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Fair Credit Decision Assurance: An Ethical Governance Framework for AI-Based Credit Scoring in Bangladesh with Islamic Finance Duties

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ABSTRACT:

Purpose: Machine-learning credit scoring can extend formal credit to people with thin files, but alternative data can also turn social disadvantage into apparently neutral risk scores. This paper develops a governance framework for AI-based credit scoring in Bangladesh and adapts it to the duties of Islamic financial institutions.

Design/methodology/approach: The study is a structured integrative review combined with policy and doctrinal analysis. It synthesizes peer-reviewed research on algorithmic lending, fairness and explainability; international benchmarks (the EU AI Act, U.S. adverse action guidance, the NIST AI Risk Management Framework and the OECD AI Principles); Bangladeshi instruments on e-KYC, credit information, digital nano-loans, e-loans and data protection; and Islamic finance sources on maqasid al-Shariah, gharar and Shariah governance.

Findings: Bangladesh now permits fully digital small-value lending, yet its current instruments say little about model validation, bias testing, reason-giving or contestation. Predictive accuracy alone is an inadequate standard because a model can improve portfolio performance while concentrating false rejections on women, rural applicants or new-to-credit borrowers.

Originality/value: The paper proposes a Fair Credit Decision Assurance (FCDA) model with six gates: lawful data, feature relevance, fairness testing, explanation, human reconsideration and monitoring. A Shariah overlay adds product-level review and treats unexplained adverse decisions as a governance concern related to gharar.

Practical implications: The model gives banks, finance companies, mobile financial service providers and Bangladesh Bank a staged route to supervising algorithmic credit without halting innovation.

KEYWORDS: AI credit scoring, algorithmic fairness, explainability, financial inclusion, Islamic finance, maqasid al-Shariah, Bangladesh
JEL Classification: G21, G28, G51, O33, Z12

1. INTRODUCTION

Credit scoring has always rested on a simple bargain. Lenders summarize past behavior into a number, and applicants accept that number as a fair proxy for their likelihood of repayment. The bargain works reasonably well for people with long, documented borrowing histories. It works poorly for people who are new to formal finance, self-employed or active mainly in informal markets. Machine learning promises to close that gap by drawing on wider data and detecting non-linear relationships that scorecards miss (Bazarbash, 2019). Studies of digital footprints and mobile phone usage show that such signals can predict repayment where bureau data are thin or absent (Berg et al., 2020; Björkegren & Grissen, 2020; Óskarsdóttir et al., 2019).

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Wider data do not automatically produce fairer decisions. Location, handset type, transaction timing and contact patterns can stand in for gender, income, religion or place-based deprivation (Barocas & Selbst, 2016; Hurley & Adebayo, 2016). Evidence from the United States shows that algorithmic lenders can reduce some forms of discrimination while pricing differences persist (Bartlett et al., 2022), and that a more accurate model can still shift benefits unevenly across groups (Fuster et al., 2022). Fairness in credit is therefore a design and governance question rather than a by-product of automation.

The question has become urgent in Bangladesh. Bangladesh Bank introduced a refinance scheme for digital nano-loans in 2022 (The Daily Star, 2022) and extended it to June 2028 (The Daily Star, 2025). A major bank–mobile wallet partnership reports more than Tk 10,000 crore disbursed to over 3.5 million borrowers since its launch in December 2021, with eligibility determined from wallet transaction histories together with the partner bank's credit policy (Alo, 2026). In May 2026, Bangladesh Bank cleared banks to offer end-to-end digital "e-loans" of up to Tk 50,000 (Bangladesh Sangbad Sangstha [BSS], 2026; The Daily Star, 2026b). At the same time, a revised e-KYC framework takes effect in September 2026 (Bangladesh Bank, 2026). These developments make algorithmic credit decisions a routine part of retail and micro-enterprise lending. Yet, as Section 4 shows, the instruments that govern this market concentrate on identity verification, loan limits, authentication and data localization. They say little about how scoring models should be validated, tested for bias or explained to rejected applicants.

Islamic financial institutions face an additional layer of obligation. Bangladesh has a well-established Islamic banking sector, and its institutions are adopting the same digital channels as conventional lenders. Islamic commercial ethics require justice, truthful disclosure, valid consent and avoidance of harm (Beekun & Badawi, 2005; El-Gamal, 2006). Technological efficiency does not suspend those duties. A credit decision that a customer cannot understand or challenge raises questions that Shariah governance should address, even when the financing contract itself is valid.

This paper asks three research questions:

- RQ1. What ethical and legal risks arise at each stage of the AI credit-scoring lifecycle, and how do international benchmarks address them?
- RQ2. How well do Bangladesh's current instruments for e-KYC, credit information, digital lending and data protection cover those risks?
- RQ3. Which controls are needed for fair and contestable AI credit scoring, and how should they be adapted to the duties of Islamic financial institutions?

The paper makes three contributions. First, it maps the credit-scoring lifecycle against four benchmark regimes and five Bangladeshi instruments, identifying specific gaps rather than calling generally for "responsible AI". Second, it proposes the Fair Credit Decision Assurance (FCDA) model, which joins statistical fairness testing with procedural rights and institutional accountability. Third, it adds a Shariah overlay that links maqasid al-Shariah, the prohibition of gharar and Shariah governance standards to concrete control points, while keeping creditworthiness assessment separate from contract compliance.

2. LITERATURE REVIEW AND THEORETICAL BACKGROUND

2.1 Machine learning, alternative data and credit access

Credit-scoring research has long compared statistical and machine-learning classifiers. A large benchmarking study found that several advanced classifiers outperform logistic regression on standard credit datasets, although the gains vary across data and metrics (Lessmann et al., 2015). Interest has since shifted from the choice of algorithm to the choice of data. Berg et al. (2020) show that simple digital footprints, such as device type and e-mail domain, carry information about default that complements bureau scores. Björkegren and Grissen (2020) find that behavior revealed in mobile phone usage predicts credit repayment, which is attractive in markets where many borrowers have phones but no credit file. Óskarsdóttir et al. (2019) report that mobile phone data and social network analytics can improve scoring for applicants with limited financial histories. Gambacorta et al. (2024) provide related evidence from a Chinese fintech lender on how machine learning and non-traditional data affect credit scoring.

For policy institutions, the attraction is inclusion. Bazarbash (2019) describes how machine learning can assess the creditworthiness of individuals and small firms that lack collateral or formal records, while warning about data quality, privacy and model risk. The Alliance for Financial Inclusion (AFI, 2025) reaches a similar conclusion in its survey of member jurisdictions. It reports that only 16 of the 32 surveyed jurisdictions had frameworks governing personal data protection in the context of alternative credit scoring, and it notes that the methodologies of alternative scoring providers are often protected trade secrets, which makes compliance and bias difficult to verify.

The Bangladeshi evidence on digital finance is mostly about payments and remittances rather than credit. A field experiment by Lee et al. (2021) found that mobile banking increased urban-to-rural remittances by 26 percent and rural consumption by 7.5 percent among active users, and that extreme poverty fell. This finding matters for credit scoring because the transaction histories generated by such services are precisely the data that nano-lenders now use to set eligibility (Alo, 2026). The welfare gains from payments do not guarantee that a scoring model built on the same data will treat all users fairly.

2.2 Algorithmic fairness in lending

The fairness literature identifies several ways in which predictive models can disadvantage protected groups. Historical labels can encode past discrimination; proxies can reproduce protected attributes that have been removed; and samples can under-represent the groups that most need access (Barocas & Selbst, 2016). In credit, these mechanisms interact with economic incentives. Bartlett et al. (2022) find that algorithmic lending reduced but did not eliminate discrimination in U.S. mortgage pricing. Fuster et al. (2022) show that moving from a simpler to a more flexible model can increase overall predictive accuracy while distributing gains unequally across racial and ethnic groups. Aggarwal (2021) argues that algorithmic credit scoring also raises questions of autonomy and privacy that anti-discrimination law alone does not capture.

Formal definitions of fairness conflict. Kleinberg et al. (2017) prove that calibration within groups and balance of error rates cannot generally be satisfied together except in special cases, and Chouldechova (2017) reaches a parallel result for recidivism prediction. Hardt et al. (2016) propose "equality of opportunity", which requires equal true-positive rates across groups. Binns (2018) shows that each metric embodies a philosophical

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position about equality and desert, so the choice of metric is a normative decision rather than a technical default. Barocas et al. (2023) reach the same conclusion in a book-length treatment.

Credit-specific studies make these trade-offs concrete. Kozodoi et al. (2022) compare fairness criteria and processors for credit scoring and assess their profit implications. Bono et al. (2021) examine how algorithmic fairness concerns arise in credit markets and how regulators might respond. Kumar et al. (2022) map fairness research onto U.S. fair-lending law and show where common technical definitions diverge from legal concepts of disparate treatment and disparate impact. Kim et al. (2026) analyze microfinance data and find that unfairness that looks modest at the aggregate level can become larger when groups are examined intersectionally; attributes such as single-parent status and number of children produced imbalanced harm alongside legally protected characteristics. For a microfinance-heavy market such as Bangladesh, this intersectional result is directly relevant.

2.3 Explainability, contestability and due process

A second body of work concerns explanation. Citron and Pasquale (2014) argue that consequential scoring systems require "technological due process", including audit trails and meaningful notice. Wachter et al. (2018) propose counterfactual explanations that tell an individual what minimal change would have produced a different outcome, without disclosing the full model. Post-hoc attribution methods such as SHAP values (Lundberg & Lee, 2017) are now widely used in credit risk to show which features drove a prediction (Bussmann et al., 2021). Bücker et al. (2022) propose a framework for transparency, auditability and explainability of machine-learning credit models that combines global and local explanation tools.

Rudin (2019) challenges the post-hoc approach. She argues that high-stakes decisions should use inherently interpretable models where these perform comparably, because post-hoc explanations of black-box models can be unfaithful to the model's actual logic. For lenders, the practical implication is that explanation quality must be validated, not assumed.

Explanation also has two audiences. Validation staff need technical detail on performance, stability and bias; applicants need plain-language reasons they can act on. A feature-importance chart that cannot explain a particular rejection serves only the first.

Human review is often presented as the remedy for opaque automation. Research on automation bias warns that reviewers tend to defer to automated recommendations, especially under time pressure, and that complacency increases when the system is usually right (Parasuraman & Manzey, 2010). A human-review requirement therefore needs defined authority, time and documentation if it is to be more than a formality.

2.4 Islamic finance ethics and Shariah governance

Islamic finance offers a normative vocabulary that overlaps with, but is not identical to, the secular fairness literature. The objectives of the Shariah (maqasid al-Shariah) are commonly read as protecting faith, life, intellect, lineage and wealth. Laldin and Furqani (2013) argue that Islamic finance should be evaluated by whether its means (wasa'il) serve these ends, and not merely by formal contract compliance. Beekun and Badawi (2005) derive duties of justice ('adl), benevolence (ihsan) and trust (amanah) toward multiple stakeholders, including customers. El-Gamal (2006) shows how the prohibitions of riba and gharar function as rules about risk allocation and information in contracts.

Gharar refers to excessive uncertainty or ambiguity in a contract that can lead to dispute or unjust enrichment. AAOIFI addresses it through a dedicated standard on controls of gharar in financial transactions (Accounting and Auditing Organization for Islamic Financial Institutions [AAOIFI], 2015). Credit scoring is not itself a contract of exchange, so classical gharar rules do not apply to it directly. However, when an Islamic bank uses an opaque model to decide whether a customer may enter a financing contract, the customer faces uncertainty about the grounds of an outcome that materially affects their access to wealth. Zahid, Hossain, and Mohammed (2025) argue in the context of AI for Islamic finance that transparency in algorithmic decision-making is needed to avoid gharar. This paper adopts that position as an interpretive extension rather than a settled juristic ruling, and recommends that Shariah supervisory boards consider it explicitly.

Shariah governance standards set the institutional structure for such review. The IFSB's guiding principles assign the Shariah board responsibility for ex ante product approval and ex post compliance review (IFSB, 2009). More recent IFSB guidance on supervising Shariah governance encourages supervisors to use supervisory technology while maintaining data security and staff capacity (IFSB, 2025). Hassan et al. (2019) review the adoption of AAOIFI standards and note variation across jurisdictions. Billah and Zahid (2026) argue that AI tools in Shariah advisory must remain under human-in-the-loop Shariah governance because juristic judgment cannot be delegated to a model. Raquib et al. (2022) propose an Islamic virtue-based approach to AI ethics that emphasizes character, intention and social good.

2.5 Theoretical lens

The paper combines three lenses. The first is procedural and distributive justice. Distributive fairness asks who receives approvals, errors and burdens; procedural fairness asks whether data were lawfully collected, reasons were intelligible and reconsideration was real (Binns, 2018; Citron & Pasquale, 2014). A lender can satisfy one dimension while failing the other. The second is the capability approach, which judges finance by whether it expands people's real freedom to pursue valued activities rather than by account counts alone (Sen, 1999). The third is maqasid al-Shariah, which supplies an objectives-based test for whether technological means serve the protection of wealth and dignity (Laldin & Furqani, 2013). These lenses converge on a common requirement: an automated credit decision should be accurate, distributively defensible, procedurally contestable and consistent with the institution's ethical commitments. The AI ethics literature identifies similar principles (Floridi et al., 2018; Jobin et al., 2019; Mittelstadt et al., 2016), but rarely translates them into lender-level controls for a specific market.

2.6 Research gap

Three gaps follow from the review. First, most fairness evidence comes from the United States, Europe and China; little addresses South Asian digital nano-lending, where loan sizes are small, volumes are high and borrowers are often first-time users of formal credit. Second, the regulatory literature compares the EU and U.S. regimes but seldom tests developing-country instruments against them. Third, Islamic finance research on AI has focused on Shariah advisory, product screening and sustainable investment rather than on consumer credit decisions. This paper addresses all three.

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3. METHODOLOGY

3.1 Design

The study uses a structured integrative review combined with policy and doctrinal analysis. An integrative review is appropriate because the relevant evidence is heterogeneous: empirical finance studies, computer science, legal scholarship, regulatory texts and Islamic jurisprudential sources. The study does not estimate model performance or collect primary data.

3.2 Sources and search strategy

Academic sources were identified through Google Scholar, Crossref and publisher platforms (Elsevier, Oxford Academic, Wiley, Springer, Emerald, ACM and the proceedings of NeurIPS and PMLR). Search strings combined the terms "credit scoring", "machine learning", "alternative data", "digital footprint", "fairness", "discrimination", "explainability", "adverse action", "Islamic finance", "maqasid", "gharar" and "Shariah governance". The search covered 2014 to 2026, and foundational works outside that window were added through backward citation tracking where later studies relied on them.

Regulatory and policy sources were collected directly from official websites: Bangladesh Bank and the Bangladesh Financial Intelligence Unit (BFIU), the Consumer Financial Protection Bureau (CFPB) and the Federal Register, EUR-Lex, the National Institute of Standards and Technology (NIST), the OECD legal instruments database, the World Bank, the Islamic Financial Services Board (IFSB) and AAOIFI. Where a Bangladeshi circular was not yet reflected in the academic literature, reputable national newspapers were used to document market developments, and these are identified as press sources in the text.

3.3 Inclusion and exclusion criteria

Sources were included if they (a) addressed consequential credit decisions, data governance for lending or Islamic contractual accountability; (b) were peer-reviewed, issued by a regulator or standard-setter, or published by a recognized international organization; and (c) could be verified through a working DOI, an official repository or a publisher page. Opinion pieces without evidence, vendor marketing material and sources that could not be verified were excluded. Each bibliographic record was checked against Crossref, a publisher landing page or the issuing authority.

Because the search was iterative and purposive rather than a single database query, the paper reports the composition of the final corpus instead of a PRISMA flow diagram. The final corpus comprises 63 sources: 37 peer-reviewed articles, scholarly books, conference papers and working papers on credit, fairness, explanation, ethics and Islamic finance; 4 related papers by members of the authors' research network on AI, Islamic finance and digital-finance governance; 15 regulatory, standard-setting, central-bank and international-organization documents and datasets; and 7 press reports used only to document recent Bangladeshi market and policy developments.

3.4 Analytical procedure

The credit lifecycle was decomposed into six stages: data acquisition, feature design, model validation, decision use, communication and monitoring. At each stage, the analysis applied four tests drawn from the theoretical lens: legitimacy of purpose, proportionality of data, distribution of error and availability of remedy. Each benchmark regime and Bangladeshi instrument was then coded for whether it addresses the stage explicitly, partially or not at all. Islamic finance sources were analyzed doctrinally to identify which duties apply to credit assessment as distinct from the financing contract. The output is a governance framework and a set of testable propositions rather than an estimate of model performance.

4. FINDINGS

4.1 International benchmarks for AI credit decisions

Four international regimes provide the most developed reference points.

The EU AI Act. Regulation (EU) 2024/1689 classifies "AI systems intended to be used for assessing creditworthiness or credit score of natural persons" as high-risk under Annex III, point 5(b) (European Union, 2024). High-risk classification brings obligations on risk management, data governance, documentation, human oversight and accuracy. Deployers of such credit systems must also conduct a fundamental rights impact assessment under Article 27. Article 86 gives an affected person the right to obtain from the deployer "clear and meaningful explanations of the role of the AI system in the decision-making procedure and the main elements of the decision taken" (European Union, 2024, Art. 86(1)).

U.S. adverse action guidance. The CFPB has issued two circulars on algorithmic credit decisions. Circular 2022-03 states that "a creditor cannot justify noncompliance with ECOA and Regulation B's requirements based on the mere fact that the technology it employs to evaluate applications is too complicated or opaque to understand" (CFPB, 2022). Circular 2023-03 adds that creditors cannot rely on the sample adverse action checklist if its reasons do not reflect the actual grounds for denial, and that broad categories such as "purchasing history" are insufficient when a specific behavior drove the decision (CFPB, 2023). In the CFPB's words, creditors "cannot simply conduct check-the-box exercises" when delivering notices.

NIST AI Risk Management Framework. The AI RMF 1.0 is voluntary and sector-neutral (NIST, 2023). It organizes risk management into the functions Govern, Map, Measure and Manage and treats fairness with harmful bias managed, explainability and accountability as characteristics of trustworthy AI. Its value for lenders lies in providing a common structure for documenting how risks were identified and treated.

OECD AI Principles. The OECD Recommendation on Artificial Intelligence, adopted in 2019 and revised in November 2023 and May 2024, sets five values-based principles: inclusive growth and well-being; respect for the rule of law, human rights and democratic values, including fairness and privacy; transparency and explainability; robustness, security and safety; and accountability (OECD, 2024).

Table 1 compares these regimes with the Bangladeshi instruments discussed in Section 4.2.

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Table 1. Coverage of AI credit-scoring controls in international benchmarks and Bangladeshi instruments

Control area	EU AI Act (2024)	CFPB circulars (2022, 2023)	NIST AI RMF / OECD	Bangladesh instruments (2020–2026)
Risk classification of credit scoring	Explicit: high-risk (Annex III, 5(b))	Not a classification regime; ECOA applies to all creditors	Voluntary, risk-based	Draft AI policy proposes risk tiers; credit scoring not identified as high-risk in press reports
Data governance and lawful basis	Explicit (data governance duties)	Indirect	Explicit (Map, Govern)	e-KYC rules on storage and localization; data protection ordinance requires explicit consent
Bias and fairness testing	Explicit (risk management, data quality)	Implicit through ECOA anti-discrimination	Explicit (harmful bias managed)	Not addressed in digital-lending instruments reviewed
Explanation to applicant	Explicit (Art. 86)	Explicit: specific and accurate reasons	Principle-level	Not addressed
Human oversight or reconsideration	Explicit (human oversight)	Not specified	Principle-level	Not addressed for credit; draft AI policy refers to human oversight for high-risk uses
Impact assessment	Fundamental rights impact assessment (Art. 27)	Not required	Recommended	Draft AI policy proposes algorithmic impact assessments for high-risk uses
Credit history verification	Not specific	Not specific	Not specific	CIB verification required, with temporary flexibility for e-loans

Source: Authors' analysis of European Union (2024), CFPB (2022, 2023), NIST (2023), OECD (2024), Bangladesh Bank (2026), BFIU (2020), BSS (2026), The Daily Star (2026a) and The Business Standard (2025).

4.2 Bangladesh's digital credit and governance instruments

Financial inclusion context. Bangladesh's National Financial Inclusion Strategy 2021–2026 set 12 goals and 69 targets, and Bangladesh Bank's NFIS Administrative Unit reports that more than 67 percent of these targets had been fully achieved by the end of 2023 (Bangladesh Bank, 2024). The same report records more than 210 million mobile financial service accounts in December 2023, of which 42 percent were held by women. Survey-based measures tell a more cautious story. World Bank (2025b) data show that account ownership among Bangladeshi adults was 52.8 percent in 2021 and 43.3 percent in 2024, against a global figure of 79 percent (World Bank, 2025a). The gap between registered accounts and active, owned accounts suggests that many people remain at the margin of formal finance, and these are the people that alternative-data scoring is meant to reach.

Credit information. Bangladesh Bank's Credit Information Bureau (CIB) was established on 18 August 1992, began online services in 2011 and reset its reporting threshold to Tk 1 to widen coverage (Bangladesh Bank, n.d.). It collects data from banks and non-bank financial institutions and is working with the Microcredit Regulatory Authority to establish a separate bureau for microfinance institutions. AFI (2025) notes that the Bangladeshi CIB does not currently collect alternative data. Alternative-data scoring therefore takes place inside lenders and their technology partners, outside the bureau's correction and dispute processes.

Digital nano-loans. Bangladesh Bank created a Tk 100 crore refinance facility for digital nano-loans in 2022, for loans of Tk 500 to Tk 50,000 with a maximum tenor of six months and an interest rate of up to 9 percent, delivered only through digital channels (The Daily Star, 2022). By December 2023, Tk 4.37 billion had been refinanced to 355,908 beneficiaries, 22.26 percent of whom were women (Bangladesh Bank, 2024). The scheme was later extended to June 2028 (The Daily Star, 2025). Market reporting on the City Bank–bKash service states that eligibility is based on customers' wallet transaction history together with the partner bank's credit policy, and that loan limits adjust to transaction and repayment data (Alo, 2026). These are the conditions under which proxy discrimination can arise: the model uses behavioral data generated by a payment service, women make up a minority of borrowers, and the decision is fully automated.

E-loans. In May 2026, Bangladesh Bank issued guidelines allowing banks to offer end-to-end digital e-loans of up to Tk 50,000 with a tenor of up to 12 months (BSS, 2026; The Daily Star, 2026b). The guidelines require biometric verification, one-time passwords with two-factor or multi-factor authentication, a six-month pilot before commercial launch, board approval, data storage in Bangladesh and verification of borrowers' credit histories, with temporary flexibility on real-time CIB inquiries until automation is complete (BSS, 2026). Press coverage reports no reference to artificial intelligence, algorithmic scoring or adverse action reasons (BSS, 2026; The Daily Star, 2026b).

e-KYC. The BFIU's e-KYC guidelines, issued under BFIU Circular No. 25 of 8 January 2020, introduced simplified and regular e-KYC tiers based on National ID verification with fingerprint or face matching (BFIU, 2020). Bangladesh Bank's BRPD-1 Circular No. 08 of 11 March 2026 issues revised guidelines for banks, finance companies, mobile financial service providers and payment service providers, effective 1 September 2026 (Bangladesh Bank, 2026). It retains the risk-based tiers, requires that customer data not be transferred outside Bangladesh without Bangladesh Bank's approval, and sets periodic review at least annually for high-risk customers and every five years for low-risk customers. On our reading, the circular does not expressly address secondary use of e-KYC data for credit scoring or customer consent to such use.

Data protection. The government gazetted the Personal Data Protection Ordinance, 2025 and the National Data Governance Ordinance, 2025 on 6 November 2025 (The Business Standard, 2025). Press reports describe explicit consent requirements before collection, storage, transfer or use of personal data and enhanced protection for sensitive data including financial and biometric information (The Business Standard, 2025). The 2026

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e-loan guidelines refer lenders to the national data protection and cybersecurity framework (BSS, 2026). The exact legislative status of these instruments after the 2026 parliamentary transition should be confirmed against the official gazette before final publication.

AI policy. The draft National AI Policy 2026–2030 proposes four risk tiers (prohibited, high, limited and low) and requires algorithmic impact assessments and human oversight for high-risk uses (The Daily Star, 2026a). Press reports list healthcare and law enforcement as high-risk examples and social scoring as prohibited, but do not mention credit scoring (The Daily Star, 2026a). Whether algorithmic creditworthiness assessment will be treated as high-risk, as it is in the EU, remains open.

Overall, Bangladesh has built strong foundations for identity, authentication, credit history and data localization. The gap lies in the decision layer: how models are validated, how bias is tested, how reasons are given and how decisions can be contested.

4.3 Risks across the credit lifecycle

Table 2 summarizes the main risk at each lifecycle stage and the evidence a lender should be able to produce.

Table 2. Lifecycle risks and assurance evidence for AI credit decisions

Stage	Material risk	Illustrative Bangladeshi exposure	Assurance evidence
Data acquisition	Weak consent, intrusive data, repurposing	Wallet and e-KYC data reused for scoring without specific consent	Data inventory, lawful basis, necessity test, retention schedule
Feature design	Proxy discrimination, spurious correlation	Transaction timing, location or handset as proxies for gender or rurality	Feature rationale, sensitivity tests, protected-group review
Model validation	Unequal error hidden by aggregate accuracy	Women are a minority of nano-loan borrowers, so errors for them are diluted in portfolio metrics	Calibration and error rates by group and intersection, with confidence intervals
Decision use	Automation bias, unsuitable overrides	Fully automated approval with no staff contact	Human-review criteria, authority, override logs
Communication	Opaque rejection, no correction path	No standard adverse-action notice in digital-lending instruments	Specific reason notice, accessible reconsideration channel
Monitoring	Drift, feedback loops, exclusion	Rejected applicants never enter repayment data	Outcome, complaint, override and new-to-credit dashboards

Source: Authors' synthesis of Barocas and Selbst (2016), Bücker et al. (2022), CFPB (2022, 2023), Kim et al. (2026), NIST (2023) and the Bangladeshi instruments in Section 4.2.

Data acquisition. Consent is weak when a borrower must surrender extensive phone or wallet data to obtain essential credit. Data gathered for e-KYC serve an anti-money-laundering purpose and should not be silently repurposed for behavioral scoring, a point strengthened by the explicit-consent principle in the 2025 data protection ordinance (The Business Standard, 2025).

Feature design. Removing a gender field does not remove gendered patterns in occupation, mobility or transaction behavior (Barocas & Selbst, 2016). In Bangladesh, women are a minority of MFS account holders and of nano-loan beneficiaries (Bangladesh Bank, 2024). Features such as transaction frequency, top-up timing or the number of distinct counterparties may correlate with gender, household role or rural residence. Each feature should therefore have a written rationale, and sensitivity tests should show how outcomes change when it is removed.

Model validation. Aggregate accuracy can conceal unequal error. If women or rural applicants are under-represented in training data, a model may have higher false-negative rates for them, wrongly rejecting creditworthy applicants, without any visible drop in overall performance. The intersectional evidence of Kim et al. (2026) suggests that analysis by single attributes is insufficient. Validation should compare approval rates, false-negative and false-positive rates and calibration across relevant groups and their intersections. Because no single metric is universally correct (Kleinberg et al., 2017), the lender must justify its choice in relation to the product and the most likely harm. For small-value credit to first-time borrowers, a false rejection may close the door to formal finance, so false-negative parity deserves particular weight.

Decision use. Fully automated nano-lending removes the loan officer entirely, and where staff do intervene, automation bias may lead them to defer to the model even against local evidence (Parasuraman & Manzey, 2010).

Communication. The CFPB circulars show that "internal policy" or generic categories are not explanations (CFPB, 2022, 2023). A rejected applicant should receive the principal specific reasons, stated in Bangla and in plain language, together with a channel for correction. Counterfactual explanations of the form "the application would have been approved if monthly wallet inflows had exceeded X over three months" can be useful where they are accurate and do not encourage gaming (Wachter et al., 2018).

Monitoring. If rejected applicants never enter the repayment dataset, the model learns mainly from people it previously approved. This selective-labels problem can entrench early exclusion. Periodic review should examine overrides, complaints and performance by group, and should test whether alternative data actually bring new-to-credit customers into sustainable borrowing.

4.4 Islamic finance duties in AI credit assessment

Islamic financial institutions in Bangladesh offer financing through contracts such as murabahah, ijarah and musharakah rather than interest-bearing loans. Credit assessment determines whether, and on what terms, a customer may enter those contracts. Three implications follow.

First, a compliant score cannot cure a non-compliant contract, and a compliant contract does not make an unjust scoring process acceptable. Contract-level compliance is governed by AAOIFI standards and the institution's Shariah supervisory board (AAOIFI, 2015; IFSB, 2009). The scoring process should be reviewed separately for consistency with justice, truthful disclosure and avoidance of harm (Beekun & Badawi, 2005).

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Second, the separation between creditworthiness and pricing requires care. An Islamic institution may use a score to decide eligibility and limits, but it must ensure that risk-based terms are implemented through permissible contractual mechanisms. Model outputs that feed directly into profit rates, penalty structures or collateral demands should pass through product-level Shariah review.

Third, the maqasid lens adds an objectives test. Protection of wealth (hifz al-mal) supports access to useful finance and protection from harmful debt. A model that systematically excludes creditworthy applicants, or that steers vulnerable borrowers into unaffordable repeated borrowing, works against that objective even when each contract is formally valid (Laldin & Furqani, 2013). Table 3 maps these principles to control points.

Table 3. Islamic finance principles mapped to AI credit-scoring controls

Principle	Meaning in credit assessment	Control point in the FCDA model	Primary owner
'Adl (justice)	Comparable applicants receive comparable treatment; errors are not concentrated on weaker groups	Fairness gate: group and intersectional error testing	Model risk with Shariah review of results
Avoidance of gharar	Customers are not left in material uncertainty about the grounds of decisions affecting their access to finance	Explanation gate: specific, accurate reasons	Business and compliance, with Shariah oversight of customer communication
Rida (valid consent)	Data use is understood and freely agreed	Lawful-data gate: specific consent, no silent repurposing	Compliance and data protection
La darar wa la dirar (no harm)	Scoring does not push borrowers into harmful or unaffordable debt	Relevance and monitoring gates: affordability features, repeat-borrowing review	Credit risk and Shariah audit
Amanah (trust)	Customer data are held in trust and used only for stated purposes	Lawful-data and monitoring gates: retention, access control	Information security and internal audit
Maqasid (hifz al-mal)	Finance expands real economic opportunity	Monitoring gate: sustainable new-to-credit approvals	Board and Shariah supervisory board

Source: Authors' analysis drawing on AAOIFI (2015), Beekun and Badawi (2005), El-Gamal (2006), IFSB (2009) and Laldin and Furqani (2013).

5. THE FAIR CREDIT DECISION ASSURANCE (FCDA) MODEL

5.1 Structure

The FCDA model contains six sequential gates, a cross-cutting governance layer and a Shariah overlay for Islamic institutions. Figure 1 shows how the six gates, the governance layer and the Shariah overlay fit together.

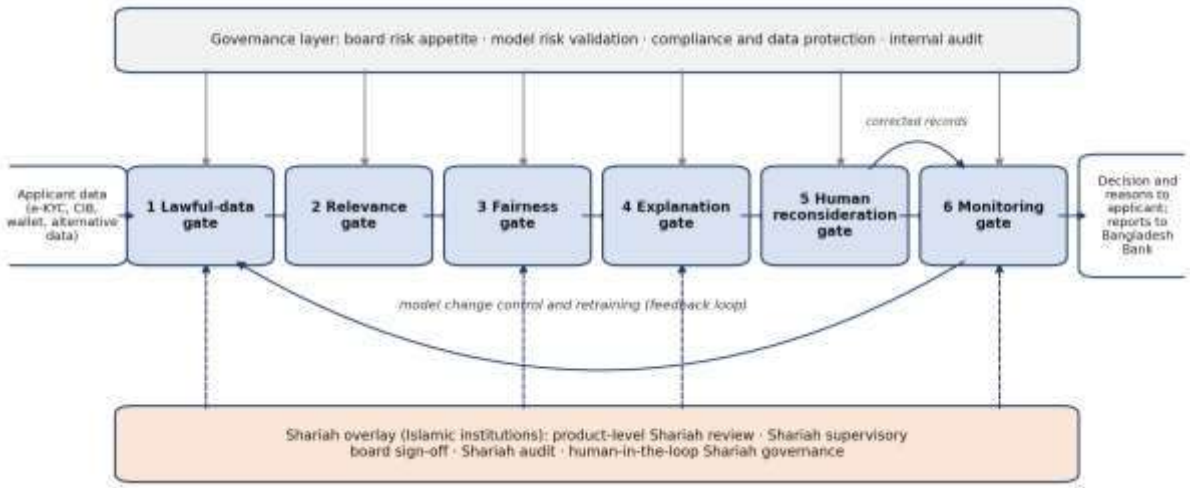


Figure 1. The Fair Credit Decision Assurance (FCDA) model
Source: Authors' own elaboration.

Gate 1: Lawful data. The lender records each data source, its lawful basis and consent, its retention period and prohibited uses. Data obtained for e-KYC or AML purposes are not used for scoring without specific consent. Intrusive data such as contact lists and message content are excluded by default.

Gate 2: Relevance. Every feature must have a defensible credit-risk rationale. Features with high predictive value but no plausible causal link to repayment, or with strong correlation to protected or vulnerable characteristics, require documented justification or removal.

Gate 3: Fairness. The model is tested for approval rates, false-negative and false-positive rates and calibration by gender, age band, rural or urban residence and, where lawful, other relevant attributes and their intersections. The lender documents which metric it prioritizes and why. Small groups are reported with confidence intervals and qualitative review rather than treated as fair because differences are not statistically significant.

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Gate 4: Explanation. Decision drivers are translated into accurate, specific, customer-facing reasons in Bangla. The lender validates that the stated reasons match the model's actual logic, which favors interpretable models or well-tested attribution methods (Bussmann et al., 2021; Rudin, 2019).

Gate 5: Human reconsideration. An applicant who receives an adverse decision can request review by trained staff who have authority to reverse it, access to the evidence and time to consider it. Overrides are logged with reasons.

Gate 6: Monitoring. Portfolio performance, approvals and errors by group, complaints, override patterns, corrected records and new-to-credit outcomes are reported to the model risk committee and linked to model change control.

5.2 Governance layer

Responsibility is divided but coordinated. The board approves the risk appetite for automated credit and receives fairness and complaint metrics alongside default rates. The model risk function validates performance, stability and fairness independently of model developers. Compliance and data protection officers assess lawful processing. Business units own customer outcomes and the quality of reason notices. Internal audit tests whether the gates operate as designed. Where a third-party provider supplies the model, as is common in wallet-based lending, the lender retains accountability; contractual opacity is not a defense when the lender makes the decision (CFPB, 2022).

5.3 Shariah overlay

In Islamic institutions, the Shariah supervisory function reviews data practices, contractual use of scores and customer communication. It does not validate the statistical model, which remains the task of qualified model experts. This division follows the human-in-the-loop principle: AI may support analysis, but Shariah judgment and accountability remain with qualified humans (Billah & Zahid, 2026). Shariah review should occur at design and change-control stages, not only after deployment. Complaint and service-recovery data should flow to the Shariah audit function, since structured feedback systems and Shariah-compliant communication help Islamic fintech providers retain customer trust after service failures (Zahid, Amin, et al., 2025).

Table 4 sets out the gates, their key questions and indicative metrics.

Table 4. FCDA gates, key questions and indicative metrics

Gate	Key question	Indicative metrics or evidence	Shariah overlay question
1. Lawful data	Is each source lawful, necessary and consented to?	Data inventory coverage; share of features with documented lawful basis	Is customer data held as amanah and used only for disclosed purposes?
2. Relevance	Does each feature have a credit-risk rationale?	Feature rationale log; proxy-correlation tests	Does any feature penalize permissible religious or social practice?
3. Fairness	Are errors distributed defensibly?	Approval-rate ratio; false-negative rate gap; calibration by group and intersection	Is the outcome consistent with 'adl?
4. Explanation	Can the applicant understand and act on the reason?	Share of adverse notices with specific reasons; reason-accuracy audit	Does the notice avoid leaving the customer in material uncertainty (gharar)?
5. Human reconsideration	Is review real and timely?	Requests received; median days to decision; reversal rate	Is a qualified human accountable for the outcome?
6. Monitoring	Is the model expanding sustainable access?	New-to-credit approvals; repeat-borrowing intensity; complaint outcomes; drift indicators	Does the portfolio serve hifz al-mal without harmful debt?

Source: Authors' proposal.

5.4 Propositions

Four propositions follow from the model and can guide empirical work.

- **P1.** AI credit scoring improves inclusion only when it increases sustainable approvals among underserved applicants without a disproportionate increase in harmful errors for those groups.
- **P2.** Specific reason notices combined with accessible reconsideration improve data quality over time, because corrected records feed better decisions.
- **P3.** Fairness metrics computed only on single attributes will understate disparities that appear in intersectional analysis of digital nano-loan portfolios.
- **P4.** In Islamic institutions, Shariah review is more effective when embedded at design and change-control stages than when added after deployment.

5.5 Piloting the model

A lender adopting the model should begin with a shadow phase in which the AI model scores applications but does not decide them. Historical back-testing can compare the model with existing practice, but historical labels may contain past discrimination. Prospective testing should therefore record recommendations, human decisions, reasons, overrides and eventual performance. An independent review group should examine a sample of adverse cases and customer notices before controlled deployment. Bangladesh Bank's six-month pilot requirement for e-loans (BSS, 2026) offers a natural vehicle: fairness and reason-quality metrics could be added to the pilot evaluation reports that banks already submit.

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6. DISCUSSION

The findings confirm, in the Bangladeshi setting, a central result of the fairness literature: predictive performance and fairness are distinct properties that must be assessed separately (Fuster et al., 2022; Kleinberg et al., 2017). Bangladesh's digital nano-lending market illustrates why. The City Bank–bKash service reports a default rate of less than 1 percent (Alo, 2026). A low default rate shows that approved borrowers repay; it says nothing about creditworthy applicants who were rejected. Those false negatives are invisible in portfolio data, and the selective-labels problem means the model never learns from them. Women formed just over a fifth of refinanced nano-loan beneficiaries by December 2023 (Bangladesh Bank, 2024). This share cannot by itself show bias, because demand, eligibility and access to wallets all differ by gender, but it is the kind of pattern that the FCDA fairness gate is designed to investigate.

The comparison with international regimes shows that Bangladesh has followed a sequence common in developing markets: identity and authentication first, decision governance later. The e-KYC framework, CIB coverage and data localization requirements compare well with peer jurisdictions. The decision layer, however, lacks the specific obligations found in Article 86 of the EU AI Act and the CFPB circulars. Introducing adverse action requirements does not require adopting the EU regime wholesale. The CFPB approach, which attaches reason-giving duties to existing credit law rather than creating a new AI regulator, may be easier to implement through a Bangladesh Bank circular.

The draft National AI Policy's risk-based approach could close part of the gap if algorithmic creditworthiness assessment is classified as high-risk. Social scoring is reportedly prohibited under the draft (The Daily Star, 2026a), which raises a definitional question. Credit scoring that draws on social-network or behavioral data from outside the financial relationship sits close to the boundary between legitimate creditworthiness assessment and social scoring. The EU AI Act draws this line by treating credit scoring as high-risk while prohibiting certain forms of social scoring (European Union, 2024). Bangladeshi policymakers will need to draw a similar line.

For Islamic finance, the analysis supports and extends existing work. Laldin and Furqani (2013) argue that Islamic finance should be judged by whether its means serve the maqasid. This paper applies that argument to a means that did not exist when most Shariah standards were drafted. Extending the logic of gharar avoidance from contract terms to decision processes is an interpretive step; it is consistent with the emphasis on transparency in AI-enabled Islamic finance (Zahid, Hossain, & Mohammed, 2025) but has not been endorsed by a standard-setter. AAOIFI and IFSB guidance currently addresses Shariah governance structures and supervisory technology (IFSB, 2025) rather than customer-facing algorithmic decisions. The FCDA Shariah overlay offers a practical starting point that Shariah boards can test and refine.

The model also connects to concerns about consumer vulnerability. Rapid growth of digital finance in Bangladesh has been accompanied by fraud and scams, and Haque et al. (2026) argue that financial literacy, cybersecurity awareness and Islamic ethical finance must work together to protect users. Clear, standardized reason notices issued through official channels can help applicants distinguish legitimate lenders from fraudulent loan offers that imitate them. Conversely, opaque rejection by legitimate lenders may push declined applicants toward informal or fraudulent sources.

Finally, studies showing that phone and digital-footprint data predict repayment (Berg et al., 2020; Björkegren & Grissen, 2020) establish feasibility, not fairness, and the AFI (2025) survey shows that Bangladesh's governance gap is shared by many developing markets.

7. IMPLICATIONS

7.1 Theoretical implications

The paper contributes to the fairness literature by separating distributive and procedural fairness in a lending framework and showing that each requires distinct evidence. Equal approval rates can conceal arbitrary data collection, and accurate reasons do not cure systematically harmful error. It also extends maqasid-based analysis of Islamic finance from products to decision processes, and proposes that the avoidance of gharar can inform how Islamic institutions communicate automated decisions. The capability lens adds a criterion often missing from credit-scoring research: whether alternative data expand real economic opportunity for new-to-credit borrowers over time, rather than only reducing defaults.

7.2 Practical implications for lenders

Banks, finance companies and MFS providers that use or plan AI credit scoring can apply the FCDA gates without waiting for regulation. Three steps are immediately feasible. First, build a data inventory that records the lawful basis and purpose for each scoring feature. Second, compute approval and error rates by gender and rural or urban residence on existing portfolios, using confidence intervals for small groups. Third, replace generic rejection messages with specific Bangla-language reasons and a simple reconsideration channel. Incentives matter too: teams rewarded only for speed, default reduction or disbursement volume will neglect explanation quality and exclusion, so scorecards should also track sustainable new-to-credit approvals, complaint outcomes and time to reconsideration.

For Islamic institutions, Shariah supervisory boards should add AI credit models to their product approval checklists, review customer notices and receive periodic fairness and complaint reports through the Shariah audit function.

7.3 Policy implications for Bangladesh Bank and government

Five policy measures follow from the gap analysis.

1. **Adverse action notices.** Bangladesh Bank could require lenders that use automated scoring for nano-loans and e-loans to give the principal specific reasons for rejection or adverse limit changes, in Bangla, through the same channel as the application.
2. **Algorithmic impact assessment.** Lenders could be required to complete and file an impact assessment for AI systems that approve, price or limit credit, covering data sources, fairness testing and complaint handling.
3. **Fairness metrics in pilots.** The six-month e-loan pilot reports could include approval and error rates by gender and location, the share of adverse notices with specific reasons, and reconsideration outcomes.
4. **Data use limits.** Guidance could clarify that e-KYC data collected for AML purposes require separate, specific consent before use in credit scoring, consistent with the explicit-consent principle in the data protection framework.
5. **Risk classification.** The National AI Policy could classify algorithmic creditworthiness assessment of natural persons as high-risk and clarify its boundary with prohibited social scoring.

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Supervisory attention can begin with high-volume retail and micro-enterprise products, where small individual decisions add up to large aggregate effects. Privacy-preserving supervisory datasets would allow Bangladesh Bank to test fairness across lenders without exposing sensitive personal data.

8. LIMITATIONS AND FUTURE RESEARCH

The study is conceptual and does not analyze proprietary lending data, so it cannot estimate the size of any disparity in Bangladeshi digital credit. Several Bangladeshi developments, including the 2026 e-loan guidelines and the draft AI policy, are documented through press reports because the primary texts were either very recent or not accessible to the authors; their final provisions may differ. The legal status of the 2025 data protection ordinances under the new parliament also needs confirmation. The Islamic finance analysis reflects the authors' interpretation of general principles and standards; it is not a fatwa, and Shariah boards may reach different views on how gharar applies to decision processes.

Protected-group information may be incomplete or legally sensitive, which complicates bias testing. Future research should (a) test the FCDA propositions on anonymized nano-loan and e-loan portfolios in partnership with lenders or Bangladesh Bank; (b) conduct interviews with declined applicants, particularly women, rural customers and micro-entrepreneurs, whose experiences are absent from datasets built only on approved borrowers; (c) survey Shariah supervisory board members on whether and how they review AI credit models; and (d) compare reason-notice designs experimentally for comprehension in Bangla.

9. CONCLUSION

AI credit scoring should be judged by the quality of opportunity and remedy it creates, not by prediction alone. Bangladesh has built the infrastructure for fully digital small-value credit: biometric e-KYC, an expanded credit bureau, data localization, refinance support and e-loan guidelines. What it lacks is a decision layer that tells lenders how to validate models for fairness, how to explain rejections and how to let applicants contest them. The Fair Credit Decision Assurance model fills that gap with six gates covering lawful data, feature relevance, fairness testing, explanation, human reconsideration and monitoring, supported by clear institutional ownership. For Islamic financial institutions, the Shariah overlay keeps justice, valid consent, avoidance of gharar and the objectives of the Shariah within the technical lifecycle, while leaving statistical validation to qualified experts and Shariah judgment to qualified scholars. Introduced through pilots and existing supervisory channels, these controls would allow Bangladesh to expand algorithmic credit without sacrificing the dignity and procedural fairness owed to every applicant.

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Author contributions: Sumaia Yasmin Keya: Conceptualization, Methodology, Writing – original draft, Project administration. Niger Sultana: Investigation, Formal analysis, Writing – review & editing. Md. Baharul Hasan: Investigation, Data curation. Md. Shahed Alamm: Methodology, Validation (Islamic finance and Shariah governance), Writing – review & editing, Supervision. Md. Aminul Islam: Investigation, Visualization. Ummey Sumaiya: Validation, Writing – review & editing. All authors read and approved the final manuscript.

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