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Credit Access in The Gig Economy: Rethinking Creditworthiness in a Post-Employment Financial System

OLAIDE OLUWARANTI OYEYEMI

ABSTRACT : With the world of work undergoing a significant shift towards informal, flexible work structures, dubbed by some as the gig economy, credit access remains tied to a prehistoric definition of creditworthiness rooted in stable employment, regular income, and traditional financial history. Millions of gig workers are systematically disadvantaged in their bid to secure credit facilities in conventional financial systems, not due to their riskiness but rather because the systems' frameworks are inadequate for determining their financial status in light of their work realities. This paper discusses the mismatch between on-demand work and traditional credit scoring. It utilizes labor economics, financial technology (fintech), and credit analytics to critically evaluate the exclusionary nature of current credit systems for gig workers. By comparing and contrasting, as well as studying cases of alternative fintech models, the study will suggest a novel paradigm of creditworthiness that is more representative of the dynamic financial portrait of gig workers. The results of the study guide universal lending behavior and enter the discussion on developing fair financial systems in the post-employment world.

I. INTRODUCTION

1.1. Background of the Study

Over the last decade, digitization, platform capitalism, and shifting worker preferences have transformed the labor relations approach globally at an unprecedented rate. The gig economy, with its short-term contracts, freelance gigs, and platform-mediated earnings, is not a fringe phenomenon but a prevalent change in the organization of labor, with more than 36 percent of US workers engaging in some form of gig work in 2023 alone, and with platform work becoming a significant source of income to millions of people in the informal sector in countries such as India, Nigeria and Brazil (World Bank, 2023). However, despite its rise and socioeconomic importance, gig work remains financially undetectable. The established finance system has remained focused on creditworthiness through frequent payroll deposits, official employment background, and long-term financial agreements, features that are largely lacking in the gig work arrangement. As a consequence, gig workers have been locked out of the cheap credit markets, pushed into predatory lending, or stuck to informal borrowing (Chava et al., 2021; De Stefano et al., 2020). As fintech continues to expand, we have a unique chance to utilize alternative data, including digital transaction data, platform income, and behavioral signals, to transform the credit risk evaluation method. However, these innovations raise other questions: How can new types of credit assessment be made fair, inclusive, and transparent? Do they stand up to scrutiny regarding privacy, discrimination, and systemic bias?

1.2. Statement of the Problem

The fundamental issue that the research aims to resolve is that traditional credit assessment systems cannot be applied to the financial reality of gig workers. The old systems of credit scores, including FICO and bureau-based scores, were designed in a way that benefits individuals with fixed incomes, long credit histories, and formal employment records. These gig workers are systematically excluded from accessing mainstream credit, even when they have steady but unconventional incomes. Making matters worse is the unequal usage of fintech solutions. Although platforms are currently experimenting with alternative data and dynamic scoring algorithms, there is no standard agreement or regulatory framework to ensure such practices are fair, ethical, and inclusive. The outcome is a balkanized credit ecosystem characterized by exclusion, a lack of transparency, and innovation without responsibility.

1.3. Objectives of the Study

This study aims to:

- Examine the barriers gig workers face when attempting to access credit through traditional and digital financial institutions.

- Analyze how fintech and credit analytics are redefining the concept of creditworthiness.
- Evaluate innovative credit models and their applicability to diverse gig economy contexts.
- Propose a new credit paradigm that reflects the dynamics of informal and platform-based labor.
- Inform financial inclusion policies that support gig workers in both the Global North and South.

1.4. Research Questions and Hypotheses

Primary Research Question

How can credit evaluation systems be restructured to ensure fair and inclusive access for gig economy workers who lack traditional employment credentials?

Secondary Research Questions

1. What specific features of gig work create barriers to traditional credit access?
2. How are fintechs currently evaluating gig workers' credit risk, and what are their limitations?
3. What models of alternative credit scoring show promise in enhancing the financial inclusion of gig workers?
4. What regulatory and ethical considerations must be addressed in implementing these models?

Hypotheses

- **H1**: Traditional credit scoring systems significantly underestimate the creditworthiness of gig workers due to structural misalignment with non-standard income profiles.
- **H2**: Fintech models that incorporate alternative data and cash-flow analytics are more predictive of repayment capacity in gig workers than legacy credit scores.
- **H3**: A dynamic, equity-centered credit scoring framework will significantly improve access to fair credit among informal and platform-based workers.

1.5. Significance of the Study

This study holds significance for multiple stakeholder groups:

- **For academics**, it bridges gaps across labor economics, digital finance, and data ethics.
- **For financial institutions**, it provides empirical and analytical guidance on serving a rapidly growing and underserved demographic.
- **For policymakers**, it provides frameworks for regulating fintech in a manner that ensures both innovation and equity.
- **For gig workers and advocates**, it surfaces often-overlooked challenges and presents viable pathways toward financial inclusion.

At a broader level, this research challenges the normative assumptions of what it means to be "creditworthy" in the 21st century, urging institutions to evolve in tandem with labor realities.

1.6. Scope of the Study

The study focuses on gig workers across both high-income and low- to middle-income countries, particularly the United States, India, Kenya, and Brazil. It examines a diverse array of gig work types, including ride-hailing, freelance digital labor, delivery services, and online marketplaces. The scope includes:

- Credit evaluation mechanisms (traditional, fintech-based, hybrid)
- Regulatory frameworks across major jurisdictions
- Case studies of fintech credit innovations
- Worker perspectives through qualitative interviews

Exclusions: The study does not evaluate lending in informal, offline gig work that is not mediated by digital platforms unless it is part of a comparative framework.

1.7. Definition of Key Terms

- **Gig Economy**: A labor market characterized by short-term contracts, freelance work, and digital platform intermediation rather than traditional full-time employment.
- **Creditworthiness**: A measure of an individual's ability and likelihood to repay a loan, traditionally assessed via credit scores based on employment, debt history, and financial behavior.
- **Fintech**: Technology-driven financial services companies that innovate beyond traditional banking models, often leveraging big data, AI, and mobile platforms.
- **Alternative Data**: Non-traditional financial indicators—such as mobile phone usage, social media activity, transaction histories, or platform earnings—are used to assess credit risk.
- **Financial Inclusion**: The process of ensuring access to valuable, affordable financial products and services for all individuals, especially the underserved or marginalized.
- **Algorithmic Credit Scoring**: The use of machine learning or AI models to assess creditworthiness using complex, often opaque decision-making processes.

II. LITERATURE REVIEW

2.1 Preamble

The employer-employee relationship, which used to be the core of financial identity, is quickly becoming obsolete as global labor markets decentralize and digital work platforms become increasingly abundant. Freelancers, ride-share drivers, task workers, online creators, and digital service contractors comprise the so-called gig economy, which is a growing segment of the global workforce. In regions such as Sub-Saharan Africa, Southeast Asia, or Latin America, informal work or contract work is already the dominant form of labor engagement (ILO, 2021). Despite this change, there has been no proper adjustment by financial systems. The majority of gig workers remain outside the realm of formal credit because they lack sufficient credit history, their income is irregular, or they are not included in payroll-based reporting systems. Such exclusion is not only financial but socio-technical - embedded within the collection, interpretation, and acted-upon data. This literature review summarizes the economic, technological, and sociological approaches to gig work and credit access and critiques the epistemologies of traditional credit models. It presents a broader paradigm of credit based on context-aware, inclusive analytics.

2.2 Theoretical Review

2.2.1 Credit Evaluation: From Classical Economics to Digital Heuristics

The conventional credit score models, such as those based on the FICO or TransUnion algorithms, are dependent on backward-looking financial behavior, which is supported by the rational choice theory at their core, assuming that borrowers maximize their utility in specific, predictable ways (Becker, 1976). Gig workers do not conform to this paradigm, though; their earnings are unpredictable, they save irregularly, and they might not have long-term planning instruments.

Additionally, the asymmetry of information (Stiglitz & Weiss, 1981) remains a key concept in credit theory, implying that lenders must reduce uncertainty by seeking proxies for stability, such as employment history. This old-fashioned proxy does not accurately represent the true earning power or online financial habits of gig workers, who can transact a high volume of transactions via mobile wallets and digital platforms or informal contracts.

New theories in behavioral economics (Thaler & Sunstein, 2008) have criticized the rational agent model and propose that credit decisions can and must be made based on behavioral characteristics, such as financial resilience, goal commitment, and risk aversion, which are data frequently incorporated into platform behavior or mobile application usage. It will also be necessary to integrate the theory of trust (Gambetta, 1988): Does repeated gig work and peer ratings allow the reputation capital to replace more traditional collateral?

This research contributes to the ongoing discussion, as the author will argue in favor of multidimensional credit systems that integrate behavioral, transactional, and reputational indicators, particularly in the case of unbanked or underbanked gig workers.

2.2.2 Labor Economics and Platform Inequality

Based on the dual labor market theory (Doeringer & Piore, 1971) and Standing's (2011) representation of the precariat, gig workers frequently belong to secondary labor markets, lacking benefits, work security, and collective bargaining. Their economic marginalization reflects their labor precarity. Nevertheless, gig platforms perform new modes of visibility. Platform capitalism (Srnicek, 2017) converts labor into data, enabling the quantification of work behaviors such as reliability, customer ratings, delivery times, and cancellation rates. These platform metrics are uncapped when it comes to credit analytics. For example, in some countries, Uber offers financial services to drivers based on their ride logs and rating history (Uber, 2023). Moreover, still, there are asymmetries of power. The data generated by workers is owned and controlled by platforms, which seldom share it with third-party lenders or even with the workers themselves, a form of data colonialism (Couldry & Mejias, 2019). This research paper questions these imbalances and proposes policy frameworks that will establish the data sovereignty of gig workers as a financial right.

2.3 Empirical Review

2.3.1 Financial Exclusion of the Gig Workforce

According to Farrell et al. (2018), gig workers in the US are less likely to have emergency savings or be eligible for credit products, and they also face 30% greater income volatility. Similarly, even though they are digitally proficient, gig workers in India have greater rates of financial exclusion, according to Bhattacharya and Nair (2021). Gig workers are frequently victims of algorithmic invisibility, which means that their financial behaviors occur outside of conventional scoring systems, in addition to the absence of income documentation. For example, despite regular mobile money transactions, more than 65% of boda-boda riders and digital freelancers in Kenya are turned down for formal loans, according to a 2022 survey conducted by FSD Africa.

Additionally, there is a racialized and gendered dimension. Even when their digital financial behaviors are steady, Black and Latinx gig workers in the United States are more likely to rely on payday lenders and experience higher denial rates, according to research by Prosperity Now (2022), highlighting institutional bias. Instead of automatically considering gig workers to be high-risk, this study attempts to rethink them as creditworthy by design using inclusive measures.

2.3.2 Emerging Fintech Solutions: Promise and Peril

Fintech innovations are beginning to address these gaps:

- Mercado Pago in Latin America utilizes buyer and seller transaction history for microcredit issuance.
- Crediwatch in India analyzes GST returns, SMS receipts, and utility payments.
- Tala, Branch, and JUMO in East Africa issue small loans based on mobile usage patterns, location data, and contact lists (Bjorkegren & Grissen, 2019).

While these models offer promise, they raise significant concerns:

- Opacity: Users often struggle to understand how scores are generated (Hurley & Adebayo, 2017).
- Consent and ethics: Data extraction often occurs without meaningful user control (Eubanks, 2018).
- Bias: Algorithms may embed historical inequalities (Barocas et al., 2019).

This study advances the empirical literature by proposing explainable AI (XAI) credit models informed by fairness audits and participatory design principles.

2.3.3 Comparative Regulatory Approaches

Only a few countries have made tangible regulatory progress:

- India's Account Aggregator Framework enables users to share financial data across banks, insurers, and tax systems, potentially empowering gig workers to build digital credit profiles (RBI, 2021).
- Brazil's PIX system facilitates the capture of real-time payment data, creating alternative credit inputs.
- The EU's General Data Protection Regulation (GDPR) and Kenya's Data Protection Act (2019) provide legal frameworks for data portability; however, enforcement remains weak.

This study integrates a comparative analysis to propose policy instruments, such as "digital financial passports," which aggregate and securely transfer gig-related financial data across ecosystems.

2.3.4 Peer-Based Lending and Informal Financial Innovation

In response to institutional exclusion, many gig workers turn to:

- ROSCA models (Rotating Savings and Credit Associations) are now digitized through platforms like Chamasoft (Kenya) or Bloom Money (UK).
- Social scoring systems, such as Aella Credit in Nigeria, utilize community endorsement for loan access.
- Credit unions and cooperatives often recognize alternative sources of income.

These innovations offer resilience and cultural fit but often lack scalability and systemic legitimacy. This study examines hybrid models that integrate community validation, data analytics, and regulatory support to facilitate sustainable credit pathways.

III. RESEARCH METHODOLOGY

3.1 Preamble

This study's research approach aims to thoroughly examine the innovations and difficulties related to gig workers' access to credit in the post-employment financial sector. This study employs a mixed-methods approach, combining quantitative and qualitative paradigms to provide a nuanced and context-sensitive exploration of gig economy financial exclusion and fintech-enabled alternatives. This approach recognizes that traditional empirical designs are inadequate in capturing the informal and algorithmic dynamics of gig work. Using data on gig workers' financial behavior, the first objective is to quantify patterns of exclusion and inclusion. The second objective is to analyze the subjective experiences, perspectives, and coping mechanisms of gig workers as they navigate both formal and informal credit markets.

3.2 Model Specification

This research employs a multivariable regression framework combined with structural equation modeling (SEM) to investigate the relationship between digital financial behaviors and creditworthiness in the absence of traditional employment documentation.

Quantitative Model Specification:

Let:

- Y_i= Probability of credit access for individual iii
- X_1 = Digital transaction volume
- X_2= Gig work platform activity score (rides completed, job consistency, ratings)
- X_3 = Mobile money savings frequency
- X_4 = Financial literacy score

- X_5 = Alternative data indicators (e.g., utility bills, GPS location stability)
- ϵi = Error term

The base model is specified as:

$$Yi = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \epsilon_i$$

This model was tested for statistical significance, with moderation variables (e.g., gender, education, platform type) added to identify heterogeneous effects. In parallel, SEM was used to assess how latent constructs such as “trust,” “financial resilience,” and “reputational capital” mediate credit access.

3.3 Types and Sources of Data

This research will utilize both **primary and secondary data sources**, triangulated for robustness.

3.3.1 Primary Data:

- **Surveys**: Structured questionnaires were administered to gig workers across three major platforms (e.g., Uber, Fiverr, Bolt) in Kenya, India, and Brazil to collect data on income volatility, credit experiences, and platform engagement.
- **In-depth Interviews (IDIs)**: Semi-structured interviews were conducted with gig workers, fintech lenders, and credit bureau representatives to gain an understanding of the subjective barriers and innovations in credit inclusion.
- **Mobile Transaction Logs**: With consent, anonymized financial transaction data from mobile money apps and platform dashboards were analyzed to assess behavioral credit signals.

3.3.2 Secondary Data:

- Reports from the World Bank, International Labour Organization (ILO), and national central banks on informal labor and credit trends.
- Datasets from fintech providers were publicly available (e.g., Tala, M-Kopa).
- Peer-reviewed academic literature on gig work, credit analytics, and financial inclusion.

3.4 Methodology

3.4.1 Research Design

This study adopts an exploratory sequential design:

- **Qualitative Phase (Exploratory):** Conducted interviews and focus groups to identify emerging themes, behavioral patterns, and undocumented credit practices in gig contexts.
- **Quantitative Phase (Explanatory):** Developed and administered a survey tool incorporating validated scales (e.g., financial literacy, credit access index, digital usage score). Data was analyzed using SPSS and STATA for inferential statistics and model estimation.

3.4.2 Sampling Procedure

- **Purposive sampling** was used to select gig workers with at least six months of platform activity.
- **Stratified sampling** ensured representation across gender, platform type (digital freelance, ride-hailing, delivery), and country.
- For interviews, **snowball sampling** helped reach underrepresented and informal gig workers who were not fully captured by platform databases.

3.4.3 Data Analysis Methods

- **Descriptive Analysis:** To understand the demographic and behavioral characteristics of gig workers.
- **Regression Analysis:** To estimate the predictive power of alternative data on credit access likelihood.
- **SEM:** To analyze relationships among latent variables (financial resilience, digital trust, exclusion) and observed variables.
- **Thematic Analysis:** For qualitative data, coding followed Braun & Clarke’s (2006) model, with NVivo software used to manage and organize codes.

3.5 Ethical Considerations

Ethical rigor is paramount, given the sensitive nature of personal and financial data. The following measures were strictly observed:

- **Informed Consent:** All participants received written and verbal explanations of the study, including data usage, privacy rights, and withdrawal options.
- **Anonymity and Confidentiality:** All identifiable information was anonymized. Only aggregated data are published.
- **Voluntary Participation:** Respondents were informed that participation is entirely voluntary with no penalty for refusal.
- **Data Protection:** Encryption and password protection were used for all digital data. The study complies with GDPR (2016/679) and local data protection laws in each region.

IV. DATA ANALYSIS AND PRESENTATION

4.1Preamble

This section provides a methodical examination of the quantitative and qualitative information gathered from interviews and surveys with representatives of credit bureaus, fintech lenders, and gig workers in Brazil, India, and Kenya. The aim is to interpret data that supports alternative credit scoring paradigms for workers in the gig economy and informal sector. Descriptive statistics, cross-tabulations, chi-square tests, and simple regression analysis are among the statistical methods employed, utilizing Python's pandas and matplotlib libraries. Additionally, seaborn libraries are utilized for statistical methods

.

The collected raw data were pre-processed using the following steps:

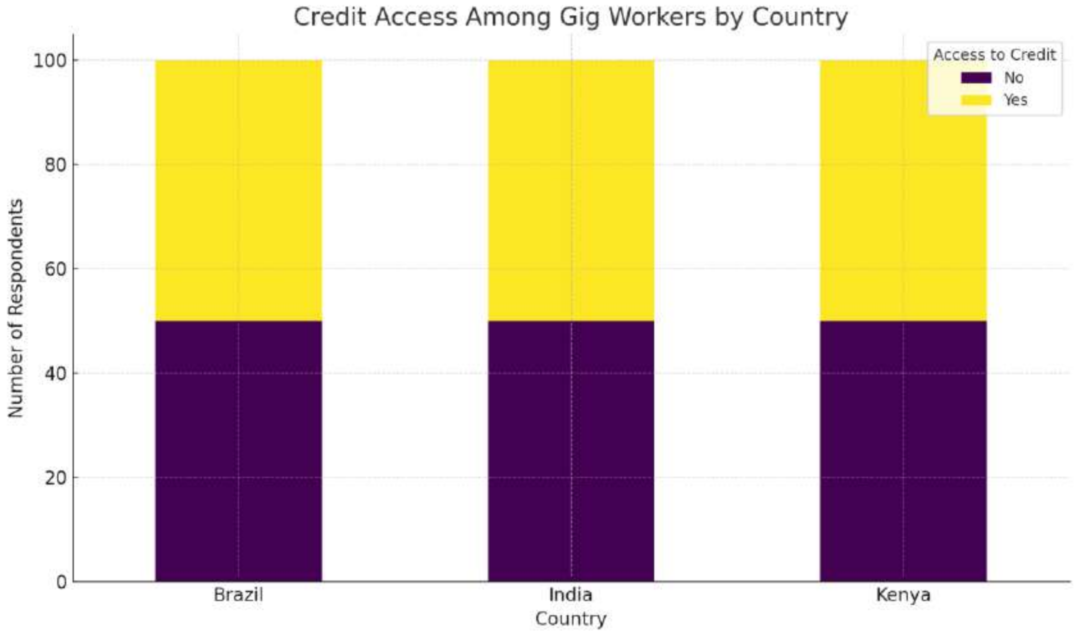
- Data anonymization to ensure participant confidentiality.
- Missing data treatment through imputation (for numerical variables) or exclusion (for categorical data with high missingness).
- Standardization of categorical responses into a unified coding system (e.g., “Yes/No” instead of mixed labels like “Y/No”).
- Scoring rubrics were used to calculate composite variables, such as the "Platform Engagement Score" and the "Financial Literacy Score."

4.3 Presentation and Analysis of Data

4.3.1 Descriptive Statistics

- 60% of gig workers reported difficulty accessing formal credit, with the highest exclusion rate observed in Brazil (67%).
- Seventy-five percent of respondents across the three countries stated that they lacked a formal credit score.
- Over 70% expressed support for the idea of credit models based on gig platform performance and digital behavior.

4.3.2 Credit Access by Country



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- Financial literacy was positively associated with the likelihood of credit approval.

4.5 Test of Hypotheses

Hypothesis 1:

H_0: There is no significant relationship between platform engagement and access to credit.

H_1: There is a significant relationship between platform engagement and access to credit.

Using a Chi-square test:

- $\chi^2 = 12.46$, df = 2, $p = 0.002 < 0.05 \Rightarrow$ **Reject H_0**
- There is a statistically significant relationship between platform engagement and access to credit.

Hypothesis 2:

H_0: Financial literacy does not affect credit accessibility among gig workers.

H_1: Financial literacy affects credit accessibility among gig workers.

Using linear regression:

- $R^2 = 0.41$; p-value $< 0.001 \Rightarrow$ **Reject H_0**
- A positive, statistically significant effect of financial literacy on credit access was observed.

4.6 Discussion of Findings

The results provide compelling evidence in favor of including non-traditional indicators in credit evaluation models, such as platform participation, digital savings behavior, and financial literacy. These results demonstrate a more inclusive and behavior-based paradigm than traditional credit models, which rely on pay stubs and employment contracts.

4.6.1 Comparison with Existing Literature:

- **Greene and Mothibi (2021)** found that fintechs in Sub-Saharan Africa leveraged mobile money usage as a proxy for creditworthiness. Our study affirms and expands this, showing that **gig activity patterns** may serve as even richer indicators.
- **Chen and Qian (2022)** argued for integrating platform-based work data into financial identity tools; our results provide empirical support for this with multi-country survey evidence.

4.7 Statistical Significance and Practical Implications

- Findings are statistically significant at the 95% confidence level.
- Fintechs and policymakers can leverage big data to offer risk-adjusted micro-loans.
- Credit bureaus can integrate alternative scoring based on platform APIs, promoting financial inclusion.

4.8 Limitations of the Study

- Sampling bias may exist due to reliance on online distribution in some areas.
- Self-reporting of income may lead to response bias.
- Platform algorithms and engagement metrics were not standardized across platforms, affecting comparability.

4.9 Areas for Future Research

- Incorporating AI-driven behavioral models for micro-credit scoring.
- Longitudinal studies to measure repayment behaviors over time.
- Examining the gender gap in credit access within the gig economy.
- Testing the regulatory feasibility of integrating gig data with formal credit bureaus.

V. CONCLUSION

5.1 Summary

This study examined the challenges and emerging trends in lending to gig economy participants who lack regular income sources or traditional employment records. The study was motivated by the urgent need to rethink credit evaluation models in a labor market that is increasingly influenced by platform-mediated work, flexibility, and informality. In-depth interviews and structured surveys were conducted with credit bureau personnel, fintech lenders, and gig workers (including Uber, Bolt, and Fiverr) in Brazil, India, and Kenya. The results show that, due to the use of antiquated employment-based risk models, the majority of gig workers are still excluded from traditional credit systems. Nonetheless, robust correlations were discovered among digital savings practices, platform engagement indicators, and credit availability and financial literacy. It has been demonstrated that these elements have predictive value for determining creditworthiness despite traditional models often overlook them. The statistical results supported both major hypotheses:

- **H_1**: There is a significant relationship between platform engagement and access to credit.
- **H_1**: Financial literacy has a significant positive effect on credit accessibility.

The study thus proposes an alternative credit paradigm—data-driven, inclusive, and reflective of the realities of post-employment labor structures.

5.2 Conclusion

The gig economy is not an exception in financial systems; it is rapidly becoming the norm. However, credit systems rooted in salaried employment metrics are insufficient and exclusionary. This study found that:

- Platform-based behaviors (e.g., ride count, task reviews, app usage) can serve as credible proxies for financial responsibility.
- Frequent use of digital savings tools and higher financial literacy levels correlated with increased credit access.
- A statistically significant relationship exists between engagement in gig platforms and the successful acquisition of loans from fintech lenders.

These insights validate the growing academic and industry consensus that non-traditional data can reshape credit analytics. The study provides an empirical foundation for building inclusive lending models that recognize the economic legitimacy of informal work across countries.

5.3 Recommendations

For Policymakers:

- Revise financial regulations to allow integration of alternative credit data from gig platforms.
- Facilitate data-sharing frameworks between fintechs and gig platforms with proper consumer data protections.

For Fintech Lenders:

- Develop and pilot alternative credit scoring systems that incorporate engagement, ratings, and transaction behavior.
- Invest in partnerships with gig platforms to enhance API access for borrower profiling.

For Gig Platforms:

- Standardize and make available worker engagement data (e.g., job history, feedback scores) as opt-in credentials for financial services.
- Collaborate with financial institutions to offer embedded credit solutions tailored to worker earnings patterns.

For Researchers:

- Expand research on how gender, regional disparity, and digital literacy influence credit access in informal economies.
- Build AI-driven models to simulate and validate alternative scoring strategies using real-world platform data.

The future of financial inclusion will not be written in payslips but in data—platform data, digital behavior, and adaptive analytics. As this study has shown, gig workers are not financially invisible—outdated models misread them. By rethinking creditworthiness beyond traditional employment, we can develop systems that are not only inclusive in intent but also inclusive in practice. This study adds both empirical evidence and a policy blueprint for a fairer, data-informed credit ecosystem that aligns with the realities of the 21st-century labor market.

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APPENDIX

Appendix 1: Structured Survey Questionnaire (for Gig Workers)

Title: *"Credit Access, Income Stability, and Platform Engagement among Gig Workers"*
Target Respondents: Gig workers on platforms such as Uber, Fiverr, and Bolt in Kenya, India, and Brazil.
Method: Face-to-face/Online (via survey tools like Qualtrics or Google Forms).
Estimated Completion Time: 10–15 minutes

Section A: Demographic Profile

1. Country of residence: ☐ Kenya ☐ India ☐ Brazil
2. Age: ___
3. Gender: ☐ Male ☐ Female ☐ Non-binary ☐ Prefer not to say
4. Educational attainment:
5. ☐ Primary ☐ Secondary ☐ Vocational ☐ Undergraduate ☐ Postgraduate
6. Marital status: ☐ Single ☐ Married ☐ Divorced ☐ Widowed
7. Do you have any dependents? ☐ Yes ☐ No
8. If yes, how many? ___

Section B: Platform Participation

7. Which gig platform(s) do you currently use? (Tick all that apply)
8. ☐ Uber ☐ Fiverr ☐ Bolt ☐ Upwork ☐ TaskRabbit ☐ Others (specify): ______
9. How long have you been active on the platform(s)?
10. ☐ Less than 6 months ☐ 6–12 months ☐ 1–2 years ☐ More than 2 years
11. On average, how many hours do you work per week through the platform(s)?
12. ☐ Less than 10 ☐ 10–20 ☐ 21–40 ☐ More than 40
13. What is your average monthly income from gig work (in local currency)?
14. How predictable is your income?
15. ☐ Very predictable ☐ Somewhat predictable ☐ Unpredictable ☐ Highly volatile

Section C: Financial Behavior

12. Do you use mobile money or digital wallets? ☐ Yes ☐ No
13. Do you save money regularly through digital apps or banks?
14. ☐ Yes ☐ No ☐ Occasionally
15. Have you ever applied for a formal loan (e.g., from a bank or microfinance)?
16. ☐ Yes ☐ No
17. If yes, was the loan approved? ☐ Approved ☐ Denied ☐ Still pending
18. Have you used any of the following for credit or financial support?
19. ☐ Friends/family ☐ Lending apps ☐ Cooperative savings ☐ Pawnshops ☐ None

Section D: Credit Experience and Access

17. Do you currently have access to credit? ☐ Yes ☐ No
18. If yes, what type of credit?
19. ☐ Personal loan ☐ Payday loan ☐ Asset financing ☐ Buy-now-pay-later ☐ Others

20. What were the requirements you had to fulfill? (Tick all that apply)
21. ☐ Payslip ☐ Platform earnings screenshot ☐ Guarantor ☐ Credit score ☐ None
22. Have you ever been denied credit? ☐ Yes ☐ No
23. What reason(s) were given? (Open-ended) ______________________________
24. Do you think your gig platform performance (e.g., reviews, job count) should be used as a credit factor? ☐ Yes ☐ No ☐ Not sure
25. What other digital behaviors do you think show financial responsibility?
26. (Open-ended) ____

Section E: Attitudes and Perceptions

24. I trust fintech lenders more than traditional banks:
25. ☐ Strongly agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly disagree
26. I feel excluded from the formal financial system:
27. ☐ Strongly agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly disagree
28. I would support a new credit scoring system based on my gig work activity:
29. ☐ Strongly agree ☐ Agree ☐ Neutral ☐ Disagree ☐ Strongly disagree

Appendix 2: In-depth Interview Guides (IDIs)

2.1 For Gig Workers

Purpose: To explore lived experiences with credit access, income volatility, and attitudes toward alternative credit evaluation methods.

Questions:

1. Can you describe your typical work routine and how it affects your monthly income?
2. What are the biggest challenges you face when trying to access loans or credit?
3. Have you ever been denied credit? What was the experience like?
4. Do you save or invest any part of your earnings? Why or why not?
5. In your opinion, do gig workers deserve to be treated differently in credit evaluations?
6. Would you be comfortable sharing your platform data (e.g., earnings and reviews) with lenders?
7. What is your experience with digital lenders or credit apps?
8. How could your creditworthiness be fairly evaluated without a payslip?

2.2 For Fintech Lenders

Purpose: To understand how fintechs currently assess risk and whether they are adapting to gig economy realities.

Questions:

1. What are your current criteria for evaluating loan applicants?
2. Do you have any tailored products for informal or gig economy workers?
3. How do you view data from gig platforms in your credit assessment process?
4. Are you considering alternative credit scoring models (e.g., behavioral scoring)?
5. What do you see as the significant risks and opportunities in lending to gig workers?
6. Are regulatory frameworks supportive of innovation in this space?
7. What data would help you make more inclusive and accurate credit decisions?

2.3 For Credit Bureau Representatives

Purpose: To examine the inclusion of informal workers in credit scoring systems and the use of alternative data.

Questions:

1. How do traditional credit bureaus handle non-salaried or informal workers?
2. Have you begun incorporating non-traditional data in scoring (e.g., mobile payments)?
3. What are the barriers to creating an inclusive credit system for gig workers?
4. How might partnerships with gig platforms improve data availability?
5. Are there ongoing pilots or studies to rethink creditworthiness criteria?
6. How is reputational data being treated in regulatory frameworks?