

From Perceived Gender Bias to Trust in AI-Enabled Digital Lending: A Procedural Fairness Framework for Nigeria

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ABSTRACT

Potential exists for AI-based and alternative data scoring to increase the availability of credit, and for discrimination based on gender or gendered data to further entrench structural disadvantage, or create an impression that gender data was used in the decision-making process. While research has previously considered statistical fairness, explainability, and technology acceptance, there is little understanding of the interpretive process through which discrimination allegations are turned into distrust. This conceptual article develops a procedural fairness process model for artificial intelligence enabled digital lending in Nigeria. It integrates contemporary research on procedural justice, algorithmic trust, and institutional assurance to outline a process in which individuals interpret decision clues, causally associate decisions with gender or gender-related data, evaluate procedural neutrality, correctness, accuracy, and appeal ability, and finally adjust their trust towards the algorithm and lending institution. Explanation, credible contestability, and successful human reassessment are considered as procedural fairness generators, rather than as alternatives to transparency. The perception of regulatory assurance dictates whether a fair process of platform lending leads to trust, while outcome favorability and attribution ambiguity determine initial assessments. The proposed framework separates perceived bias from measured disparity, procedural from distributive fairness, and trust from continued use despite financial necessity. Nigeria is viewed as a setting that defines the study due to the nature of informality, inequality of digital footprints, device sharing practices, different levels of literacy, and emerging consumer protection institutions. The article formulates revised hypotheses, competing theories, and a multi-method agenda for empirical research.

Keywords: algorithmic fairness; artificial intelligence; digital lending; gender bias; Nigeria; procedural fairness; regulatory assurance; trust

INTRODUCTION

The rise of digital lending has changed the way in which households and microenterprises acquire short-term credit. Interfaces, identification verification, non-traditional data sources, and machine learning models allow lenders to assess applicants efficiently in volumes that are hard to replicate for traditional branch underwriting. This possibility becomes especially appealing in countries with partial credit histories and large informality rates. However, the transition moves crucial assessments from open face-to-face interactions to complex data-driven processes, the inputs of which are frequently invisible to applicants. As a result, efficiency comes with a legitimacy problem: while a borrower receives a quick decision, they do not know the reason behind it, whether other comparable applicants are treated consistently, or how to redress any mistake made.

Gender compounds this legitimacy problem. Credit algorithms can exclude gender as an explicit variable and still learn gender-related patterns from income regularity, occupation, mobile phone usage, location, mobility, transaction network, or presence of a digital footprint. History data can encode preexisting inequalities in labor market participation, asset ownership, and access to formal finance. Data gaps can themselves be socially structured. Hence, the relevant harm goes beyond intentional discrimination and includes reproduction of existing inequalities through neutral variables and lack of users' capacity to detect, challenge, and solve the process behind the decision (Bartlett et al., 2022; Fuster et al., 2022; Mehrabi et al., 2021).

A technical audit can show differences in error rates, approval probabilities, or calibration among various groups. However, such an analysis alone cannot establish whether users perceive the process as a fair one. On the other hand, users can experience bias when a model meets some chosen statistical criteria. An explanation of a rejection, a comparison with another borrower, bad data quality, repeated bad experiences, a public scandal, or lack of opportunities for review on the side of the platform can lead to a perception of bias. The difference is important since behavior is driven by experiences and interpretations of those. A credit model may be statistically justified but not generate trust, whereas another may work to borrowers' benefit but avoid scrutiny due to problematic design. New literature suggests that explanations, perceptions of fairness, and users' interpretations of algorithmic procedures affect trust and acceptance (Shin, 2021; Shulner-Tal et al., 2023).

Trust is crucial in digital credit since users expose themselves to multiple vulnerabilities. They share their personal and behavioral data, undergo an opaque assessment process, become obliged to repay the loan, and get subject to consequences of the decision for their future ability to acquire credit. Hence, trust is about more than accuracy of predictions. In this paper, the competence of the platform, its integrity, proper use of data, and respect of power asymmetries are assumed. Such trust claims can be precarious in case of limited choices available to consumers or when there is little confidence in the effect of complaining.

The hypothesis advanced here is that procedural fairness is the missing link between perceived gender bias and trust. New algorithmic fairness research shows that people evaluate automated authorities based on more than just outcomes. Neutrality, consistency, accuracy, voice, correctability, and ethics of the decision process play a role as well (Lee et al., 2019; Shulner-Tal et al., 2023). This means that in the context of automated credit decisions, users want to make sure that relevant information is taken into account, similar cases are treated similarly, decision can be explained, and mistake can be fixed by an independent reviewer. Gender bias damages trust since it suggests that those procedural requirements are not met.

Nigeria serves as an interesting theoretical environment. Digital lending in Nigeria brings together a significant demand for easy access to small-value loans and imperfect formal credit histories, substantial informal economy, digital disparities, and emerging consumer protection and data protection laws. Studies on digital finance in developing countries show that new technologies can expand access to financial products while access to the latter, their affordability, people's digital capacity, and institutional conditions determine the beneficiaries (Ozili, 2018). This means that there is a key contradiction: digital lending may increase access but at the same time make eligibility of users dependent on data footprints, which vary by social group.

This paper seeks to answer the following question: How does perceived gender bias impact trust of users in AI-enabled digital lending platforms, and how do procedural fairness mechanisms mediate the relationship in Nigeria? Four contributions are made here. First, a distinction is made between objectively measured disparity and perceived gender bias, and both are recognized as important but not interchangeable concepts. Second, procedural fairness is seen as an intermediary variable explaining how bias perception impacts trust judgment. Third, explanation, appeal, human review, and regulatory assurance are identified as mechanisms of procedural fairness, the effectiveness of which depends on their substantive legitimacy. Fourth, the above relationships are situated within the context of Nigeria rather than treated as a mere control variable. This framework is directly testable and can be used as a basis for further empirical investigation.

The proposed framework is developed as a process rather than simply as a combination of independent predictors. Borrowers observe certain cues first: adverse decision, a request for irrelevant information, comparison with another applicant, generic explanation, and non-responsive complaint channel. Then they make an attribution of causes of the decision. If gender or situations related to gender become the reasons for an unfavorable result, the attribution allows them to judge the fairness of the procedure, which then influences trust in the competence of the algorithm and integrity of the lender. The sequencing is critical since explanations, appeals, and human reconsiderations cannot be introduced indiscriminately as moderators. Instead, they constitute organizational mechanisms, which ensure observability of neutrality, accuracy, voice, and correctability.

In the above way, a simple process sequence is outlined while retaining context's complexity. Not only it explains why bias perceptions can undermine trust but also when certain safeguards can rectify misunderstandings, reveal actual procedural problems, and even decrease inappropriate trust. The normative goal is warranted and calibrated trust rather than maximizing trust.

Conceptual Review Approach

This article makes an integrative review of the literature in a critical manner that seeks to bridge research that would normally be conducted separately within information systems, fintech, organisational justice, human-computer interaction, law and development. An integrative approach is relevant here since the focal issue is not captured by one empirical tradition alone: technical research measures disparities among groups, behavioral research looks at perceptions of justice, trust research measures willingness to take risks, while legal research specifies rights and obligations.

The review took the form of combinations of such terms as algorithmic bias, gender discrimination, digital credit, alternative data, procedural justice, perceived fairness, explainable AI, contestability, human review, institutional trust, financial inclusion and Nigeria. In order to stay up-to-date with the evidence, only peer-reviewed journal articles from 2017 to 2026 were used as scholarly references. Legal statutes and regulations from Nigeria were analysed as context-specific legal sources but were not listed as references in journal articles.

There were three steps to conducting the synthesis: the first step consisted of differentiating the constructs in order to avoid collapsing the constructs into each other: perceived bias from audited disparity, procedural fairness from favorable outcomes and trust from adoption or continued usage. The second step was determining the causal ordering, which involved examining what users could notice before, during and after the lending decision. Finally, propositions were proposed based on the theoretical mechanisms explaining how one construct changes another.

AI-Enabled Digital Lending and Gendered Data Production in Nigeria

Inclusion potential and data dependence

Traditional loans normally need documented income, collateral, bureau reports, and previous banking relationship. The criteria can place individuals at a disadvantaged position because of irregular income, unformalized business operations, or the lack of property under one's name. Digital finance providers try to solve the problem of information gaps through utilizing transaction history, device/account information, payment behavior, and other forms of digital footprints. International literature suggests that digital footprints can help predict creditworthiness in cases of poor conventional credit information (Berg et al., 2020) and change the process of underwriting through the change in its speed, scope, and basis (Jagtiani & Lemieux, 2019).

However, the inclusion argument should not be taken for granted. Alternative data are generated through the access to devices, connectivity, formal accounts, stable employment, and transactions digitization. A sparse digital footprint can reflect the experience of being structurally excluded from finance rather than poor creditworthiness. Different positions of women in the process of data generation can be caused by the difference in income, property ownership, form of occupation, care responsibilities, mobility, and household control over technology. Cross-national literature still confirms gender gaps in internet and mobile connectivity, especially in economically and socially unequal societies (Fatehkia et al., 2018). If the ability to generate positive data is unequally distributed, the neutral scoring system can transform the social inequality into a risk signal.

The Nigerian path of financial inclusion proves this duality. Digital finance has the potential to increase access to finance of people left outside the scope of traditional underwriting, but its inclusion effects depend on infrastructural support, affordability, literacy, consumer protection, and institutional quality (Ozili, 2018). Therefore, digital credit has the potential to provide services to people ignored by conventional financing and at the same time create a segmented market where financially vulnerable people use small, expensive, and limited products based on assumptions they are not able to examine. The question is not about inclusiveness or

exclusiveness of digital lending in abstract, but about the cases when the processes of underwriting will be considered legitimate from different situations of users.

The important point is not just the algorithm but also the data generating environment. Unpaid labor, shared devices, household control of accounts, and limited access to identification documents influence the amount of digital traces and their interpretation as a risk despite the limited opportunities for generation of formal data. The device-level factors can describe the whole household rather than the individual user. Therefore, gendered data generation becomes the point of technical disparity and perception of unfairness.

Gender discrimination can go beyond approval. Limits on credit usage, pricing, repayment terms, requests for personal connections, and collection practices can become the stages of the process of perceived bias. The approach focused on acceptance/rejection dichotomy will therefore miss these critical stages of digital credit relations.

Evolving consumer and data governance

Increasingly, governance of Nigeria understands that digital lending poses issues related to privacy, consumer protection and accountability of decision-making. Principles of lawfulness, fairness and transparency of processing, and rights of data accuracy and automated decision-making are established under the Nigeria Data Protection Act 2023. The Nigeria Data Protection Commission's General Application and Implementation Directive also makes clear the requirements for automated decisions having legal or equivalent significance, including the importance of human intervention and challenge.

While the Federal Competition and Consumer Protection Commission had developed an interim registration framework in 2022, the Digital, Electronic, Online or Non-Traditional Consumer Lending Regulations 2025 go beyond the former one by regulating registration, disclosure, market conduct, data usage, complaints and the roles of actors engaged in digital or collaborative lending transactions. While the emergence of formal rules makes regulatory assurance a theoretical possibility, the presence of rules can never be taken to mean that users know of and trust such rules.

For users to be assured by the rules formally adopted, they must feel that these rules are comprehensible, accessible and enforceable. It is easy to see how a registration badge or privacy notice may serve as a signal of legitimacy. This signal loses power if the complaints are answered with boilerplate answers or if the responsibility is dispersed among the lender, the technology provider, data provider and the collection agent. This dispersion of responsibility is particularly problematic for algorithmic decisions, where no single actor can seem to be the owner of the process.

Contextual condition	Mechanism in digital lending	Theoretical implication
Informal and irregular earnings	Reduces conventional records and increases reliance on proxies	Changes both model inputs and users' judgments of relevance
Unequal digital access	Produces uneven depth and quality of behavioural data	Can translate structural inequality into apparent credit risk
Shared devices and household accounts	Blurs the link between a digital trace and an individual borrower	Raises accuracy and correctability concerns
Credit urgency and limited alternatives	Encourages continued use despite distrust	Separates trust from behavioural reliance
Literacy and language variation	Changes the usability of explanations and appeals	Makes equal procedures produce unequal experiences

Fragmented ecosystem	provider	Disperses responsibility across lender, vendor and data provider	Weakens accountability and remedy
Evolving enforcement	regulatory	Creates variable awareness and confidence in redress	Conditions whether fair procedure becomes durable trust

4 Conceptual Foundations

Construct	Conceptual definition	Distinct from	Role
Perceived gender bias	A causal attribution that gender or a gender-linked condition unjustifiably shaped treatment.	Audited statistical disparity or proven legal discrimination.	Interpretive antecedent.
Procedural fairness	Evaluation of neutrality, consistency, accuracy, voice, correctability and ethicality.	Outcome favourability and distributive equality.	Principal mediating mechanism.
Algorithmic trust	Willingness to rely on the scoring system based on expectations of competence and dependability.	Trust in the lender or regulator.	Proximal trust outcome.
Organisational trust	Willingness to accept vulnerability based on expectations of lender integrity and responsible conduct.	Algorithmic accuracy or continued use.	Primary relational outcome.
Procedural safeguards	Credible explanation, contestability and effective human reconsideration.	Disclosure volume or nominal human presence.	Antecedents of experienced fairness.
Regulatory assurance	Belief that institutions set, monitor and enforce meaningful protections.	Formal compliance claims alone.	Institutional boundary condition.
Constrained reliance	Continued use because of need or limited alternatives despite weak trust.	Voluntary adoption grounded in confidence.	Downstream behavioural condition.

Perceived gender bias as causal attribution

"Perceived gender bias" does not necessarily mean that there is an occurrence of a protected attribute in the algorithm. An algorithm can omit gender but use proxies; use gender for fair intervention; etc. Rather, the construct relates to how a person interprets what causes certain treatment and concludes that gender, a gender-related pattern, or a gender-conditioned situation has had an influence without proper reasons. This can refer to approval, credit limit, interest rate, repayment terms, collection practices, or amount of personal data asked.

The distinction between the perception of discrimination and actual disparity is essential because otherwise, one would commit at least one of the following two mistakes: either underestimate perception until there was discrimination proved legally or scientifically; or think that every perception is discrimination. The former ignores the psychological and informational disadvantages that users of the product have while the latter does not leave room for erroneous conclusions, results-based evaluations, and insufficient information. Consequently, the practical consequence is twofold: lenders need thorough auditing of models and processes that generate credible fairness.

The attributive nature of the construct implies the existence of observable triggers. A user cannot examine the training dataset, feature engineering process, and model weights. Therefore, s/he attributes causes of a certain

treatment using clues like timing of the decision, phrasing of a decision, cases for comparison, gender-biased questions, regularity of decisions, inaccuracy of data, controversy around a model, and practices related to appeals. Thus, attribution ambiguity becomes crucial as the same outcome can be attributed to many different causes.

Procedural fairness and distributive outcomes

Procedural fairness considers the process involved in making the decision. Current studies on algorithmic decision-making consider consistency, reducing bias, accuracy, correctability, voice, and ethics to be key elements in the sense of legitimacy (Lee et al., 2019; Shulner-Tal et al., 2023). In the context of automated credit decision-making, this means consistent criteria, relevant information, valid rationales, correctability measures and a review mechanism that might change the decision made initially.

The distributive aspect of fairness relates to the distribution itself: which people get credit and on what terms. There is some relationship between the aspects, although they cannot be confused. Rejection can be acceptable when there are clear reasons that are relevant and subject to correctability. On the other hand, acceptance can be seen as an intrusion and discrimination. Hence, both the outcome and the process need to be separately considered when developing future tests. This will help to understand the reasons why a positive decision may hide structural problems.

Differentiated trust and constrained reliance

Trust involves the acceptance of vulnerability under the assumption of competence, reliability and alignment of the artificial or organizational agent with the user's best interest. In AI-assisted lending, there are layers of trusted objects. A user could trust the model's competence, the platform's integrity, the company's benevolence and the regulator's assurance abilities; all these objects must be assessed separately since according to scientific evidence trust in AI systems results from performance indicators as well as relational and institutional cues (Glikson & Woolley, 2020).

Trust is not identical to continuing use. Urgency for credit and lack of options can lead to dependence even in the absence of confidence. It is especially true for Nigeria, where a borrower might return to an untrusted platform several times due to necessity. Hence, the framework conceptualizes trust as belief and the willingness to accept vulnerability, and the use of a service becomes a potential outcome.

The framework makes a difference between algorithmic and organizational trust. Algorithmic trust relates to the expectation of model competence and proper calibration. Organizational trust has to do with objective setting, vendor management, data responsibility and the ability to redress. A borrower can trust predictive competence of an algorithm but doubt the lender's practices regarding pricing and debt collection. Institutional trust remains separate from either of them.

Theoretical Foundations

Procedural justice as the primary lens

The theory of procedural justice offers insights into why individuals bestow legitimacy on decision authorities despite the failure to receive desired decisions. The procedures send messages of neutrality, dignity and respect; they also minimize the uncertainty about one's future experience. In the algorithmic system, the decision authority is shared among the software, the organisation's policy and governance by humans. Users are unable to see behind the scenes of development, and therefore they draw conclusions regarding procedural justice based on certain factors such as questions posed, rationale provided, consistency of the decision, correctability and appealability.

The inferential nature of this theory renders gender bias especially devastating. The inference of the role played by gender in the decision-making process shows that bias suppression has failed. When the gender-related data are not relevant to the decision, it also negates accuracy and ethics. Without appeal, there is no correctability. One assumption, thus, triggers several procedural issues at once.

Attribution theory and fairness interpretation

The process starts with attribution. Users look for causes of significant, unexpected, or unpleasant occurrences, but algorithmic processes deny users direct access to the causes. Observable clues will thus have disproportionate value. If a denial occurs after the user asked gender-specific questions, after asking something similar to another woman's story, or where no rational explanation by the platform is available, then gender may be attributed as a cause. Research on algorithm aversion and human reactions to automatic decision aids reveals that observable flaws, lack of control and the way the system behaves can change algorithm reliance (Burton et al., 2020). If users have few other ways to make inferences, attribution ambiguity should heighten the effect of explanations and examples of comparable cases.

The theoretical framework will thus ensure that the paper does not treat every user perception as an indication of technical discrimination. User perceptions might be right, wrong, driven by outcomes, or informed by past experiences. The significance of the perceptions to the analysis does not hinge on their legal validity because they affect the fairness judgment and readiness to be vulnerable.

Trust theory and calibrated reliance

The theory of trust includes the content of the resulting judgment. Competence is associated with the ability to make proper judgments about credit; integrity is linked with following acceptable rules; benevolence pertains to avoiding exploitation of consumers' weakness. Gender bias may undermine all these factors. This assumption implies that the technology is incompetent and that the norms it follows do not take into account the interests of those who get affected. In such a way, procedural fairness can help to fulfill these expectations by demonstrating the validity of data, consistency of rules, legitimacy of the reason for decision making, and effectiveness of remedy.

Algorithmic trust should be associated with the factors of competence, predictability, and reliability. Organizational trust should consider the aspects of integrity and responsible handling of information, as well as the readiness to remedy damages. It is possible for an individual to see a model as competent, but to distrust the organization that uses it, or vice versa. Human trust in artificial intelligence is supported by the research on this topic (Glikson & Woolley, 2020).

Algorithmic fairness and the abstraction problem

A sociotechnical concept of fairness does not posit that bias lies only in the model code. The harms can be introduced at the stage of problem definition, data collection, labelling, features used, deployment, user interface and feedback process. For lending, the prediction target itself might reflect past access to formal credit and not the inherent ability or willingness to pay back. This way, technical optimization becomes a reproduction of institutionally created outcome (Fuster et al., 2022; Köchling & Wehner, 2020; Mehrabi et al., 2021).

Fairness perceptions are created at the interface of technical and user experience. A borrower gets asked questions, permission requests, time to decide, framing of decision, price, credit limit and complains behavior. All of these become evidence through which legitimacy is created. The studies on explainability and human-centered AI show that the quality of explanation and perceptions of the fairness of the process influence trust and acceptance (Shin, 2021; Shulner-Tal et al., 2023).

Signalling and institutional assurance

Since the potential applicant cannot look at a model directly, he has to depend on signals. Adverse action due to a particular reason may act as an indicator of technical competence, a timely appeal may indicate integrity, and independent monitoring may act as an indicator of enforceability. If signals are difficult to fake and are associated with some form of accountability, then they are credible; otherwise, they could be viewed as mere tokens of compliance.

6 Critical Synthesis Research Gap and Rival Explanations

Literature stream	Established insight	Unresolved problem	Theoretical move
Algorithmic bias	Models can reproduce historical inequality and proxy discrimination.	Technical disparity does not explain user interpretation or remedy.	Link audited fairness with experienced legitimacy.
Digital credit	Alternative data can expand prediction and access.	Reach is often treated as inclusion despite unequal data production.	Theorise gendered data visibility upstream of scoring.
Gender and finance	Women face structural constraints in income, assets and formal finance.	Gender is often a control variable rather than a causal mechanism.	Model perceived gender bias as attribution.
Procedural justice	Neutrality, accuracy, voice and correctability support legitimacy.	Safeguards are frequently treated as parallel predictors.	Position procedural fairness as the central mediator.
Trust in AI	Fairness and explanations affect acceptance.	Trust objects and constrained reliance are conflated.	Differentiate algorithmic, organisational and institutional levels.
African digital finance	Institutional and infrastructural conditions shape access.	Context is commonly treated as a location or control.	Make Nigerian conditions constitutive of causal relationships.

This review highlights four gaps. The phenomenon gap refers to the coexistence of inclusion and exclusion; the alternative data architecture that facilitates thin-file borrowing can also punish individuals whose digital footprint signals structural inequality. The perception gap exists since many papers on fairness investigate whether an algorithm produces disparities rather than whether users perceive and react to them. The mechanism gap exists whenever fairness and trust are incorporated as parallel variables, without any explanation of the relationship between the two. Lastly, the contextual gap exists because the current literature is dominated by findings from high-income countries regarding algorithmic perception, and there is little discussion of institutional guarantee in African consumer finance.

This paper attempts to close those gaps with the help of a process model. Rather than viewing gender-based bias as a demographic variable, we regard it as an attribution related to the causality of decisions. Perceived procedural fairness is not regarded as an ethical notion but a specific assessment of consistency, bias suppression, accuracy, correctability and voice. Lastly, we distinguish between trust and adoption. Nigeria will be included in our framework due to availability of data, necessity of lending, digital inequality and credibility of regulatory remedies.

The core of research gap lies in processes. While some papers have proven that there is a relationship between fairness/explainability and trust, the order of events and interpretations that allow a user to go from decision-related cues to gendered bias, then to procedural fairness assessment and ultimately to differentiated trust is not discussed at all.

The process under study has to be distinct from no less than five competing theories. The perceived favourableness of an outcome can make dissatisfied applicants perceive the process as unfair. Algorithm aversion as such can lower the level of trust as a result of any visible mistake, independent of the gender of the people involved. Concerns about privacy can lead to objections to alternative data being used regardless of whether there are any attributions of discrimination. Distrust towards banks can influence reactions even before the application starts. Lastly, urgency can lead to repeated usage that appears to be acceptance but is actually distrust.

Revised Conceptual Framework and Propositions

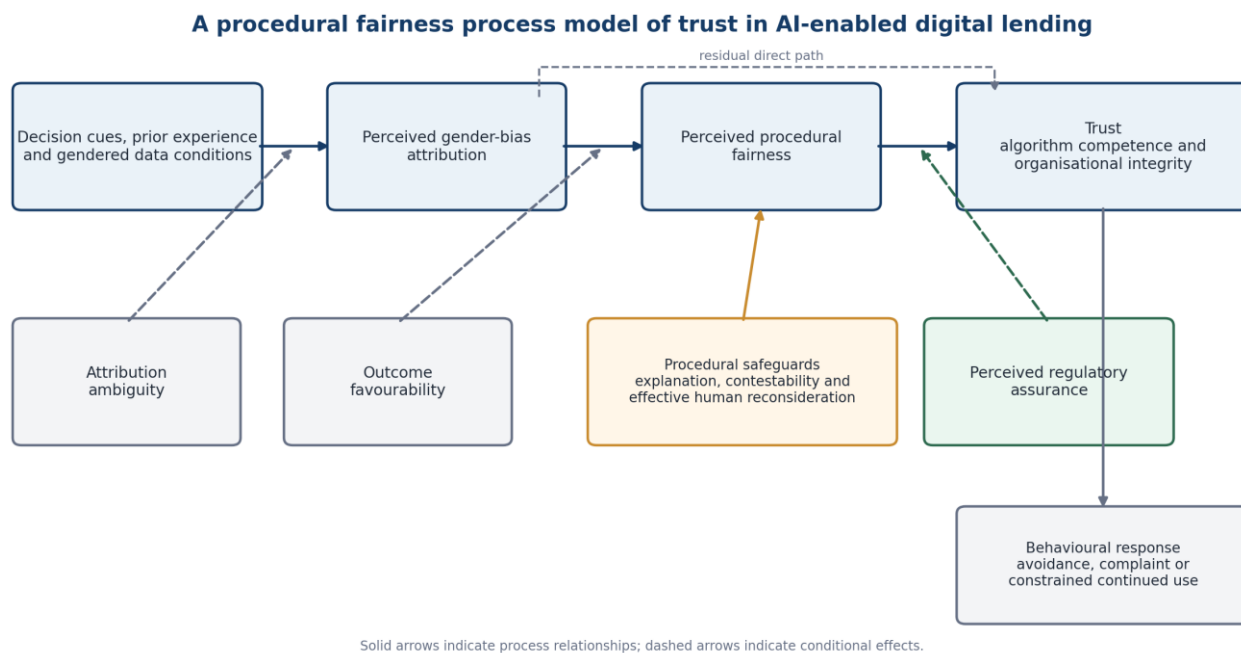


Figure 1. Procedural fairness process model for perceived gender bias and trust in AI-enabled digital lending.

Decision cues and gender bias attribution

Borrowers develop causal theories based on partial information. An unexpected negative result, apparently unrelated data request, inappropriate comparison, flawed records, gendered language, or even public allegations of discrimination make gender a credible cause. Discriminatory experience in the past makes it easy for borrowers to access this explanation, whereas explicit and accurate reasons may lower the level of uncertainty or prove the use of an ambiguous proxy variable. Thus, the theory starts from the moment preceding the perception of discrimination rather than considering it as an inexplicable starting point.

Proposition 1: Ambiguous adverse-decision signals and financial discrimination experience in the past raise the probability of borrowers explaining an AI-driven lending decision based on gender and gender-related variables.

Perceived gender bias and procedural fairness

When a user perceives that a decision about credit has been made on the basis of gender, there is an issue regarding the lack of bias suppression, which is one of the major procedural requirements. In addition, the perception of gender-based biasing could call into question the accuracy of the decision process when gender-specific factors do not have any bearing on the capability of the individual to repay the loan; it may be inconsistent, unethical, or all three of these. The problem of opacity is that the user cannot test any other possible explanations for the decision. However:

Proposition 2: The perception of gender bias in AI-enabled lending decisions has a negative impact on perceptions of procedural fairness.

Procedural safeguards and experienced fairness

Explanation, contestability and effective human reconsideration are observable arrangements whereby users assess a procedure. Quality of explanation involves clarity, specificity, fidelity and actionability. Contestability involves the ability to challenge inputs, present relevant evidence and get authoritative reconsideration. Effective human reconsideration occurs only if a qualified and independent reviewer is able to alter data and deviate from automated recommendation. Since these arrangements embody accuracy, voice and correctability, they are modeled as antecedents of procedural fairness instead of moderating variables.

Proposition 3a: Clarity, specificity, faithfulness and actionability of explanation are positively related to procedural fairness, except in case of explanation that shows credible use of a gender-related unjustifiable factor.

Proposition 3b: Contestability involving changing of data, reasoning or outcome is positively related to procedural fairness.

Proposition 3c: Effective human reconsideration is positively related to procedural fairness provided that reviewer is qualified, authoritative and independent.

Procedural fairness and differentiated trust

Procedural fairness provides information on the scoring process as well as the organisation that is managing it. The accuracy of the inputs and the appropriate grounds for those support the belief in the intelligence of the algorithm. Consistent criteria, respectful treatment, voice, and corrective action support the belief in the integrity of the organisation.

Proposition 4a: There exists a positive relationship between perceived procedural fairness and trust in the competence and reliability of the credit-scoring algorithm.

Proposition 4b: There exists a positive relationship between perceived procedural fairness and trust in the integrity of the digital lending organisation.

Direct and mediated effects

The bias perception process may also influence organisational trust via mechanisms such as identity threat, moral judgment, reputation spillover, and expectations for future discrimination. This list is not exhaustive in terms of the examination of any given process. Hence, the direct route is maintained as the residual effect, whereas the procedural fairness approach is kept as the core explanation.

Proposition 5: Gender bias perception is negatively related to organisational trust, regardless of its mediation through procedural fairness.

Proposition 6: Procedural fairness is a mediator for the negative relationships between gender bias perception and algorithmic and organisational trust.

Regulatory assurance and outcome favourability

Regulatory assurance exists at a higher level compared to the user-platform dynamic. In the case where users perceive that there is assurance that regulators have defined their responsibilities, ensure compliance with regulations and provide remedy, then there is a greater likelihood that a procedurally fair platform will generate organizational trust. The favourable outcome comes before that.

Proposition 7: Regulatory assurance increases the positive effect of procedural fairness on organizational trust.

Proposition 8: The negative effect of gender bias perception on procedural fairness is stronger after an unfavorable loan outcome compared to a favorable one.

Trust and constrained reliance

Trust does not necessarily turn directly into usage. A borrower may keep using the same distrusted system where credit is desperately needed or no other option exists. On the other hand, even a trusted system may not be used if the price or the offer is not appropriate. Behavioural effects must be treated separately, therefore.

Proposition 9: Financial constraints and the absence of alternative sources of credit make the effect of trust on continued usage less positive.

Proposition	Relationship	Mechanism	Expected direction
P1	Decision cues and prior discrimination → bias attribution	Causal search and attribution accessibility	Positive
P2	Bias attribution → procedural fairness	Failure of neutrality, accuracy and ethicality	Negative
P3a–c	Procedural safeguards → procedural fairness	Explanation, voice and correctability	Positive or diagnostic
P4a–b	Procedural fairness → differentiated trust	Competence and integrity inferences	Positive
P5	Bias attribution → organisational trust	Identity threat, moral and reputational judgment	Negative
P6	Bias → fairness → trust	Process mediation	Negative indirect
P7	Regulatory assurance on fairness → organisational trust	Institutional enforceability	Strengthens positive
P8	Outcome favourability on bias → fairness	Outcome-dependent scrutiny	Adverse outcome strengthens negative
P9	Financial constraint on trust → continued use	Constrained reliance	Weakens positive

DISCUSSION

The updated model captures the erosion of trust through an interpretive process rather than a fixed relationship. Users see few signals, impute potential causes in terms of gender and/or gender-related circumstances, evaluate the process against justice criteria, and adjust their level of trust both in the algorithm and in the company. Platform security changes the information available in making such a decision, while regulatory assurance allows for a determination of whether the locally just process is institutionally enforced.

The separation of technical and experiential measures of fairness is central to the framework. Technical metrics are crucial in identifying discrepancies among groups, yet none of them encompasses the social essence of fairness. Experiential fairness concerns the capacity for individuals affected by the process to question, challenge, and remedy it. It means that lenders could pass an audit and still be socially unacceptable. The reverse might be true as well – users would trust the system operating unfairly due to positive results, persuasion, or reputation in the market. Responsible governance should take into account both types of errors.

A number of paradoxes arise from the framework. Transparency is likely to expose the discriminatory logic and undermine trust, which may be precisely the right thing to do. Human review is capable of restoring voice but might reintroduce discrimination or automate it. A borrower might keep using the platform despite his lack of trust as a result of desperate need. Fair processes might lead to different experiences when access to explanations and appeals depends on literacy levels, Internet access, or languages. These paradoxes suggest that trust maximization should not be the policy target. The right one should be warranted and calibrated trust based on accountability.

This case study of Nigeria highlights many of the arguments of the previous section as alternative data sources might serve as a mechanism of inclusion and inequality recording at the same time. The framework suggests that trust would depend not only on algorithmic outcomes but on whether users consider data relevant, explanations understandable, and remedies feasible and if the institution in question is capable of enforcing them. National context becomes part of the causal logic rather than a descriptive preamble.

Technical and experienced fairness

The model does not put perception above technical data. An audit examines whether a system creates biases, uses credible data points, and works effectively among different groups. Fairness by experience tests whether an individual can comprehend, challenge, and rectify a critical decision. Governance falls short in either case: an algorithm that complies statistically can still be illegitimate socially, while an effective user interface can lend credibility to an unfair system.

Theoretical Contributions

To begin, the article theorizes perceptions of gender bias as a causal attribution based on observation rather than as a demographic variable or synonym for audit discrimination. This is a way to identify the underlying process that is left unexamined in current fairness-trust frameworks.

Next, the article shows how procedural fairness is the mechanism for translating bias perception into differential trust. The theory explains the connection between neutrality, accuracy, voice and correctability and trust in algorithms and institutions.

Also, the article solves the common problem of explanation, contestation and meaningful human deliberation by using these concepts as safeguards to generate fairness. They do not automatically produce trust, but they have to be credible and powerful enough to have any effect.

Further, the article differentiates between algorithmic trust, organizational trust and regulatory assurances, and also separates all three from constrained usage of the platform. It is why using the platform is possible despite lack of trust in the high-need credit market.

Finally, Nigeria is a defining part of the theory. Informality, digital footprint inequality, shared devices, literacy difference, necessity for credit and changing enforcement modify the information input to the model, visible cues and usefulness of procedural rights.

Practical and Regulatory Implications

Digital lenders and technology providers

Digital lenders must assess fairness through the entire lifecycle of decision-making. Predeployment analysis should include examinations of data provenance, representation, missing values, and proxies. Validation should assess disaggregated performance by gender, as well as approvals, pricing and errors rather than an overall accuracy number. Post-deployment monitoring should involve investigation into drift, complaints, reversals, and difference in user experience. Documentation should define intended use, limitations and circumstances of human escalation.

User interface design should provide concrete grounds for adverse decisions and the information that can be corrected. Explanation should be tested by actual users and adjusted to different languages and literacy. Appeals should be clearly communicated, affordable and time bound. An appeal should give a reviewer an authority to modify data and decision outcome; otherwise, the process becomes symbolic. Firms should measure procedural fairness directly while acknowledging outcome favourability bias in survey responses.

Fairness is not the responsibility of a model vendor. Duties and roles of parties should be defined in contract with respect to testing, documentation, incident investigation, and regulatory reaction. Information about

technical and consumer differences should be communicated to senior management. A fairness incident must be viewed as a product and governance failure, not merely a PR problem.

Procedural criterion	Required lending practice
Consistency	Apply stable decision and reconsideration rules across comparable applicants.
Bias suppression	Conduct gender-disaggregated audits of approval, price, limits, errors and complaints.
Accuracy	Provide accessible data review and correction before and after a consequential decision.
Voice	Allow applicants to submit context and evidence through affordable channels.
Correctability	Give reviewers power to change data, reasons, terms or outcomes.
Representativeness	Test interfaces and explanations across gender, income, language and digital-literacy groups.
Ethicality	Restrict unjustified proxies and abusive collection or disclosure practices.

Regulators and consumer protection

There needs to be integration between the Nigeria Data Protection Act 2023, NDPC General Application and Implementation Directive 2025, and FCCPC Digital, Electronic, Online or Non-Traditional Consumer Lending Regulations 2025. Supervisory guidance must include how to handle adverse-decision explanations, meaningful human intervention, data correction, complaint escalation and responsibility for lenders, scoring vendors, data providers and collection agencies.

The regulations must specify minimum standards for adverse-decision explanations, data corrections, complaints escalation and human reconsiderations. Reporting of gender disaggregated data can show any persistent problem but it must come with safeguards against re-identification and simplistic league tables. Supervision will need to look at the full chain of decisions and involve data brokers, outsourced scoring service and collection agents.

Nigerian Data Protection Act offers a good base for fair and transparent processing, while consumer protection regulation can turn these principles into sector-specific obligations. Effective implementation requires public guidance, coordination among the competent authorities and demonstrable results. Regulatory sandboxes and innovation programmes must include tests of fairness and contestability, and not just feasibility and market potential.

Consumer organizations can assist consumers in challenging decisions, rectifying their record and recognize the abusive practices. Public awareness will need to educate about the benefits and limitations of automated credit scoring. The purpose is not to develop any unfounded distrust, but rather enhance the ability to discern legitimate risk assessment from arbitrary and discriminatory one.

Boundary Conditions and Limitations

The model is bounded by various factors. First, a feeling of gender bias might be based on disappointment with the results instead of real use of gendered information. Both experiments and longitudinal research are necessary to distinguish between attribution and performance. Second, the gender category is not uniform. Factors such as income, disability, age, place of residence, ethnicity, marital status and occupation can intersect with gender to impact data accessibility and processing.

Third, the quality of explanation will likely affect the model relationship differently in some cases. A truthful explanation proving that reliance on a doubtful proxy led to discrimination will only increase the perception of injustice. Fourth, it is useful for human review to be performed by competent, discretionary and independent reviewers. Fifth, regulation assurance is a subjective perception which can vary greatly among different users even within the same regulatory environment.

The paper also does not imply that procedural justice will fix substantive injustice. The procedure may be consistent and explainable but still distribute credits in a way that makes a vulnerable position worse. Distributive impact, fit of products, pricing and collecting practices must be considered. Finally, the model is conceptual; it needs an empirical testing to make any claims about causality.

Sixth, the gender should not be operationalized as a uniform or exclusively binary variable. The model mechanisms might differ depending on intersections with income, disability, age, marital status, occupation, ethnicity and location. Seventh, procedural guarantees can be differentially accessible. Equal explanation and appeal procedures might lead to unequal access because of different languages, literacy, access to internet or devices.

Future Research Agenda

Research question	Recommended design	Key evidence	Primary contribution
How are gender-bias attributions formed?	Factorial vignette varying outcome, proxy cue and reason	Attribution, ambiguity and prior discrimination	Tests P1 and separates attribution from disappointment.
Does fairness mediate trust erosion?	Three-wave borrower study	Bias attribution, procedural fairness and two trust targets	Establishes temporal ordering for P2, P4 and P6.
When do safeguards work?	Field experiment or appeal-policy introduction	Explanation comprehension, appeals, reversals and fairness	Tests substantive versus symbolic safeguards.
Do perceived and technical fairness converge?	Linked model audit and borrower study	Group metrics, individual reasons and user perceptions	Connects system behaviour with experienced legitimacy.
How does regulation create assurance?	Comparative state or country design	Awareness, enforcement credibility and redress outcomes	Tests P7 at the institutional level.
When does use conceal distrust?	Longitudinal transaction study	Trust, alternatives, financial urgency and repeat borrowing	Identifies constrained reliance under P9.
How do intersecting identities matter?	Mixed methods and multigroup analysis	Gender, income, location, disability and work form	Avoids homogeneous gender assumptions.

The first phase of the programme design should balance control and field realism. A factorial manipulation of outcome favourability, gender-related cue, explanation quality and possibility of effective reconsideration may be undertaken using an experimental design. Then, a longitudinal field study could assess perceptions immediately after application, after receiving an explanation and after making an appeal. Comparing these with platform records and independent audits would identify where convergence and divergence occur between perceived and measured disparities.

The measures should account for the revised categories. Procedural fairness would need to be modelled through neutrality, consistency, accuracy, voice, correctability and ethicality. Algorithmic trust would involve competence and dependability, while organisational trust would require integrity and responsibility. Regulatory assurance should measure perceived monitoring, enforcement and availability of remedy. In addition, continued use would need to be measured along with financial urgency and available alternatives in order to ensure reliance is not confused with confidence.

Qualitative research is still needed. Cognitive interviews can explore how people comprehend gender-related proxies, explanations and reconsideration mechanisms before the measurement phase. The researcher needs to focus on shared artefacts, household financial situations, informal income, languages and gender-based experiences of data collection. Invariance across measurements should be investigated before cross-group comparisons are conducted on gender or socioeconomic status.

CONCLUSION

With the help of artificial intelligence and digital lending platforms, credit availability can be expanded, but new sources of opacity, proxy discrimination and perception of unfairness are created. This paper argued that gender-biased perceptions gain relevance through a process whereby the borrower interprets decision signals, attributes a possible causation to gender or gender-related factors, evaluates the procedure and revises trust in the score and the lending institution. Therefore, procedural fairness is not just another predictor of trust; it is the main interpretive tool for turning a suspicion into willingness or unwillingness to assume risk.

This framework highlights why credible governance cannot be simplified to explanations. Borrowers require reasons that are understandable and accurate, mechanisms for contestation, authoritative reviewers and institutions that can enforce remedies. This would allow for correcting misunderstanding, identifying discrimination when there is one and appropriately reducing misplaced trust. The goal is calibrated trust based on demonstrable trustworthiness.

In Nigeria, the problem is to safeguard the inclusion potential of alternative-data lending without letting unequal digital footprints, informal economies and gender-based social factors become unjustified risk markers. Legitimacy will depend on whether the borrower can understand the relevant factors, rectify mistakes, challenge decisions and obtain reconsideration. Hence, technical fairness and procedural justice must be regulated together.

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