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# Algorithmic Credit Scoring and Financial Inclusion: A Theoretical Framework of Information, Exclusion and Over-Indebtedness in Digital Lending Markets

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## ABSTRACT

*Digital lenders across Africa now approve small loans within minutes to borrowers whom no bank has ever assessed, relying on mobile-phone, transaction and behavioural data rather than on collateral or a documented credit history. The financial-inclusion literature has treated this as a largely benign expansion of access, while a separate consumer-protection literature has documented high prices, repeat borrowing and distress among the same borrowers; the two bodies of work rarely speak to each other, and neither explains why the same technology produces inclusion in one setting and harm in another. This paper develops a theoretical framework that resolves the tension. It distinguishes three analytically separate effects of alternative-data scoring: an assessment effect, which enlarges the population a lender can evaluate at all; an acceptance effect, which changes who within that population is approved; and a pricing effect, which changes the cost and structure of the loans that approved borrowers receive. The first effect is inclusive almost by construction, whereas the second and third can be exclusionary and extractive at the same time, so that a market can simultaneously widen access and deepen harm. The paper is a theoretical synthesis built from peer-reviewed journal articles published between 2023 and 2026, each verified against its Crossref publisher record and screened for retractions and expressions of concern. It specifies a welfare model in which the net effect of digital credit depends on the interaction of scoring accuracy, lender competition, loan design and borrower financial capability, and derives five propositions about when algorithmic lending produces inclusion and when it produces over-indebtedness. Nigeria's digital-lending market anchors the analysis, with Kenya as the comparator. The paper concludes that interest-rate disclosure, data governance, credit-bureau integration and conduct supervision act on different parameters of the model and must therefore be combined rather than substituted for one another.*

***Keywords:*** digital lending; algorithmic credit scoring; alternative data; financial inclusion; over-indebtedness

# Algorithmic Credit Scoring and Financial Inclusion: A Theoretical Framework of Information, Exclusion and Over-Indebtedness in Digital Lending Markets

## 1. INTRODUCTION

The standard account of why poor households and small firms are excluded from credit is an information story: lenders cannot observe repayment capacity or intention, collateral substitutes for information, and those without collateral or a documented history are rationed out regardless of their true creditworthiness. Algorithmic credit scoring on alternative data promises to break this constraint directly. If airtime purchases, mobile-money flows and app usage predict repayment, the lender no longer needs the collateral or the file, and the population that can be lent to expands to include almost anyone with a phone. The promise has been realised at scale, though not evenly: across 79 countries, fintech and big-tech credit is larger where banking mark-ups are high and regulation less stringent, and in richer economies than in poorer ones (Cornelli et al., 2023), while in East Africa, by widely reported accounts, the mobile loan became a familiar feature of household finance within a few years of its introduction.

The evidence on what this has done for borrowers is uncomfortable to summarise. In Malawi, most borrowers of a digital loan priced at ten per cent over fifteen days were unaware of its terms, repaid late and incurred substantial late fees; a short phone-based financial-literacy intervention improved their knowledge but did not improve timely repayment, modestly raised their demand for the loan and, in the end, raised the likelihood of ever defaulting (Brailovskaya et al., 2024). In Mexico, borrowers whose loan reached them some ten hours later than others' were about a fifth less likely to default, apparently because the delay changed how they planned to use the money (Burlando et al., 2025), which, on this paper's reading, suggests that part of the appeal of instant credit is precisely that it allows decisions the borrower would not make on reflection. In Kenya, loans from mobile-banking channels are less accessible to women, the less educated and casual workers than loans from app-based fintech lenders, and greater access has not automatically benefited vulnerable groups (Kim & Duvendack, 2025). In Nigeria, as a matter of public record rather than of the research literature, the same instant-loan model arrived with a wave of unlicensed applications whose collection practices, including the harvesting of borrowers' contact lists for public shaming, prompted the consumer-protection authority to impose a registration regime in 2022, followed in July 2025 by formal regulations on digital consumer lending. None of this sits comfortably with the inclusion narrative, yet none of it refutes the fact that millions now hold a loan they could not previously have obtained.

This paper explains why both descriptions can be true at once. It argues that the inclusion and consumer-harm literatures describe different stages of the same lending process and that the confusion arises from treating "access" as a single quantity. Algorithmic scoring changes who can be assessed, because a model can produce a score for a person with no file; it changes who, among the assessable, is accepted, because the model ranks them differently from a loan officer or a bureau score; and it changes what the accepted borrower receives, because the price and structure of the loan are themselves outputs of the model and of the lender's commercial strategy. The assessment effect is inclusive almost by construction, since it can only enlarge the set of people a lender is able to consider. The acceptance and pricing effects have no fixed sign and, in markets with weak competition and weak borrower capability, tend to become exclusionary for some and extractive for others at the same time.

From this decomposition the paper builds a welfare model in which the net effect of digital credit depends on the interaction of scoring accuracy, lender competition, loan design and borrower financial capability, derives five propositions, and maps the regulatory instruments available to African supervisors onto the parameters they actually move, with Nigeria as the anchoring case and Kenya as the comparator. The approach is theoretical and the evidence base is deliberately recent: every research finding on which the argument rests comes from a peer-reviewed article published between 2023 and 2026 whose publisher record has been verified, while

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the institutional and regulatory facts about the two anchoring markets are reported descriptively from public record and carry no evidential weight for the propositions.

## 2. LITERATURE REVIEW

### 2.1 CONCEPTUAL REVIEW

Three concepts carry the argument. Algorithmic credit scoring refers to the use of statistical or machine-learning models to estimate repayment probability from data that are not, in the main, the borrower's financial history. The defining feature is not the algorithm, since bureau scores are also algorithmic, but the data: call-detail records, mobile-money transactions, handset and app metadata and the social graph. Recent work shows that mobile attributes beyond call records, such as web browsing and social-media use, improve the accuracy with which individuals can be classified by credit risk, especially when combined with call-detail records, which the authors read as a route to scoring people without formal credit histories (Razavi & Elbahnasawy, 2025), and that a machine-learning model built on non-traditional data at a Chinese fintech lender predicts losses and defaults better than traditional models, with the advantage largest for borrowers with short credit histories and in periods when credit supply contracts (Gambacorta et al., 2024).

Financial inclusion is used here in a demanding sense: not the holding of an account or the receipt of a loan but the ability to use a financial product on terms that leave the user better off. A loan repaid by rolling it over at a high price has been accessed but has not included anyone. Over-indebtedness is the condition in which obligations can no longer be serviced out of income without sacrificing consumption the borrower would, on reflection, have protected. It is a state of the household rather than of the loan, which is why the same product can be inclusive for one borrower and ruinous for another.

Information runs in both directions: the lender's information about the borrower determines assessment and acceptance, the borrower's information about the loan determines whether acceptance improves welfare, and the framework below models the two flows together where the inclusion and harm literatures have each attended to one.

### 2.2 THEORETICAL REVIEW

The theory of credit markets under asymmetric information explains exclusion as rationing: when a lender cannot distinguish good from bad risks, raising the price selects for the bad and the lender prefers to ration quantity. Collateral solves part of the problem by making the borrower bear the loss, which is why collateral-poor borrowers are the ones rationed. Data can substitute for collateral. Gambacorta et al. (2023) show, using big-tech lending to small firms in China, that credit extended on the basis of transaction data responds to the firm's business activity rather than to local property prices, which is exactly what one would expect if information had replaced the house as the lender's protection. Huang and Winton (2026) treat continued access to credit as "soft collateral" that gives a borrower without pledgeable assets a reason to repay, and ask how strictly a credit registry should exclude those who have defaulted; their answer, that the optimal registry is as lenient toward past defaulters as repayment incentives allow when lending funds are ample, and that a more graduated registry is not necessarily a better one, is a reminder that information infrastructure has a design problem of its own.

The second theoretical strand concerns the behaviour of the borrower under limited attention and limited understanding. The empirical findings that faster delivery raises default (Burlando et al., 2025) and that most borrowers do not know the terms of their loan (Brailovskaya et al., 2024) only make sense in a model in which the borrower's choice is not fully informed. Lusardi and Mitchell (2023) have argued that financial literacy is best treated as a form of human capital that is unevenly distributed, and they draw on two decades of evidence on the consequences of financial illiteracy for household financial decisions. If that is right, then the welfare effect of a given loan contract is a function of who takes it, and a scoring model that selects for people with little financial capability will produce different outcomes from one that selects for people with more, even at the same default rate.

A third strand, drawn from the economics of fairness in prediction, deals with the acceptance effect. Hurlin et al. (2026) show that a scoring model built to separate good from bad risks can also, without anyone intending it, discriminate between people who share a protected attribute and everyone else,

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that the source can lie in the training data or in the model itself, and that fairness can be formally tested, traced to the variables responsible and traded off against predictive performance rather than simply assumed. A more accurate model is not necessarily a more inclusive one; it may simply be more accurate about whom to exclude. Against this stands evidence that automation can reduce discrimination rather than encode it. Howell et al. (2024) find, in the United States Paycheck Protection Program, that Black-owned firms obtained their loans mainly from automated fintech lenders, especially where racial animus was high, and that traditional banks' lending to Black-owned firms rose once they automated their own processing, which the authors attribute to smaller loans, wider reach and the removal of human bias; Jansen et al. (2025) find in a randomised experiment in vehicle lending that algorithmic underwriting produced lower default and higher profit than human underwriters, with the gap widest for riskier loans and where agency conflicts were strongest. Theory alone cannot sign the acceptance effect.

Finally, the literature on the industrial organisation of fintech credit supplies the competition parameter. Cornelli et al. (2023) find that fintech and big-tech credit volumes are higher where bank markups are higher, which suggests entry is attracted by rents, while Hodula (2023) finds, across 78 countries, that growth in fintech and big-tech credit is associated with lower income inequality, but only in countries that already have a high level of financial inclusion. Neither result guarantees that entry drives prices down for the marginal borrower; both are consistent with entrants sharing existing rents while leaving pricing intact.

### 2.3 EMPIRICAL REVIEW

The empirical work of the last three years divides between studies of the lender's information problem and studies of the borrower's.

On the lender's side, the most consistent finding is that alternative data expand the set of borrowers who can be ranked. Aiken et al. (2023), in a setting outside credit but with the same information structure, show that machine-learning models built on mobile-phone data can target an anti-poverty programme in Afghanistan nearly as accurately as conventional survey-based methods: the phone is enough to form a view of someone who has no documents. Di Maggio and Ratnadiwakara (2026) find that a United States fintech platform using education, employment and other non-traditional variables approves fifteen to thirty per cent of the low-score applicants that traditional models reject, offers them lower rates, and particularly benefits "invisible primes", borrowers with thin files and low scores but low default risk, whose subsequent financial outcomes improve. Ghosh et al. (2026) show that borrowers' use of cashless payments improves their access to fintech credit and predicts lower default, with the effect strongest for payment technologies that carry more precise information, and Dalton et al. (2024) find in a randomised trial with Kenyan small and medium enterprises that adopting an electronic-payment technology increased their access to mobile loans by at least half, which they attribute to the reduction in information asymmetry that digital transactions bring. The payment trail becomes the collateral of the digital age, and the network externalities in card adoption that Higgins (2024) documents in Mexico suggest that the scorable population may grow faster than linearly once a threshold of digital activity is crossed.

On the borrower's side, the findings are more sobering. Kim and Duvendack (2025) find that Kenya's mobile-banking loans are harder for women, the less educated and casual workers to obtain than app-based fintech loans, and that wider access does not automatically benefit vulnerable groups, while Johnen and Mußhoff (2023) find from nationally representative Kenyan household surveys that formal digital credit has, contrary to expectation, widened the gender gap in financial inclusion, a gap they tentatively attribute mainly to gender differences in socio-economic characteristics combined with limited variation in contract terms in that market; a product designed to be impersonal has not escaped the social structure of credit. Chen et al. (2023) document a fintech gender gap across many countries explained in part by women's lower willingness to adopt new financial technology, which bears directly on whose data are available to be scored. Annan (2025), in a field experiment with mobile-money vendors in Ghana, shows that misconduct defined as unethical and fraud-indicative market conduct fell by 21 percentage points under programmes that gave information about it to both consumers and vendors, working through more accurate consumer beliefs and vendors' concern for their reputations; the setting is

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payments, but the information structure is that of a digital borrower confronted with an opaque fee.

A smaller body of work addresses the institutional environment. Kowalewski and Pisany (2023) find that fintech firms form more readily where bank lending is limited and where technological and research capacity is strong, with strict regulation acting as an obstacle, and Mothobi and Kebotsamang (2024) show, from survey data across nine sub-Saharan African countries linked to the location of mobile towers, that network coverage is a significant determinant of the adoption of digital financial services. Doerr et al. (2026) provide the cleanest evidence on privacy regulation and lending, and it does not run the way the inclusion debate assumes: after California's consumer-privacy law gave borrowers rights over their data, fintech lenders relied more on non-traditional scoring, denied more applications, cut their rates relative to other lenders, saw default fall by more than rivals did and expanded mortgage originations, a pattern the authors read as better screening from richer data rather than as a contraction of credit. McCallum and Aziakpono (2023) assess whether the conditions for an effective regulatory sandbox exist in South Africa and find most of them in place, with others needing remediation; Giudici and Raffinetti (2023) propose that AI in finance be judged on sustainability, accuracy, fairness and explainability together; and Chen et al. (2024) show that the explanations produced by common interpretation methods (LIME, SHAP) become less stable as class imbalance rises, a caution for any regime that relies on post-hoc explanations of credit models.

What the literature lacks is a structure relating these findings to one another, which the framework in Section 4 attempts to supply.

## 3. MATERIALS AND METHODS

This is a theoretical paper and its method is one of structured synthesis. The research design proceeds in three steps. The first identifies the mechanisms through which algorithmic scoring alters credit-market outcomes by decomposing the lending process into stages at which information enters and decisions are taken. The second builds a welfare model in which the sign of the net effect of digital credit depends on the interaction of parameters identified in the literature, and derives propositions that are falsifiable in principle. The third reads the model against the Nigerian digital-lending market, with Kenya as a comparator, to assess which regulatory instruments move which parameters.

The evidence base was constructed under a fixed protocol: only peer-reviewed journal articles with a volume year between 2023 and 2026 were eligible. Each candidate was retrieved from the Crossref registry by its digital object identifier, which supplied the bibliographic details used here, and was screened for retractions, corrections and expressions of concern through the registry's update metadata, which incorporates the Retraction Watch database; no cited article carried such a notice. Each attributed finding was then checked against the article's published abstract, or, where a statement went beyond the abstract, against an openly available version of the full text, and is reported within the limits of that evidence; where the argument extends a finding, the extension is identified as this paper's own reading. Working papers, preprints, conference proceedings, policy reports and book chapters were excluded, at a cost: some of the most direct evidence on Nigerian digital lending exists only in regulatory reports, and the paper refrains from quoting market statistics it cannot source to a verified article. This standard governs the research findings on which the propositions rest. Institutional and regulatory facts about Nigeria and Kenya, such as the timing of licensing regimes and the arrangements for sharing credit information, are reported descriptively from public record; they illustrate the framework and are not evidence for or against any proposition.

Generative artificial-intelligence tools were used to assist with drafting, with the organisation of the reference list and with checking the correspondence between in-text citations and reference entries. Every source was selected, verified and interpreted by the authors, who take full responsibility for the content. The main limitation of the design is that it is non-empirical: the propositions are derived, not tested, and the Nigerian illustration is interpretive rather than evidentiary.

## 4. RESULTS AND DISCUSSION

### 4.1 RESULTS

Consider a population of potential borrowers, each with a true repayment probability that neither party observes perfectly. A conventional lender can form an estimate only for those with a file, collateral or a relationship; an algorithmic lender can form one for

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anyone who generates digital data. The assessment effect is the enlargement of the set of people for whom a score exists at all. It is what the inclusion literature measures when it counts new borrowers, and it is inclusive almost by construction, because the previously unassessable had a loan supply of zero and a score can only add to it. The strength of the effect depends on the data environment: on network coverage (Mothobi & Kebotsamang, 2024), on the diffusion of digital payments and the externalities that accelerate it (Higgins, 2024; Ghosh et al., 2026) and on the willingness of particular groups to adopt fintech at all (Chen et al., 2023). Where women, rural residents or the very poor leave a thinner trail, the assessment effect is correspondingly weaker for them, which is one reading of why Kenyan digital credit has widened rather than closed the gender gap (Johnen & Mußhoff, 2023).

The acceptance effect is what the model does with the scores it produces: the ranking changes relative to a human or bureau-based decision, so that some previously rejected are approved and some previously approved are rejected, and the threshold changes, because the lender chooses the cut-off that maximises profit given the model's accuracy and the price it can charge. Whether the effect is inclusive depends on whose ranking has moved. If automation removes human bias or the agency conflicts of human underwriters, as it did for Black-owned firms in Howell et al. (2024) and for riskier vehicle loans in Jansen et al. (2025), or if the model detects invisible primes (Di Maggio & Ratnadiwakara, 2026), acceptance becomes more inclusive. If instead the model learns that the poor default more and proxies for poverty through a hundred innocuous variables, acceptance becomes exclusionary in a way that no individual variable reveals; this is the unintended discrimination that Hurlin et al. (2026) show how to test for and trace to its source. Both outcomes can occur in the same market. Competition enters here as well, because a lender contesting the marginal borrower with rivals sets a lower cut-off than one that faces none. Accuracy determines how finely the model sorts; it does not determine what the sorting is for.

The pricing effect is the least studied and, this paper argues, the most consequential. Algorithmic scoring allows the rate, tenor, size, fees and schedule of an approved loan to be individualised on predicted willingness to pay as well as predicted risk. A borrower whose data reveal urgency, a payday pattern of airtime top-ups, a late-night application, a previous rollover, can be charged more not because they are riskier but because they will accept. In a competitive market this surplus would be competed away; where a few lenders hold the data and the borrower has no bureau score to carry elsewhere, it is not, which is why a mobile loan can be very expensive for a borrower whose record is, by the lender's own model, good. Table 1 summarises the three effects, the mechanisms behind them, the conditions that determine their sign and their expression in the Nigerian market, the last column being descriptive illustration from public record rather than evidence.

**Table. 1. The assessment–acceptance–pricing framework**

| Effect | Mechanism | What determines its sign | Nigerian expression (descriptive) |
|---|---|---|---|
| Assessment | A score can be produced for anyone who generates digital data; the scorable population expands | Data environment: network coverage, payment digitisation, willingness to adopt fintech | Smartphone-based lending has reached salaried and informal workers with no bank credit history; thinner trails for rural and female borrowers limit reach |
| Acceptance | The model re-ranks the scorable and sets a profit-maximising cut-off | Whether the model corrects human bias and detects invisible primes, or proxies for poverty; competition for the marginal borrower | Rapid approvals for urban phone users; evidence on whom the models reject is not public, and the 2025 Regulations make no provision for supervisory review of scoring models |
| Pricing | Price, size, tenor and fees are individualised on predicted risk and predicted willingness to pay | Lender competition, portability of the borrower's record, disclosure of the effective rate, borrower capability | Short-tenor, high-fee loans whose effective annualised cost has rarely been disclosed in standardised form, with borrowers' records not readily portable to rival lenders |

*Source: authors' synthesis of the cited literature.*

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The welfare model follows from the table. Let the net welfare effect of digital credit for a borrower be the gain from a loan that smooths consumption or finances a productive use, less the loss from a loan that is mispriced, misunderstood or taken impulsively. Four parameters govern the balance. Scoring accuracy raises the gain from acceptance by reducing the share of approved borrowers who default, but it also sharpens the lender's ability to price-discriminate; it does not change the size of the assessment effect, which is set by the data environment rather than by the quality of the model. Lender competition determines whether the surplus created by better information goes to the borrower or the lender; it is the only parameter that reliably moves the pricing effect in the borrower's favour. Loan design, including delivery speed, tenor, fees and cooling-off periods, determines how much of the acceptance effect is converted into impulsive borrowing, and the finding that a delay of roughly ten hours in disbursement reduces default by about a fifth (Burlando et al., 2025) is the sharpest illustration. Borrower financial capability determines whether the borrower can read the price and resist the nudge; where it is low, as the Malawi evidence suggests it often is (Brailovskaya et al., 2024), the pricing effect falls on people least able to bear it.

The interaction matters more than the levels: high accuracy with low competition produces precise extraction, high competition with low accuracy produces an adverse-selection spiral in which lenders compete for borrowers they cannot sort and recover their losses through price, and good loan design with low borrower capability protects the borrower from impulse but not from a price they cannot read.

**Proposition 1.** The assessment effect of alternative-data scoring is weakly positive for every borrower and strictly positive for borrowers previously unassessable, and its magnitude increases with the density of the borrower's digital trail; it is therefore smallest for the groups the inclusion agenda most wants to reach.

**Proposition 2.** The acceptance effect is inclusive where the model replaces discretionary human judgement that was biased or inefficient, and exclusionary where the model is trained on outcomes that encode structural disadvantage; improvements in scoring accuracy do not change the direction of the effect, only its precision.

**Proposition 3.** The pricing effect is extractive whenever scoring accuracy is high and the borrower's record is not portable across lenders, because the lender can condition price on predicted willingness to pay without fear of losing the borrower; credit-bureau integration therefore does more to discipline pricing than any disclosure rule applied to a single lender.

**Proposition 4.** Over-indebtedness emerges from the interaction of fast delivery, short tenor and low borrower capability rather than from the price alone; a market can have high prices without widespread distress if loans are slow and infrequent, and widespread distress at moderate prices if loans are instant and repeated.

**Proposition 5.** The four regulatory instruments act on distinct parameters of the welfare model: interest-rate disclosure on borrower capability, data governance on scoring accuracy through the data environment and on competition through the portability of the borrower's record, credit-bureau integration on competition, and conduct supervision, which includes the auditing of scoring models, on loan design. Because no instrument moves every parameter, no single instrument can shift a market from extraction to inclusion, and a partial regime will produce displacement rather than improvement.

### 4.2 DISCUSSION

The framework's first implication is that the inclusion literature and the harm literature have been measuring different things and that both are right. Counting new borrowers measures the assessment effect, which is positive; measuring distress measures the joint outcome of acceptance, pricing and design, which can be negative. A policy that celebrates the first while ignoring the second will produce, where competition and capability are weak, a growing number of people included into a bad bargain, which the Kenyan evidence that wider access has not automatically reached vulnerable groups (Kim & Duvendack, 2025) and the Malawian evidence of uninformed borrowing (Brailovskaya et al., 2024) describe from two angles.

The second implication concerns the limits of accuracy as a policy goal. A more accurate model leaves the assessment effect untouched, tightens the acceptance effect and raises the lender's capacity to price on willingness to pay, so whether the borrower benefits depends on competition, which the model does not create. Fintech credit is attracted to markets

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with high bank mark-ups (Cornelli et al., 2023): entrants go where rents are, and the question is whether they compete them away or share them. The association between fintech credit and lower inequality that Hodula (2023) finds holds only where financial inclusion is already high, which is a condition most African markets do not meet, and it says nothing about a market dominated by a few applications in which the borrower has no portable score. Hurlin et al. (2026) add a further caution: fairness and predictive performance trade off against each other, and improving fairness for protected groups while keeping accuracy high is an optimisation that lenders and regulators must undertake deliberately, not a property a model acquires simply by leaving protected attributes out, since other variables can act as proxies for them.

Third, the framework reframes the debate over data governance, which is often conducted as if privacy rights and inclusion were simple opposites. The Californian evidence of Doerr et al. (2026) says otherwise: once borrowers held rights over their data, fintech lenders substituted non-traditional scoring for the data they lost, rejected more applicants, charged lower and more dispersed rates, suffered fewer defaults and lent more. In the framework's terms, a data-rights regime changes which data feed the assessment effect rather than simply shrinking it, tightens the acceptance effect as lenders screen harder on what remains, and compresses the pricing effect only where competition forces the gains from better screening through to borrowers. That last condition is the one a concentrated African market may fail: where few lenders hold the data and the borrower has no score to carry elsewhere, a data-rights rule that leaves portability untouched changes what the lender knows without changing whom the borrower can turn to. The appropriate design in such a market is therefore not less data but more portable data, a registry through which the borrower's record follows them and makes the pricing effect contestable, and the record most worth carrying is the positive repayment history, which is precisely the information a concentrated lender has least incentive to release.

Nigeria illustrates each of these points, and the account that follows is descriptive of the market's public record rather than a test of the propositions. The assessment effect has been large: smartphone-based lenders reach salaried and informal workers who have never held a bank loan, and the interim registration framework for digital lending that the Federal Competition and Consumer Protection Commission introduced in 2022, and the Digital, Electronic, Online, or Non-Traditional Consumer Lending Regulations 2025 that took effect in July 2025, were responses to the market's scale and conduct. The acceptance effect is unobservable from outside, because the 2025 Regulations require a creditworthiness assessment but make no provision for supervisory review of the scoring models, and lenders do not, so far as the public record shows, publish approval rates by borrower group; that Proposition 2 cannot currently be tested in Nigeria is itself a finding. The pricing effect is where the harm has concentrated: short-tenor loans with fees that compound into very high annualised rates and repeat borrowing to service earlier loans map onto Propositions 3 and 4, since the borrower's record was not portable, delivery was instant and tenor was short, while the collection practices that weaponised borrowers' contact lists are a matter of conduct rather than of price. Nigeria has private credit bureaux licensed under the Credit Reporting Act 2017 and, since 2020, the central bank's global standing instruction allowing a bank to recover an unpaid loan from a defaulter's accounts at other banks, but that instrument improves the lender's recovery rather than the borrower's bargaining position. The 2025 Regulations allow the Commission or a sector regulator to direct digital lenders to furnish their service data to recognised credit bureaux, but the public record does not show that digital lenders' positive repayment histories are yet systematically integrated into the bureaux, and conduct regulation, which now covers the disclosure of interest rates, fees and repayment terms and prohibits automatic or pre-authorised lending, does not on its face address delivery speed, rollover or concurrent borrowing.

Kenya offers the comparison, again on the public record. Its market is older, concentrated around a single mobile-money operator and its lending partners, and, under the Central Bank of Kenya (Amendment) Act 2021 and the Digital Credit Providers Regulations 2022, subject since 2022 to central-bank licensing and conduct supervision of digital credit providers. Before that regime, digital lenders reported borrowers to the credit bureaux for small defaults, producing a large population of negatively listed individuals, and the central bank

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then barred the listing of small loans. Kenya shows that bureau integration can be done and that integration which transmits only negative information turns the bureau from an instrument of competition into an instrument of exclusion, as the framework predicts: a bureau that carries defaults but not repayments strengthens the exclusionary side of the acceptance effect without touching the pricing effect, since a good borrower still has nothing to carry to a rival lender. The reversal is also consistent with the logic of Huang and Winton's (2026) registry model, in which exclusion should be no stricter than repayment incentives require when lending funds are ample; on this paper's reading, excluding small defaulters more harshly than that erodes the soft collateral on which uncollateralised lending rests.

The policy instruments can now be placed against the parameters of the welfare model. Interest-rate disclosure acts on borrower capability; it is necessary, because a borrower who cannot read the price cannot respond to competition, but it is not sufficient and may not be benign on its own, since the Malawian literacy intervention improved knowledge without improving timely repayment and modestly raised both demand and the chance of ever defaulting (Brailovskaya et al., 2024), while the Ghanaian evidence suggests that information delivered to both sides of the market disciplines misconduct, partly by engaging the provider's reputation (Annan, 2025). Data governance acts on scoring accuracy, by determining what data the lender may use, and on competition, by determining whether the borrower's record travels, so it must be designed with portability rather than restriction as the goal. Credit-bureau integration acts most directly on competition, and it must carry positive information to do so. Conduct supervision acts on loan design, and the delivery-speed evidence (Burlando et al., 2025) supports a mandated waiting period of some hours between approval and disbursement; the framework further implies, as this paper's own proposition rather than a finding of that study, that such a period, or a limit on concurrent loans, would do more to reduce over-indebtedness than a price cap, which would narrow the acceptance effect by raising the cut-off. Conduct supervision also has to reach the scoring model itself, since a supervisor that cannot see whom the model rejects cannot judge whether the acceptance effect is inclusive or exclusionary.

Several boundary conditions apply. The framework assumes the data trail is informative, which holds for transaction and usage data but may not for the thin trails of the very poor, where the assessment effect is small and the pricing argument moot. It assumes lenders are profit-maximising rather than cross-subsidising credit to build a payments franchise, in which case the pricing effect may be benign for a time and then reverse. It treats borrower capability as fixed, whereas Lusardi and Mitchell (2023) treat it as human capital that can be built, though the Malawian experiment is a caution about how quickly. And it treats the model as given, whereas Giudici and Raffinetti (2023) propose metrics through which the trustworthiness of AI models in finance can be assessed and monitored over time, which is what would make Proposition 2 testable, although Chen et al. (2024) caution that post-hoc explanations of credit models become less stable as class imbalance rises.

Future research should test the propositions directly. Proposition 2 requires approval data disaggregated by borrower group, which a supervisory sandbox of the kind McCallum and Aziakpono (2023) discuss could provide; Proposition 3 could be tested by comparing pricing before and after the introduction of positive-information sharing; and Proposition 4 is testable with the experimental designs already used in Mexico and Malawi, extended to Nigeria, where instant delivery and weak capability coincide most acutely.

## 5. CONCLUSION AND RECOMMENDATION

Algorithmic credit scoring has expanded who can be assessed for credit, and that expansion is the real achievement the inclusion literature records. It has not, by itself, determined who is accepted or on what terms, and it is in those further stages that the harms recorded by the consumer-protection literature arise. Because the first effect is inclusive almost by construction while the second and third have no fixed sign, a market can widen access and deepen distress at the same time, with the balance set by the interaction of scoring accuracy, lender competition, loan design and borrower capability.

The recommendations follow from Proposition 5. Nigerian supervisors should treat the four instruments as complements acting on different parameters rather than as alternatives. Disclosure of the effective annualised cost of every digital loan should be mandatory and standardised, understood as

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a precondition for competition rather than a remedy in itself. The private credit bureaux should be required to receive, and digital lenders to report, positive repayment histories, using the reporting power that the 2025 Regulations already provide, so that the good borrower acquires a record that can be carried to a rival lender, and negative-only reporting should be avoided given the Kenyan experience. Data-protection rules should be written with portability rather than restriction as the organising aim. Conduct supervision should extend beyond disclosure and collection practices to loan design, with particular attention to delivery speed, concurrent borrowing and rollover, and it should include the auditing of scoring models, since a supervisor that cannot see whom the market rejects cannot claim to be managing inclusion.

## 6. CONTRIBUTION TO EXISTING KNOWLEDGE

The paper offers an explicit decomposition of algorithmic lending into assessment, acceptance and pricing effects, which reconciles the inclusion and consumer-harm literatures by showing that they measure different stages of the same process. It specifies a welfare model in which the interaction of scoring accuracy, lender competition, loan design and borrower capability determines the sign of the net effect, derives five testable propositions, and maps the four regulatory instruments onto the parameters they move, which explains why partial reform produces displacement rather than improvement. Grounded in Nigeria and its Kenyan comparator, the framework is portable to other emerging markets in which alternative-data lending has outrun the information infrastructure that would make it contestable.

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