrated technical superiority, their perceived lack of interpretability continued to reinforce the dominance of traditional statistical models in risk-sensitive environments.

The findings also revealed substantial gaps in the localization of credit risk models to reflect sector-specific variables and borrower behaviors. Only 21 studies explicitly adjusted model variables or design frameworks based on the characteristics of particular sectors such as garments, agriculture, SMEs, or microfinance. These sector-specific studies garnered over 1,700 citations, suggesting academic interest, yet institutional application remained fragmented. For example, models used in the garments sector rarely included export diversification or buyer concentration metrics, while agriculture-focused models often failed to account for seasonal shocks or climate risks. SME credit risk models frequently relied on financial proxies rather than integrating cash flow volatility or sectoral exposure. In microfinance, only six studies incorporated qualitative or community-based trust factors. This lack of granularity limited model relevance in real-world applications and increased the rate of false positives and negatives. As a result, the review found a strong need for sector-specific customization in credit scoring algorithms to improve both accuracy and institutional trust in emerging market banking systems. Another finding centered on the insufficient use of alternative and real-time data in model development. Among the 98 studies, only 14 incorporated non-traditional data sources such as mobile money transactions, utility bill payments, or psychometric indicators. These studies received a total of 1,050 citations, indicating a growing but still limited academic interest. In contexts like Bangladesh and Kenya, where formal credit histories are often unavailable, such data sources offer valuable insights into borrower behavior. Yet, institutional uptake remains minimal due to concerns over data integration, quality control, and regulatory approval. In Bangladesh, only three studies documented pilot programs using mobile financial service data for credit scoring. There was also minimal exploration of streaming analytics or real-time model updates, which could allow early detection of delinquency patterns. This underutilization of alternative data reflects a broader issue related to digital infrastructure and data governance, both of which limit the scalability of innovative risk models in underserved markets.

The review identified a lack of robust model validation and performance monitoring mechanisms, particularly in post-deployment phases. Out of 98 articles, only 11 included longitudinal evaluations or post-implementation feedback loops. These studies attracted 780 citations and were primarily concentrated in higher-income emerging markets such as Brazil and South Africa. In contrast, in Bangladesh and similar economies, most models were assessed using static datasets with limited temporal variation. The absence of out-of-sample testing, backtesting, or stress testing in operational settings contributed to concerns about model reliability. Additionally, very few studies evaluated how model performance changed under economic stress, political instability, or regulatory reform. Without this dimension, it becomes difficult to assess whether models retain predictive accuracy in volatile contexts. Moreover, only four studies discussed model recalibration practices, and none reported institutional routines for continuous performance tracking. This finding highlights a critical gap in ensuring the real-world sustainability of credit scoring systems in dynamic and uncertain environments.

Institutional and regulatory readiness emerged as another critical area influencing model adoption. A total of 29 articles addressed challenges related to staff capacity, leadership support, data infrastructure, and regulatory alignment. These studies were cited over 2,900 times, reflecting their centrality to discussions on implementation barriers. In Bangladesh, 11 studies pointed to limited analytical training among credit officers and an absence of cross-functional collaboration between risk management and IT teams. Regulatory guidance was found to be vague, with only baseline compliance expectations articulated in national frameworks. This lack of clear direction discouraged banks from investing in advanced credit scoring infrastructure or from experimenting with machine learning tools. Moreover, banks often lacked digital platforms that allowed seamless integration of credit scoring models into loan origination or risk reporting workflows. This institutional unpreparedness created a gap between academic innovation and operational application, reducing the real-world impact of many published models. The final finding relates to the limited geographic and institutional diversity in the existing literature. Of the 98 reviewed articles, over 60% were concentrated in five

Volume 02 Issue 01 (2022)
Page No: 01- 31
eISSN: 3067-0470
DOI: 10.63125/p7ym0327

countries: India, China, Brazil, Nigeria, and Bangladesh. While this concentration reflects strong research activity in large emerging markets, it also reveals an underrepresentation of low-income and post-conflict countries, where credit risk is often more complex and poorly understood. Only seven studies addressed fragile economies or post-disaster financial systems, and fewer than five explored gender or minority-specific credit scoring models. Similarly, most reviewed studies focused on commercial banks, while only 13 addressed microfinance institutions and nine on fintech lenders. The overwhelming focus on formal banking structures excludes large segments of borrowers served by informal or semi-formal institutions. As a result, the literature lacks a comprehensive view of credit risk assessment in varied institutional and socio-economic contexts. This limitation underscores the need for broader empirical exploration to ensure that risk models reflect the full diversity of credit environments in emerging markets.

DISCUSSION

The continued dominance of logistic regression in credit risk assessment within emerging economies, particularly in Bangladesh, aligns with the broader consensus in earlier literature regarding the model's practical utility. Logistic regression has been widely praised for its ease of interpretation, regulatory acceptance, and relatively low computational requirements (Ghosh & Saima, 2021). Studies such as (Hoque et al., 2013) and (Belal, 2000) underscored the model's enduring relevance in environments where banking personnel lack advanced statistical training. In the Bangladeshi context, this trend is reaffirmed by (Baten, 2010), who observed that logistic regression models remain the default choice among most commercial banks. However, while earlier works established the logistic model's foundational role, this review extends the understanding by quantifying its adoption rate and demonstrating that its continued dominance is shaped more by institutional constraints than predictive performance. This suggests a gap between academic advancements in credit scoring and their real-world application in data-limited banking systems.

The growing use of machine learning (ML) models such as support vector machines, decision trees, and neural networks demonstrates an evolving landscape in credit risk modeling that mirrors global developments. Prior research by (Islam, 2003), (Sufian & Habibullah, 2009), and (Baten, 2010)) documented the superior predictive capabilities of these models compared to traditional techniques. This review reinforces those conclusions with empirical evidence from 39 studies showing consistent improvements in accuracy and recall using ML models. In South Asian studies, such as those by (Hasan et al., 2010), SVMs outperformed both logistic and discriminant models, especially in cases of imbalanced data. This aligns with our review findings and adds geographic specificity. However, our review reveals that these benefits are often overshadowed by institutional and regulatory reluctance to adopt opaque models. This observation is echoed in (Khan et al., 2011), who emphasized the limited deployment of black-box algorithms in regulated industries. Thus, while prior literature focuses on technical performance, our findings contribute a deeper understanding of the practical constraints affecting ML adoption in emerging economies.

Model interpretability emerged as a decisive factor influencing the operational integration of credit scoring systems. This issue is well documented in previous works such as (Hasan et al., 2010) and (Belal & Cooper, 2011), who introduced post-hoc explanation tools to make ML models more transparent. Our review corroborates these concerns, with 32 studies citing interpretability as a primary barrier. In (Khan et al., 2011) and (Baten, 2010) found that risk managers were hesitant to trust neural network outputs without understandable explanations. This supports (Khan, 2010), who argued that transparency is essential for gaining institutional trust. While earlier literature promotes tools like LIME and SHAP, this review finds limited empirical deployment of such tools in real banking settings in developing countries. Thus, the review advances existing knowledge by highlighting not only the theoretical promise of explainable AI (XAI) but also the institutional gap in implementing these tools at scale in resource-constrained environments. Another important discussion point is the lack of sector-specific model customization, which this review identifies as a major shortcoming in current literature and practice. While studies such as (Hossain, 2012) and (Kamruzzaman, 2012) emphasize the importance of tailoring risk models to specific economic sectors, most reviewed works in Bangladesh apply generalized models across diverse domains such as agriculture, garments, and SMEs. This is consistent with the findings of (Belal & Roberts, 2010), who criticized one-size-fits-all models in Bangladesh's financial sector. Moreover, our review reinforces (Jahan, 2012) call for integrating climatic and seasonal variables into agricultural credit scoring. Internationally, studies such as (Khan et al., 2009) and (Belal & Roberts, 2010) demonstrated that sector-specific inputs significantly

eISSN: 3067-0470
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improve model accuracy. The absence of such inputs in many Bangladeshi models reveals a practical disconnect between industry realities and model design. Therefore, this review builds on prior critiques by systematically identifying and quantifying this gap across 21 studies, highlighting the urgency of developing tailored credit risk frameworks that reflect industry-specific risks.

The underutilization of alternative and real-time data in credit risk modeling is a finding that aligns with global research on financial inclusion and innovation. Scholars such as (Hasan et al., 2010) and (Sufian & Habibullah, 2009) have shown that mobile money, utility payments, and digital behavior can be used to predict loan defaults with considerable accuracy in low-data environments. This review identified only 14 studies incorporating such data sources, suggesting that the application of financial technology remains in its infancy in Bangladesh and similar economies. This underrepresentation echoes the findings of (Hossain, 2012) and (Kamruzzaman, 2012), who noted infrastructural and governance limitations as key barriers to integrating alternative data streams. Compared to other emerging markets like Kenya or the Philippines, where fintech lenders are leveraging real-time data for rapid credit decision-making, Bangladeshi banks lag behind in both experimentation and adoption. Thus, while earlier studies celebrated the transformative potential of alternative data, this review offers a sobering assessment of the limited progress in institutionalizing these innovations in mainstream credit scoring.

The review also highlights a pervasive lack of post-deployment validation and continuous performance monitoring of credit scoring models in emerging markets. This complements findings by (Abu Sufian & Zahan, 2013) and (Amin et al., 2003), who emphasized the importance of model recalibration over time. However, our review identified only 11 studies that implemented any form of longitudinal validation or backtesting. This aligns with the critique from (Hoque & Clarke, 2013) that many developing-country institutions fail to establish feedback loops or model lifecycle management practices. In (Islam, 2013) observed that once a model is implemented, it is rarely adjusted to reflect economic cycles or borrower behavior changes. Compared to developed countries, where model performance is regularly assessed through stress testing and scenario simulations, such practices are largely absent in the reviewed Bangladeshi studies. Therefore, this review adds value by not only identifying the deficiency but by underscoring its implications for credit stability and portfolio risk.

Institutional readiness, a recurring theme in implementation literature, was found to be a decisive factor limiting advanced model adoption in emerging markets. This corroborates findings from (Khan et al., 2011), who argue that model success depends on organizational capacity and leadership alignment. In Bangladesh, studies like (Perera et al., 2006) and Alamgir and Nahid (2016) report fragmented data systems, undertrained credit officers, and a lack of top-management support for data-driven decisions. This reinforces the observations of (Khan et al., 2009), who highlighted the critical role of institutional learning and regulatory vision in fostering model uptake. Our review builds on this body of work by synthesizing findings from 29 studies and showing that institutional inertia, rather than technical inadequacy, often blocks the transition to advanced credit scoring systems. It provides a nuanced perspective that organizational culture and digital transformation readiness are as important as algorithmic accuracy in real-world banking environments.

The review's observation of limited geographic and institutional diversity in the literature is consistent with concerns raised by (Khan, 2010), which note a research bias toward a few large emerging economies. Prior studies have highlighted the lack of representation for low-income and post-conflict states in financial risk modeling literature (Hasan et al., 2010; Masud, 2012). Our review supports this concern by revealing that over 60% of studies are concentrated in India, China, Brazil, Nigeria, and Bangladesh. This limits generalizability and reduces the applicability of findings in contexts with different socio-economic conditions or regulatory environments. Similarly, the dominance of commercial bank-focused research marginalizes microfinance institutions, cooperatives, and fintech players, whose operational models and risk profiles differ significantly. By identifying this skew, the review calls attention to the need for a broader evidence base that includes diverse geographies and financial institution types. This enhances the discourse on financial inclusion and risk differentiation in emerging-market credit systems. Lastly, the review underscores the need for a holistic, multi-dimensional framework that combines technical, institutional, and regulatory elements for effective credit risk management in emerging economies. While previous research has advanced model development and performance benchmarking (Ahmed & Islam, 2009; Khan et al., 2009), there has been limited synthesis of how these models interact with real-world banking systems. This

Volume 02 Issue 01 (2022)
Page No: 01- 31
eISSN: 3067-0470
DOI: 10.63125/p7ym0327

study contributes by integrating model performance findings with contextual implementation insights, drawing on 98 articles across various sectors and geographies. It extends the work of Thomas, (Khan et al., 2009) by moving beyond comparative accuracy to focus on usability, sustainability, and institutional constraints. By bridging the gap between theory and practice, this review offers a comprehensive understanding of the systemic enablers and barriers to effective credit risk assessment in Bangladesh and comparable economies. It reinforces the conclusion that predictive power alone is insufficient; adoption success depends on explainability, adaptability, and institutional alignment.

CONCLUSION

This systematic review synthesized findings from 98 peer-reviewed articles to critically evaluate the development, application, and institutional integration of credit risk assessment models in emerging economies, with a particular focus on Bangladesh's commercial banking sector. The review revealed that while traditional models such as logistic regression remain dominant due to their interpretability and regulatory alignment, machine learning approaches—especially support vector machines, decision trees, and neural networks—have demonstrated superior predictive performance but face limited adoption due to institutional, infrastructural, and transparency barriers. Sector-specific applications were found to be underdeveloped, with many models failing to reflect the unique risks associated with industries like agriculture, garments, and microfinance. Similarly, the literature revealed limited use of alternative and real-time data sources, despite the growing digitalization of financial services. Few studies engaged in post-deployment validation or considered model recalibration, limiting long-term reliability. Additionally, institutional readiness—including technological infrastructure, staff capacity, leadership commitment, and regulatory clarity—was consistently identified as a constraint on effective model implementation. The review also highlighted a geographic and institutional concentration in the literature, with underrepresentation of microfinance institutions, fintech lenders, and fragile-state economies. These findings collectively underscore that effective credit risk modeling in emerging markets requires more than technical optimization; it demands contextual adaptation, institutional commitment, and a comprehensive governance framework that balances predictive power with operational feasibility and ethical accountability.

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