American Journal of Advanced Multidisciplinary Innovation and Research (AJAMIR)

E-ISSN: XXXX-XXXX ● Website: www.ajamir.com ● Email: editor@ajamir.com

Alternative Credit Scoring and Borrower Dignity

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Abstract

Alternative credit scoring has expanded the informational possibilities available to lenders by incorporating data beyond conventional credit histories, including cash-flow information, rent and utility payments, transaction behavior, psychometric indicators, and selected digital footprints. Such approaches can improve the assessment of thin-file or previously difficult-to-score applicants, yet broader data availability also creates significant questions concerning privacy, relevance, discrimination, explainability, and the borrower's ability to challenge consequential decisions.

This study examines alternative credit scoring through the concept of borrower dignity, defined as a condition in which applicants can seek credit without unnecessary informational extraction, arbitrary profiling, unexplained adverse treatment, or loss of meaningful procedural agency. Because no verified borrower-level dataset was supplied, a transparent simulation-based design involving 160 synthetic credit-assessment cases was developed. Five dimensions were incorporated: Access Gain, Data Minimization, Explanation and Appeal, Human Review, and Governance Maturity. The cases were categorized into four governance stages: Extractive, Access-Led, Rights-Aware, and Dignity-Centered. The simulated analysis produced a Pearson correlation of $r = 0.835$ between governance maturity and borrower dignity. Mean Borrower Dignity increased from 47.9 under Extractive scoring to 57.5 under Access-Led scoring, 66.5 under Rights-Aware governance, and 77.0 under Dignity-Centered arrangements.

The findings illustrate that broader credit access alone is insufficient to establish responsible inclusion. Alternative scoring becomes more dignity preserving when predictive expansion is accompanied by proportionate data use, meaningful reasons for consequential decisions, accessible correction and appeal procedures, and accountable human oversight.

The study proposes that high-quality alternative credit scoring should be evaluated through a dual standard of predictive inclusion and procedural dignity. The paper contributes a borrower-centered governance framework suitable for subsequent empirical validation in fintech, consumer credit, microfinance, and small-enterprise lending contexts.

Keywords: alternative credit scoring; borrower dignity; alternative data; financial inclusion; algorithmic lending; credit fairness; explainability; data minimization; fintech lending; borrower rights

1. Introduction

Credit scoring reduces informational uncertainty by converting information about applicants into assessments of expected repayment risk. Conventional scoring systems generally depend on established credit histories, previous repayment performance, outstanding debt, account characteristics, and related financial indicators. This approach can work effectively for applicants with sufficiently developed credit records but is less useful for people or enterprises with thin, incomplete, or nonexistent formal histories. Early research by the Consumer Financial Protection Bureau documented a substantial population with limited or unscorable conventional credit information, illustrating why alternative approaches to establishing credit visibility became an important policy concern.

Alternative credit scoring attempts to address this limitation by incorporating information not conventionally contained in traditional credit files. The Consumer Financial Protection Bureau has described alternative data as potentially including rental payments, utility or telecommunications payments, bank-account transactions, education or occupation information, and in some cases online or digital behavior. The agency has simultaneously emphasized both the potential for improved credit access and the risks associated with privacy, discrimination, opacity, and increasingly complex decisions. Empirical research also demonstrates genuine predictive potential. Berg, Burg, Gombović, and Puri found that relatively simple digital-footprint variables contained substantial information for predicting consumer default and complemented rather than merely substituted for conventional bureau information.

The inclusion potential is particularly relevant for applicants whose economic reliability is not adequately reflected by conventional borrowing histories. Arráiz, Bruhn, and Stucchi examined psychometric screening among small-business owners in Peru and found that such information could help identify creditworthy entrepreneurs who might otherwise remain difficult to assess through traditional scoring procedures. The World Bank's credit-scoring guidance similarly recognizes that innovative data and analytical approaches may widen financial inclusion, improve risk assessment, and increase efficiency. Yet the same guidance emphasizes model governance, fairness, privacy, interpretability, accountability, and consumer protection.

This dual potential creates the central problem addressed by the present study. A borrower can become more credit visible while simultaneously becoming more informationally exposed. A model may approve applicants who previously lacked conventional scores while requiring them to surrender increasingly intimate information about transactions, devices, communications, consumption, or behavior. Hurley and Adebayo warned that big-data credit scoring can incorporate variables whose relationship to creditworthiness is not intuitively apparent, while Barocas and Selbst demonstrated more broadly how data-driven systems can reproduce or generate discriminatory effects even without explicitly discriminatory intent.

The present paper therefore introduces borrower dignity as a complementary criterion for evaluating alternative credit scoring. Borrower dignity refers to whether a person is assessed through relevant and proportionate information, receives understandable treatment, can identify and correct material errors, has meaningful opportunities to challenge consequential outcomes, and remains subject to accountable human and institutional oversight. This framing is supported by research on perceptions of algorithmic justice. Binns and colleagues found that people evaluating algorithmic decisions raised concerns involving arbitrariness, generalization, justice, and dignity, indicating that affected individuals care about more than computational accuracy. The study consequently asks not only whether alternative credit scoring improves prediction, but whether it allows applicants to enter formal lending systems as respected and procedurally empowered participants.

2. Objectives of the Study

2.1 Evaluating Inclusive Credit Visibility

The first objective is to examine the capacity of alternative scoring to improve responsible credit visibility for applicants whose conventional financial records are incomplete. Alternative data can reveal payment regularity or cash-flow behavior that may not appear within a standard bureau file. Official U.S. regulatory discussions before 2021 recognized that information such as recurring payments and cash-flow data might enable more accurate assessments of applicants otherwise poorly represented by traditional scoring.

The objective is not to presume that every applicant should receive credit. Responsible inclusion requires identification of genuinely relevant information capable of distinguishing repayment capacity without weakening prudent underwriting. The present study therefore separates Access Gain from Borrower Dignity so that a system can perform strongly on inclusion while still being evaluated critically on transparency, privacy, or procedural safeguards.

2.2 Measuring Procedural and Informational Dignity

The second objective is to operationalize borrower dignity as a measurable construct. The proposed framework treats dignity as multidimensional, incorporating data proportionality, understandable explanation, correction mechanisms, appeal opportunities, accountable human review, and respectful treatment.

This perspective is consistent with research on algorithmic decision making showing that perceptions of justice depend on the nature of the information used and the explanation provided. Binns and colleagues found that individuals evaluate algorithmic decisions using familiar dimensions of justice and can react negatively when decision systems appear arbitrary or reductive. Related work on counterfactual explanations by Wachter, Mittelstadt, and Russell argued that explanations can be valuable when they help affected persons understand an outcome, contest it, or determine what would need to change to obtain a different result.

2.3 Developing a Dignity-Centered Scoring Governance Model

The third objective is to distinguish alternative scoring systems according to governance maturity rather than technological sophistication alone. A highly complex machine-learning model is not necessarily more responsible than a simpler statistical model. Governance quality depends on how information is selected, validated, explained, monitored, and subjected to human accountability.

The proposed model therefore identifies four stages: Extractive, Access-Led, Rights-Aware, and Dignity-Centered. The final stage does not reject alternative data. Instead, it seeks the minimum information reasonably necessary for a defensible credit assessment and combines that information with fairness monitoring, explanation, correction, appeal, and responsible human intervention.

3. Review of Literature

3.1 Alternative Data, Thin-File Borrowers, and Predictive Inclusion

Alternative credit scoring emerged partly because conventional credit systems can struggle to assess applicants without established formal histories. The World Bank's guidance on alternative data recognizes the potential for nontraditional information to support digital financial-service access for individuals and small enterprises operating outside conventional formal-information systems. Such information may be particularly useful where the absence of a bureau score reflects limited prior borrowing rather than inability to repay.

Arráiz, Bruhn, and Stucchi provide important empirical evidence through their study of psychometric screening among entrepreneurs in Peru. Their research evaluated a psychometric tool designed to distinguish credit risk and potentially increase access among small-business owners. The findings indicated that alternative behavioral assessment could provide useful information where established credit histories were unavailable. The contribution is important because it demonstrates that alternative scoring can genuinely address informational exclusion rather than functioning only as a technological novelty.

Berg, Burg, Gombović, and Puri later demonstrated that digital footprints can also contain meaningful predictive information. Their 2020 *Review of Financial Studies* article found that relatively simple online variables could match substantial parts of the information content contained in credit-bureau scores and could complement existing financial information. These findings establish a credible economic case for examining alternative information, but they simultaneously enlarge the ethical question concerning how far lenders should extend data collection merely because additional information has predictive value.

3.2 Data Relevance, Discrimination, and Privacy

Alternative data create a potential tension between predictive accuracy and informational proportionality. Hurley and Adebayo observed that big-data credit assessment can involve variables such as purchasing patterns, social networks, and other behavioral traces that may lack an intuitively obvious connection to a borrower's ability to repay. When models employ large numbers of weak or indirect signals, borrowers may find it increasingly difficult to understand why a decision occurred or what aspects of their behavior affected their eligibility.

Discrimination remains a related concern. Barocas and Selbst explained how data-mining systems can generate disparate outcomes through historical patterns, proxy variables, target definitions, and other mechanisms even where protected characteristics are not directly entered into a model. The Federal Trade Commission likewise framed big data as capable of supporting both inclusion and exclusion and encouraged businesses to examine whether data practices could produce discriminatory or unfair consequences.

Privacy creates another layer of concern because alternative scoring can transform information generated for one context into evidence used within another. Prabhakar's 2020 analysis of digital credit scoring highlighted the potential financial-inclusion benefits of alternative data while also identifying privacy, data security, discrimination, and weak accountability as significant concerns in emerging digital lending environments. Borrower dignity therefore requires more than secure storage. It also requires a defensible reason for why particular information should be collected and used in the first place.

3.3 Explainability, Contestability, and Human-Centered Credit Decisions

Credit decisions are consequential because rejection, pricing, limits, and loan terms can affect housing, education, enterprise development, emergency resilience, and broader economic opportunity. For that reason, explainability has practical rather than merely technical importance. The World Bank's Credit Scoring Approaches Guidelines identify interpretability, governance, accountability, and consumer rights as key components of responsible scoring.

Wachter, Mittelstadt, and Russell proposed counterfactual explanation as one method through which affected individuals could understand which changes would have produced a different automated outcome without requiring complete disclosure of a model's internal architecture. Their framework emphasizes three practical purposes of explanation: understanding why an outcome occurred, developing grounds to contest the outcome, and identifying changes that might lead to a different future decision. In credit contexts, these purposes align closely with borrower dignity because explanations become useful when they restore some practical agency to the person being scored.

Regulatory discussions before 2021 similarly recognized that sophisticated machine-learning models do not remove obligations to communicate adverse credit decisions. The Consumer Financial Protection Bureau specifically discussed the challenge of providing adverse-action reasons when lenders use AI or machine-learning models. Borrower dignity therefore requires a decision system that does not allow complexity itself to become a reason for withholding meaningful information.

4. Research Methodology

4.1 Research Design and Analytical Scope

The present study adopts a quantitative simulation-based design. No real borrowers, lenders, protected characteristics, credit applications, repayment records, loan amounts, or algorithmic platforms are represented in the numerical analysis. Simulation is used because no verified primary dataset was supplied and because invented observations should not be presented as completed empirical research.

A reproducible synthetic corpus of 160 credit-assessment cases was generated using a fixed random seed. Six standardized variables were constructed on scales ranging from 0 to 100: Governance Maturity, Access Gain, Data Minimization, Explanation and Appeal, Human Review, and Borrower Dignity.

Governance Maturity represents the overall quality of policy and operational controls surrounding alternative-data use. Access Gain captures the potential expansion of assessment opportunities. Data Minimization represents the extent to which information collection remains proportionate and relevant. Explanation and Appeal measures procedural transparency and

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contestability. Human Review reflects the availability of accountable human intervention in consequential or disputed cases.

4.2 Proposed Borrower-Dignity Measurement Instrument

Future empirical research could operationalize borrower dignity through applicant surveys conducted after a credit application or decision. The following five questions are proposed for validation and were not administered to actual borrowers.

Table 1: Proposed Borrower-Dignity Measurement Instrument

Item	Construct	Proposed Questionnaire Statement	Measurement Purpose
Q1	Data proportionality	The information requested from me appeared reasonably relevant to evaluating my credit application.	Measures data minimization and relevance
Q2	Process understanding	I understood the main information and factors that could influence the credit decision.	Measures procedural transparency
Q3	Explanation	If the decision was unfavorable, I could obtain an understandable explanation of the main reasons.	Measures interpretability
Q4	Correction and appeal	I had a realistic opportunity to correct inaccurate information or request reconsideration of an important decision.	Measures contestability
Q5	Borrower dignity	I felt that the credit-assessment process treated me as a person deserving fair, respectful, and accountable consideration rather than merely as a data profile.	Measures overall dignity

4.3 Governance Classification and Simulation Procedure

Cases were divided into four governance stages according to Governance Maturity. Scores below 35 were categorized as Extractive, reflecting high reliance on data collection with comparatively weak borrower safeguards. Scores from 35 to below 55 were classified as Access-Led, reflecting emphasis on expanded scoring coverage. Scores from 55 to below 75 were classified as Rights-Aware, representing stronger proportionality, explanation, and review. Scores of 75 or higher were categorized as Dignity-Centered.

The simulated Borrower Dignity Index was generated as a weighted function of governance quality, access gain, data minimization, explanation and appeal, human review, and random variation. Governance-related safeguards were modeled as positively associated with governance maturity, while Access Gain was allowed to vary more independently. This structure reflects the theoretical proposition that a lender can expand credit access without necessarily developing equally mature rights protections.

Pearson correlation was calculated descriptively between Governance Maturity and Borrower Dignity. Because the dataset is synthetic, inferential statistical significance would not establish a real-world population relationship. The analysis instead demonstrates the structure of an empirical model that could subsequently be tested with borrower surveys, lender audits, algorithmic assessments, and administrative decision data.

5. Analysis

5.1 Comparative Outcomes Across Governance Stages

The synthetic corpus contains 18 Extractive cases, 59 Access-Led cases, 54 Rights-Aware cases, and 29 Dignity-Centered cases. The mean Borrower Dignity Index rises systematically as governance safeguards become more developed.

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Table 2: Simulated Alternative Credit Scoring and Borrower Dignity Outcomes

Governance Stage	Simulated Cases	Mean Governance Maturity	Mean Access Gain	Mean Data Minimization	Mean Explanation and Appeal	Mean Human Review	Mean Borrower Dignity
Extractive	18	27.8	61.4	43.0	38.5	50.4	**47.9**
Access-Led	59	45.8	64.5	52.7	50.0	54.7	**57.5**
Rights-Aware	54	64.2	67.2	63.8	61.5	62.0	**66.5**
Dignity-Centered	29	85.9	70.1	76.2	74.2	71.6	**77.0**

The table demonstrates an important distinction between access progression and rights progression. Mean Access Gain increases relatively modestly between governance stages, while Data Minimization, Explanation and Appeal, and Human Review improve much more substantially. This reflects the central proposition that lenders can achieve important inclusion benefits before they develop mature borrower protections.

5.2 Governance Maturity and Borrower Dignity

Across the 160 simulated cases, Governance Maturity and Borrower Dignity produce a Pearson correlation of approximately $r = 0.835$. Within the analytical model, this represents a strong positive association.

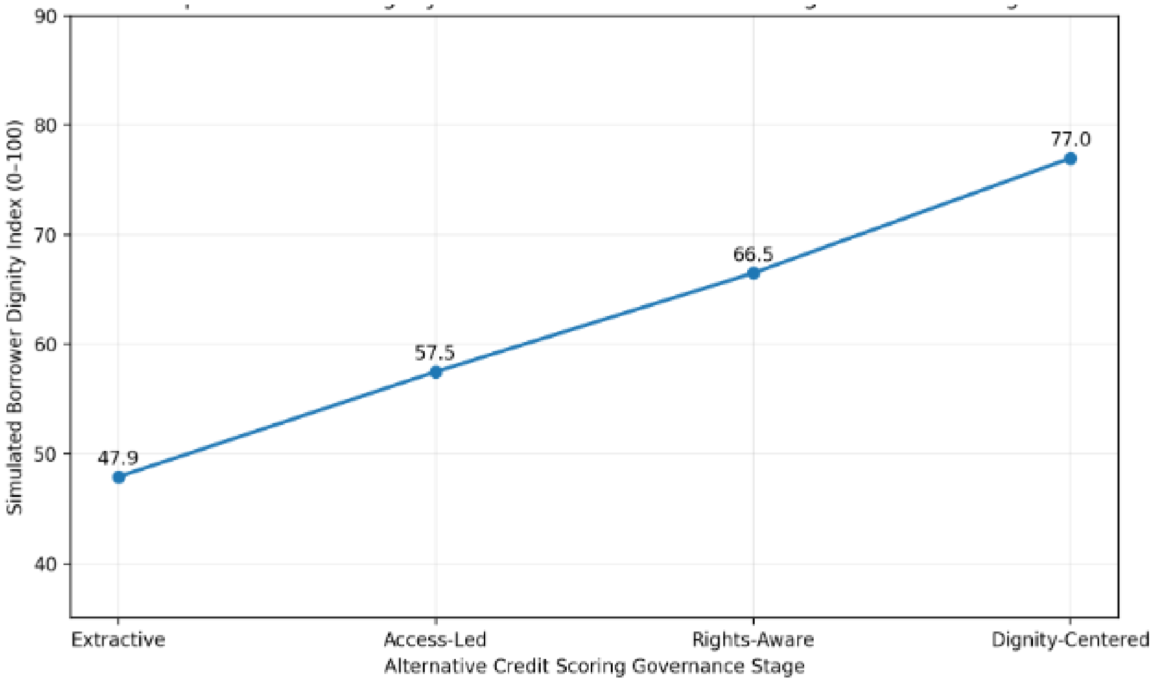
The coefficient should not be interpreted as an empirical estimate. Its analytical value lies in demonstrating how borrower-centered governance can be modeled independently from predictive accuracy or default performance. Future research could test whether actual borrowers report greater procedural fairness and dignity when lenders provide more understandable explanations, restrict irrelevant data collection, and offer meaningful appeal mechanisms.

The simulation also reinforces a broader methodological principle. Credit-scoring studies should not restrict performance evaluation to measures such as area under the receiver operating characteristic curve, approval rate, default rate, or lender profitability. Those outcomes remain important, but responsible scoring additionally requires borrower-level outcome indicators relating to understanding, fairness, privacy, and contestability.

5.3 Graphical Interpretation of the Dignity-Centered Model

The graph below displays the simulated progression of Borrower Dignity across the four governance stages.

Graph 1: Borrower Dignity Across Alternative Credit Scoring Governance Stages



The progression illustrates why inclusion alone should not define responsible innovation. The movement from Extractive to Access-Led scoring generates an improvement because more applicants gain an opportunity to demonstrate creditworthiness. The larger institutional transformation occurs when lenders add data proportionality, meaningful explanation, correction procedures, appeal mechanisms, and human accountability.

Key Finding: Alternative credit scoring reaches its strongest borrower-centered form when expanded credit visibility is combined with procedural visibility—the borrower can understand how the decision was made, identify relevant errors, and obtain accountable reconsideration where appropriate.

6. Discussion

6.1 From Credit Inclusion to Dignified Credit Visibility

Alternative credit scoring can solve a genuine informational problem. Applicants who have limited formal borrowing histories should not necessarily be treated as inherently risky simply because conventional scoring systems possess insufficient data about them. Research by Arráiz and colleagues demonstrates the potential of psychometric information in small-enterprise lending, while Berg and colleagues show that digital footprints can contain meaningful information beyond traditional bureau scores.

The difficulty begins when inclusion is defined as maximizing the quantity of data collected about previously invisible applicants. Credit visibility should not require complete behavioral visibility. The CFPB's early alternative-data discussions explicitly recognized this tension by highlighting both potential access benefits and risks involving complexity, privacy, transparency, and discrimination.

A dignity-centered model therefore applies a proportionality test. Lenders should ask not merely whether a variable improves prediction but whether its additional predictive contribution is sufficient to justify the intrusion, complexity, and potential disparate effects created by its use. Cash-flow information with a direct connection to repayment capacity may be easier to justify than highly indirect behavioral or social-network proxies. The aim is not data scarcity for its own sake but purpose-limited informational adequacy.

6.2 Explanation and Appeal as Components of Financial Agency

A borrower who cannot understand or challenge a consequential score has limited practical agency within the lending relationship. This problem becomes more serious as machine-learning models incorporate numerous variables and nonlinear interactions. Hurley and Adebayo warned that big-data credit systems may make financial decisions increasingly difficult for consumers to understand, particularly where variables have no obvious relationship to creditworthiness.

Explanation should therefore be designed around usefulness rather than technical completeness. Borrowers do not necessarily require mathematical disclosure of every model coefficient. They require sufficiently specific information to understand the main adverse factors affecting a decision and to determine whether those factors are accurate. Wachter, Mittelstadt, and Russell's counterfactual approach is valuable in this respect because it focuses on helping individuals understand how an outcome could have been different and providing information capable of supporting contestation or future action.

Appeal is equally important. An explanation without a mechanism for correction may merely inform an applicant that an error has harmed them. Rights-Aware and Dignity-Centered scoring therefore require practical processes for correcting misattributed records, outdated information, erroneous identity matches, or other material inputs. Human review should be available where automated decisions are disputed, unusual, or consequential.

6.3 Human Oversight, Fairness, and Responsible Predictive Innovation

Automation can reduce some forms of inconsistent human judgment, but it does not eliminate human responsibility. People determine the outcome to be predicted, the variables available for modeling, the training data, optimization criteria, threshold values, pricing rules, fairness metrics, and governance procedures. Algorithmic decisions therefore remain institutionally designed decisions.

Barocas and Selbst's analysis is particularly important because discriminatory effects can emerge from historical data, proxy variables, and seemingly neutral modeling choices. Binns and colleagues further demonstrate that affected individuals evaluate automated decisions through justice concepts that include arbitrariness, relevance, and dignity. Responsible governance should therefore combine quantitative fairness audits with qualitative attention to how borrowers experience scoring processes.

Human oversight should not mean a superficial employee confirmation of every algorithmic output. It should involve authority to investigate anomalies, interpret contextual information where legitimately relevant, correct data problems, and reconsider outcomes when automated decisions cannot be adequately justified. The purpose of humans in the loop is accountable judgment rather than ceremonial approval.

7. Conclusion

Alternative credit scoring offers meaningful opportunities to extend credit assessment to individuals and small enterprises that conventional scoring systems may inadequately represent. Psychometric assessments, cash-flow information, payment histories, and selected digital signals can provide additional evidence of creditworthiness and potentially reduce the disadvantage created by limited conventional credit histories. The economic rationale for responsible alternative scoring is therefore credible.

However, greater predictive visibility can create new risks when applicants become visible only by surrendering extensive personal information to opaque systems. The key ethical and governance challenge is consequently not whether alternative data should be categorically accepted or rejected. It is determining which information is sufficiently relevant, proportionate, explainable, fair, and governable to justify its use in consequential lending decisions.

The simulation developed in this study illustrates the value of this distinction. Mean Borrower Dignity progresses from 47.9 under Extractive scoring to 57.5 under Access-Led systems, 66.5 under Rights-Aware governance, and 77.0 under Dignity-Centered scoring. Governance Maturity and Borrower Dignity produce a modeled correlation of $r = 0.835$. These values are explicitly simulated and should not be interpreted as estimates derived from actual borrower experiences.

The principal contribution of the study is therefore the dignified credit visibility framework. Responsible alternative scoring should provide previously difficult-to-score applicants with a fair opportunity to demonstrate creditworthiness while simultaneously limiting unnecessary data extraction, communicating important decision reasons, enabling correction and appeal, testing for discriminatory effects, and retaining meaningful human accountability. Future empirical research should validate this framework through borrower surveys, controlled experiments, lender governance audits, complaint records, model-fairness assessments, and comparisons between traditional and alternative scoring systems. The strongest alternative credit-scoring system is not simply the model that predicts repayment most accurately. It is the system that improves risk assessment while ensuring that the person being assessed remains an informed, respected, and procedurally empowered participant in the credit relationship.

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