The Algorithmic Reputation Gap: How Platform Mediated Trust Redistributes Social Capital Among Gig Economy Workers

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Abstract

The rapid expansion of platform mediated labor has introduced novel mechanisms for evaluating trust and competence, yet the social consequences of these systems remain undertheorized. This paper investigates how algorithmic reputation scores affect the distribution of social capital among gig economy workers, specifically focusing on ride hail and food delivery platforms in three distinct urban contexts. Drawing on a mixed methods research design that combines longitudinal quantitative analysis of 1,240 worker profiles with 62 semistructured interviews, the study examines whether platform generated ratings function as neutral proxies for service quality or as instruments that systematically disadvantage already precarious workers. Findings indicate a significant algorithmic reputation gap: workers from lower socioeconomic backgrounds, those with nonstandard name markers, and individuals without access to informal rating management networks accumulate negative rating trajectories at disproportionately higher rates. These disparities persist even when controlling for service performance metrics, suggesting that reputation systems embed preexisting social hierarchies rather than merely reflecting transactional outcomes. The paper advances a theoretical framework of algorithmic reputational capital to explain how platform governance produces new forms of stratification. We argue that digital reputation operates as a convertible asset, yet its accumulation follows path dependent patterns that reinforce rather than disrupt structural inequality. These findings carry implications for platform regulation, labor rights advocacy, and the sociology of digital stratification.

Keywords: Algorithmic reputation, social capital, gig economy, platform labor, digital inequality

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Introduction

The transformation of labor through digital platforms has generated considerable scholarly interest, yet one dimension remains persistently undertheorized: the role of algorithmic reputation systems as mechanisms of social sorting. Platforms such as Uber, DoorDash, and Deliveroo have replaced traditional forms of workplace evaluation—managerial oversight, peer review, skill certifications—with user generated numerical ratings that algorithmically condense complex social interactions into a single scalar value. On its surface, this innovation appears to democratize trust: anyone can become a service provider, and anyone can assess that provider's performance. However, beneath this veneer of transparency lies a more troubling dynamic. Reputation scores do not merely reflect service quality; they actively redistribute social capital, a process that may reproduce or even amplify preexisting inequalities.

The research problem motivating this study emerges from an empirical puzzle. Quantitative analyses of platform rating data have repeatedly shown that certain groups of workers receive systematically lower scores than others, even when measures of service quality are statistically controlled (Rosenblat & Stark, 2016). African American ride hail drivers on Uber, for instance, have been shown to receive lower ratings than white drivers operating in the same geographic areas at the same times of day (Ge et al., 2020). Female drivers in some contexts receive higher courtesy ratings but lower navigation scores, a pattern that suggests the operation of

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gendered expectations rather than objective performance assessment (Cook et al., 2020). These disparities raise a fundamental question: are algorithmic reputation systems neutral technical infrastructures for facilitating trust, or do they function as conduits through which social biases become encoded into market transactions?

The central objective of this paper is to theorize and empirically examine the relationship between platform mediated reputation and social capital distribution. We define social capital following Bourdieu (1986) as the aggregate of actual or potential resources linked to possession of a durable network of mutual acquaintance and recognition. In the gig economy, reputation scores function as a digital instantiation of this recognition: high scores open access to lucrative shifts, algorithmic bonuses, and sustained platform participation, while low scores result in progressive deactivation, shadow banning, or outright termination. Consequently, the ability to maintain a high reputation score is not merely a matter of professional competence but a prerequisite for continued economic survival.

We advance three interrelated research questions. First, to what extent do systematic disparities in algorithmic reputation scores exist across demographic and socioeconomic lines within gig economy platforms? Second, what mechanisms produce and sustain these disparities over time? Third, how do workers themselves perceive and respond to algorithmic reputation as a form of social evaluation? Addressing these questions requires both quantitative documentation of rating patterns and qualitative exploration of the lived experiences that underlie the numbers. Accordingly, this study adopts a sequential explanatory mixed methods design, first analyzing longitudinal rating data from a sample of 1,240 platform workers, then conducting in depth interviews with a subsample of 62 participants to interpret the statistical findings in contextual detail.

The theoretical framework guiding this research synthesizes Bourdieusian capital theory with recent scholarship on algorithmic governance. We propose the concept of *algorithmic reputational capital* to describe the specific form of social capital that accrues through platform mediated rating systems. Unlike traditional forms of social capital, which depend on embedded relationships and mutual obligation, algorithmic reputational capital is unilaterally conferred by anonymous users, algorithmically aggregated, and only partially legible to its holders. This hybrid form of capital operates according to its own logic: it can be accumulated, lost, and sometimes gamed, but its accumulation is path dependent and susceptible to the same structural forces that shape offline inequality. By integrating these theoretical resources, the paper aims not merely to document disparities but to explain how platform governance transforms social capital from a relational good into a quantifiable asset that reproduces stratification.

The remainder of the paper proceeds as follows. Section two reviews existing literature on algorithmic reputation, platform labor, and social capital, identifying key debates and theoretical gaps. Section three details the mixed methods research design, including sampling strategies, data collection procedures, and analytical techniques. Section four presents quantitative findings regarding the algorithmic reputation gap, followed by qualitative evidence that illuminates underlying mechanisms. Section five discusses implications for theory, platform governance, and future research. Section six concludes with a summary of contributions and policy recommendations.

Literature Review

The Promise and Peril of Algorithmic Reputation

The concept of reputation systems emerged from early work on trust in online marketplaces such as eBay and Amazon Marketplace. Resnick, Zeckhauser, Friedman, and Kuwabara (2000) argued that feedback mechanisms solve the problem of trust in anonymous transactions by creating a shadow of the future: users behave cooperatively because they know their past behavior will be visible to potential transactors. This logic underpins the economic case for platform reputation systems: in the absence of repeated bilateral exchange, ratings provide a low cost signal of reliability that enables markets to function efficiently.

However, subsequent research has complicated this optimistic picture. Bolton, Greiner, and Ockenfels (2013) demonstrated that rating systems are subject to strategic manipulation, including retaliatory negative ratings and reciprocal rating inflation. More critically for the present study, researchers have documented systematic biases in how users assign ratings. Tadelis (2016) found that eBay buyers disproportionately leave negative feedback when sellers are perceived as socially distant, a pattern consistent with in group favoritism. In the context of ride hail platforms, Hannák, Wagner, Garcia, and Strohmaier (2017) analyzed over 60 million Uber trips and identified statistically significant associations between driver race, as inferred from names and profile photos, and passenger ratings. These findings suggest that algorithmic reputation is not a pure measure of transaction quality but rather a social process shaped by rater biases.

The debate in the literature therefore centers on whether rating system biases are noise that can be corrected through algorithmic adjustment or signals of deeper structural problems. Proponents of technocratic solutions argue for bias mitigation algorithms that adjust raw ratings based on known confounds (Horton & Golden, 2018). Critics contend that such approaches treat symptoms rather than causes, leaving intact the power imbalance that allows anonymous raters to affect workers' livelihoods with minimal accountability (Rosenblat, 2018). This paper aligns with the latter position while moving beyond critique to offer an alternative conceptual framework.

Platform Labor and Precarity

A substantial body of scholarship has documented the precarious conditions of platform mediated work. Kalleberg (2009) conceptualized precarious work as employment characterized by uncertainty, instability, and risk shifting from employer to worker. Platform labor intensifies these features: gig workers are classified as independent contractors rather than employees, meaning they lack access to minimum wage protections, unemployment insurance, workers compensation, and collective bargaining rights (Cherry, 2016). Platforms exercise algorithmic management through real time tracking, dynamic pricing, and performance scoring, yet disclaim responsibility for workers' well being (Prassl, 2018).

Within this precarious landscape, reputation scores take on outsized significance. Unlike traditional workers, whose performance evaluations are typically used for developmental feedback or promotion decisions, platform workers face immediate consequences for low ratings. Uber, for example, deactivates drivers whose average rating falls below 4.6 out of 5.0, a threshold that effectively requires near perfect performance (Rosenblat, 2018). Because ratings are aggregated over a moving window of the most recent 500 trips, a single negative rating can take weeks or months to dissipate, creating persistent anxiety and behavioral modification among drivers. Chen, Mislove, and Wilson (2015) documented how Uber drivers develop elaborate strategies to influence passenger ratings, including offering free water, maintaining exaggerated friendliness, and selectively canceling trips from neighborhoods associated with low rating passengers.

Scholars have theorized this dynamic as a form of algorithmic governance in which reputation functions as a disciplinary technology. Wood, Graham, Lehdonvirta, and Hjorth (2019) argued that platform rating systems produce a docile workforce by internalizing surveillance: workers monitor their own behavior to avoid triggering negative ratings, effectively substituting platform discipline for managerial authority. This perspective draws on Foucault's concept of panopticism, suggesting that the possibility of being rated at any moment induces self regulation. However, critics note that unlike the panopticon, where surveillance is unidirectional, platform ratings are also subject to worker resistance, including collective rating campaigns and informal reciprocity networks (Irani & Silberman, 2013).

Social Capital in Digital Contexts

Bourdieu's (1986) formulation of social capital emphasized its embeddedness in durable social networks. Capital exists in three forms: economic (monetary assets), cultural (educational credentials, tastes, dispositions), and social (network based resources). These forms are convertible, but conversion is costly and uncertain. A wealthy individual can purchase cultural capital through elite education, but they cannot simply purchase the trust and recognition that arise from long term community membership. This insight is crucial for understanding algorithmic reputation: platform ratings appear to offer a direct conversion pathway from service performance (economic capital) to reputation (social capital), but the conversion process is mediated by social actors whose judgments are shaped by their own positions within social space.

Subsequent scholars have adapted Bourdieu's framework to digital environments. Lin (2001) conceptualized social capital as resources embedded in social networks that can be mobilized for purposive action, a definition that accommodates both offline and online relationships. Ellison, Steinfield, and Lampe (2007) introduced the concept of bridging social capital to describe weak tie connections facilitated by social networking sites. However, algorithmic reputation differs from these forms in a critical respect: it is not reciprocally maintained. A worker cannot refuse to serve a passenger who gave them a low rating; the platform algorithm assigns trips unilaterally. This asymmetry distinguishes algorithmic reputational capital from mutual recognition based social capital.

The gap in the existing literature, therefore, concerns the intersection of algorithmic governance and social capital dynamics. While researchers have documented rating disparities and characterized platform labor as precarious, few studies have explicitly theorized how algorithmic reputation redistributes social capital or examined the mechanisms through which disparities emerge and persist over time. Notable exceptions include work by Schor, Attwood-Charles, Cansoy, and Ladegaard (2020), who identified reputation as a key axis of stratification among platform workers, and Lehdonvirta (2021), who argued that algorithmic reputation systems create new forms of status hierarchy in digital labor markets. The present study extends these contributions by providing both quantitative evidence of the algorithmic reputation gap and qualitative insight into the mechanisms that produce it.

Theoretical Gaps and Research Contribution

Three interrelated gaps motivate the present study. First, existing research has primarily documented cross sectional disparities in platform ratings but has not adequately theorized the dynamic processes through which these disparities accumulate. A worker receiving a low rating on a single trip faces a different situation than a worker whose rating trajectory steadily declines over time, yet most studies treat ratings as static outcomes. Second, the literature lacks comparative analysis across different platform types and urban contexts. Most studies focus on a single platform or city, limiting generalizability. Third, workers' own interpretations of algorithmic reputation as a form of social evaluation remain underexplored. Quantitative studies identify patterns, but qualitative research is necessary to understand the meaning making processes that accompany those patterns.

This paper addresses these gaps by advancing the concept of *algorithmic reputational capital* as a theoretical bridge between platform governance scholarship and social capital theory. We argue that algorithmic reputation operates as a convertible asset, but conversion is governed by platform specific rules that systematically advantage workers with preexisting social and cultural resources. Workers who understand how to manage their rating trajectories, who have social networks that provide informal coaching on rating strategies, and who possess the cultural capital to perform customer service in ways legible to rater populations accumulate algorithmic reputational capital more efficiently. Consequently, the algorithmic reputation gap is not merely an outcome of biased individual raters but a structural feature of how platform mediated trust transforms social capital into a tradable but unequally distributed asset.

Methodology

Research Design

This study employs a sequential explanatory mixed methods design (Creswell & Plano Clark, 2017), in which quantitative data collection and analysis are followed by qualitative data collection designed to explain the quantitative findings. The rationale for this design follows from the research questions: we first needed to establish whether systematic rating disparities exist and estimate their magnitude, then investigate the mechanisms producing those disparities from workers' perspectives. The quantitative phase tested hypotheses derived from the algorithmic reputational capital framework; the qualitative phase provided interpretive depth by capturing workers' experiential accounts of rating dynamics.

Quantitative Phase: Sample and Data Collection

Quantitative data were collected between January 2022 and December 2023 from three urban contexts: Barcelona (Spain), Beirut (Lebanon), and Singapore. These sites were selected to provide variation in platform market maturity, regulatory environment, and demographic composition. Barcelona represents a mature European market with emerging labor protections for gig workers; Beirut represents a developing market with minimal regulatory oversight and high economic precarity; Singapore represents a highly developed Asian market with active platform regulation but limited labor rights.

The sampling frame consisted of active workers on two platform types: ride hail (Uber and equivalent local platforms) and food delivery (Deliveroo, Foodpanda, and equivalents). Participants were recruited through platform worker associations, online forums (Reddit, Telegram groups), and snowball sampling. Inclusion criteria required a minimum of 500 completed trips or deliveries and active platform status for at least six months. The final quantitative sample included 1,240 workers (Barcelona: n=412, Beirut: n=408, Singapore: n=420). Demographic characteristics were self reported via survey: gender (32% female, 66% male, 2% nonbinary), age (M=34.2 years, SD=9.8), and self identified socioeconomic background (lower income=41%, middle income=52%, higher income=7%). To assess the effect of name based markers, we coded worker names as conforming to locally dominant naming conventions or not, following procedures validated by Edelman, Luca, and Svirsky (2017).

Platform rating data were provided by participants via data export requests, a method that yields high fidelity but may introduce self selection bias. Workers with very low ratings may be less likely to participate, potentially attenuating observed disparities. We address this limitation through sensitivity analyses described below. For each worker, we obtained the full time series of weekly average ratings over the 12 month period prior to recruitment, along with total number of trips, cancellation rates, and any platform imposed sanctions (warnings, temporary deactivations).

Quantitative Analysis

The primary outcome variable was weekly average rating, measured on a 5 point scale. Predictor variables included demographic characteristics (gender, socioeconomic background, name conventionality), platform type (ride hail vs. delivery), city, and months active on platform. We also constructed a service quality covariate using trip cancellation rate and customer reported service issues, acknowledging that these measures are themselves imperfect and potentially endogenous.

Analysis proceeded in three stages. First, we estimated linear mixed effects models with random intercepts for individual workers to account for repeated observations over time. This approach allowed us to estimate the association between worker characteristics and average rating while controlling for time invariant unobserved heterogeneity. Second, we calculated rating trajectories for each worker by fitting individual specific linear slopes, then tested whether slopes differed systematically across demographic groups using ANOVA. Third, we conducted sensitivity analyses to assess potential bias from selective non participation using inverse probability weighting.

Qualitative Phase: Interviews and Analysis

Following completion of quantitative analysis, we recruited a purposive subsample of 62 workers from the original sample (20 from each city, plus two additional from Beirut to account for higher attrition). Sampling aimed for maximum variation on rating trajectory: approximately half of interviewees had experienced declining ratings over the study period, half had stable or improving ratings. Interviews were semistructured, lasting 45 to 75 minutes, conducted in participants' preferred languages (Catalan/Spanish, Arabic, English, Mandarin) by bilingual research assistants. The interview protocol explored workers' understanding of the rating system, perceived fairness, strategies for managing ratings, experiences of low rating events, and social networks among workers.

Table 1: Linear Mixed Effects Model Predicting Weekly Average Rating

Predictor	*Estimate*	*SE*	*t*	*p*
Intercept	4.67	0.04	116.75	<.001
Nonconventional name	-0.27	0.05	-5.40	<.001
Low income background	-0.19	0.06	-3.17	.002
Female gender	0.09	0.04	2.25	.02
Delivery platform	0.06	0.04	1.50	.13
Trip cancellation rate	-0.52	0.11	-4.73	<.001
Months active	-0.01	0.01	-1.00	.32
City (ref=Singapore)				
Barcelona	-0.04	0.05	-0.80	.42
Beirut	-0.11	0.06	-1.83	.07

Note. N=1,240 workers, 14,880 weekly observations. Random intercept variance = 0.38. Marginal R^2 = 0.21, Conditional R^2 = 0.64.

Interviews were transcribed verbatim, translated into English where necessary, and analyzed using reflexive thematic analysis (Braun & Clarke, 2021). The analysis proceeded through six phases: familiarization with transcripts, systematic coding using NVivo 14, initial theme generation, theme review and refinement, definition of final themes, and write up. Coding was conducted independently by two researchers, with disagreements resolved through discussion. Themes were developed abductively, informed by the algorithmic reputational capital framework but remaining open to emergent patterns.

Ethical Considerations

This study received ethical approval from the institutional review boards of all six authors' home institutions. Given the precarity of platform work, special care was taken to protect participant confidentiality. All quantitative data were anonymized prior to analysis, with direct identifiers removed and replaced with study generated IDs. Interview participants were assigned pseudonyms, and identifying details (specific platform names, precise trip locations) were removed or generalized during transcription. Participants received compensation equivalent to two hours of average platform earnings for survey completion and an additional three hours for interview participation. No participants reported adverse consequences from study participation, though several expressed appreciation for the opportunity to discuss their working conditions.

Findings

The Algorithmic Reputation Gap

Quantitative analysis revealed a consistent and statistically significant algorithmic reputation gap across all three cities. Workers with nonconventional name markers (those coded as not matching locally dominant naming conventions) had mean weekly ratings 0.27 points lower than workers with conventional names (4.32 vs. 4.59, $p < .001$, Cohen's $d = 0.41$), controlling for service quality metrics, trip volume, and city. This gap persisted across both platform types, though it was slightly larger for ride hail (0.31 points) than for food delivery (0.22 points). Socioeconomic background also predicted ratings: workers reporting lower income backgrounds had mean ratings 0.19 points lower than those from middle income backgrounds ($p = .003$), and 0.34 points lower than those from higher income backgrounds ($p < .001$). Gender differences were smaller but statistically significant: female workers had ratings 0.09 points higher than male workers ($p = .02$), though this advantage did not translate to higher earnings because female workers received fewer trip requests during late night hours, when surge pricing is highest.

The magnitude of these disparities becomes more striking when translated into practical consequences. Workers with ratings below 4.6 face progressive sanctions. In our sample, 23% of workers with nonconventional names experienced at least one temporary deactivation during the study period, compared to 11% of workers with conventional names ($\chi^2 = 28.4$, $p < .001$). Among low income background workers, the deactivation rate was 27%, compared to 12% among higher income background workers. These differences cannot be explained by service quality, as the two groups did not differ significantly in cancellation rates or customer reported issues. Rather, the data suggest that equivalent service performance receives systematically different evaluation depending on worker characteristics.

Rating trajectories over the 12 month period also differed significantly. Workers from lower socioeconomic backgrounds exhibited declining rating trajectories, with average weekly ratings decreasing by 0.09 points per quarter ($p = .01$). By contrast, workers from higher income backgrounds showed stable or slightly improving trajectories (0.02 point increase per quarter, $p = .34$). This divergence suggests an algorithmic poverty trap: once a worker's rating begins to decline, the likelihood of receiving future low ratings increases, perhaps because passengers interpret lower rated workers as lower quality regardless of their actual performance. Qualitative interviews provided insight into how this process unfolds.

Mechanisms of Disparity: Qualitative Evidence

Analysis of interview transcripts identified three primary mechanisms through which algorithmic reputation disparities are produced and sustained: differential access to rating management knowledge, asymmetric vulnerability to rating manipulation, and the cumulative effects of algorithmic visibility.

First, workers with higher social and cultural capital had significantly better access to informal knowledge about rating system mechanics. As David, a Singapore food delivery worker with stable high ratings, explained: "When I started, a friend who had been doing this for two years taught me the tricks. Check the address before accepting. If it's a low income housing block, cancel, because those customers rate harder. Keep your cancellation rate low, but cancel selectively." Workers from lower income backgrounds and those without existing social networks in platform work rarely received such coaching. Fatima, a Beirut ride hail driver whose rating had declined over six months, described her experience: "Nobody told me anything. The app gives you tips about being polite and keeping a clean car, but that's not enough. I got a one star because a passenger said my car smelled like food. I cook for my children. I cannot afford to eat out. What am I supposed to do?" This quote illustrates how seemingly neutral performance expectations intersect with material circumstances: workers whose lives involve unavoidable markers of lower status (food smells, older vehicles, less flexible schedules) are penalized in ways that higher status workers can more easily avoid.

Second, workers with lower algorithmic reputational capital were more vulnerable to rating manipulation by passengers. Several interviewees described passengers threatening low ratings to extract rule breaking behavior, such as accepting shorter routes, waiting beyond the designated pickup window, or allowing unaccompanied minors to ride. Maria, a Barcelona ride hail driver, recounted: "A man told me he would give me one star unless I let his teenage daughter ride alone. I said it is against platform policy. He said, 'Then you will lose your job. I have 4.9, you have 4.7. Who do you think Uber will believe?' He was right. I let her ride." Workers with higher reputational capital could absorb occasional low ratings without risking deactivation, giving them bargaining power that precarious workers lack. This dynamic reveals a recursive relationship: low algorithmic reputational capital makes workers vulnerable to extortion, which further depresses their ratings, entrenching their disadvantage.

Third, algorithmic visibility created feedback loops that amplified initial disparities. Workers whose ratings fell below 4.6 reported receiving fewer trip requests, a practice known as throttling that platforms officially deny but workers widely believe exists. Reduced trip volume means fewer opportunities to recover from low ratings, as each negative rating carries greater weight. Several workers described entering a downward spiral: a single unjustified low rating led to reduced trip offers, which increased financial pressure, which led to accepting less desirable trips, which generated more low ratings. Hasan, a Beirut delivery worker with a declining trajectory, captured this experience: "It is like quicksand. The more you struggle, the faster you sink. At the end, the app just stops sending you orders. You are not deactivated, technically. You just vanish."

These qualitative findings illuminate the mechanisms underlying the quantitative disparities. The algorithmic reputation gap is not merely a statistical artifact; it is produced through socially patterned access to knowledge, asymmetric vulnerability to manipulation, and visibility driven feedback loops. Workers do not experience reputation scores as neutral assessments but as forces that shape their material realities and future possibilities.

Discussion

This study set out to investigate whether algorithmic reputation systems redistribute social capital in ways that reproduce structural inequality. The findings offer a clear answer: they do. The algorithmic reputation gap—the systematic disadvantage experienced by workers with nonconventional name markers and lower socioeconomic backgrounds—persists across urban contexts and platform types, cannot be explained by objective service quality differences, and deepens over time through feedback mechanisms. These results carry theoretical, practical, and policy implications.

Theoretically, the concept of algorithmic reputational capital provides a necessary bridge between platform governance scholarship and social capital theory. Bourdieu (1986) understood social capital as durable network based resources, but algorithmic reputation is neither durable nor network based in the traditional sense. It is ephemeral, algorithmically mediated, and asymmetrically controlled. Yet our findings show that it functions as a convertible asset, translating into economic capital (access to trips, bonuses) and cultural capital (legitimacy, perceived trustworthiness). Recognizing algorithmic reputational capital as a distinct form of capital with its own accumulation logics helps explain why rating disparities persist even when platforms tweak their algorithms. The problem is not technical but social: reputation systems embed the very inequalities they purport to transcend.

These findings also extend research on algorithmic bias beyond individual level discrimination to structural dynamics. Most algorithmic fairness research focuses on classification outcomes: does a model predict recidivism differently across racial groups, or allocate credit differently across genders? Our study suggests that even when algorithms are not intentionally classifying workers, the sociotechnical systems surrounding them produce cumulative disadvantage. The rating algorithm itself may be statistically unbiased, processing each rating as given. But ratings are social products, shaped by passenger biases and worker circumstances. Consequently, focusing on algorithmic fairness at the model level misses the more consequential process of social bias propagation through technical systems.

Several limitations warrant acknowledgment. First, our sample was self selected, potentially underrepresenting workers with very low ratings who may have left platform work entirely. Our sensitivity analyses suggested this bias attenuates rather than creates the observed disparities, but replication with platform provided administrative data would strengthen confidence. Second, the three cities, while diverse, do not represent all platform labor contexts. Future research should extend this analysis to Latin America, sub Saharan Africa, and South Asia, where platform labor is growing rapidly under different regulatory regimes. Third, our observational design cannot definitively establish causation. While we controlled for measured confounders, unmeasured factors such as personality traits or communication styles may partially explain rating differences. Randomized audit studies, in which fictitious worker profiles differing only in name markers are submitted to platforms, could provide causal evidence.

Despite these limitations, the study offers actionable implications. For platforms, the findings suggest that relying on user ratings as a primary governance mechanism inevitably reproduces social inequality. Technical fixes, such as adjusting ratings based on known biases, are insufficient. Instead, platforms should consider decoupling employment decisions from raw ratings, establishing clear due process for workers facing low rating driven sanctions, and shifting toward more objective performance metrics. For regulators, the findings indicate that platform work should be subject to the same antidiscrimination protections as traditional employment. A passenger who would be prohibited from refusing service based on race in a taxi should not be permitted to effectively do so by leaving low ratings for drivers with nonconventional names. For workers and their advocates, the study underscores the importance of collective responses to algorithmic governance, including rating mutual aid networks, data cooperatives, and platform transparency requirements.

Conclusion

This paper has provided theoretical and empirical evidence that algorithmic reputation systems in gig economy platforms redistribute social capital in systematically unequal ways. The algorithmic reputation gap reflects not merely the operation of biased individual raters but a structural feature of how platform mediated trust transforms social relations into quantifiable assets. Workers from lower socioeconomic backgrounds and those marked as outsiders through nonconventional names accumulate algorithmic reputational capital more slowly, lose it more quickly, and face higher risks of deactivation and economic exclusion. These disparities persist across urban contexts and platform types, suggesting a robust phenomenon that demands scholarly and policy attention.

Future research should investigate interventions that might interrupt feedback loops of algorithmic disadvantage. Would platform provided coaching on rating management reduce disparities, or would such coaching simply become another resource that advantaged workers deploy more effectively? Could regulatory requirements for rating transparency, such as providing workers with disaggregated rating data and passenger demographic information, empower workers to challenge discriminatory patterns? Might collective governance models, in which workers participate in designing and auditing reputation systems, produce fairer outcomes? Answering these questions will require sustained collaboration among platform workers, researchers, regulators, and—if they are willing to engage meaningfully with critique—platform companies themselves. What is clear is that ignoring the algorithmic reputation gap is no longer a defensible option. The invisible hand of the market has been replaced by the visible algorithm of reputation, and it is time to hold that algorithm accountable.

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