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Algorithmic Inequality in African Digital Labour Markets:The Economic Effects of AI-Based Selection on African Gig Workers

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Abstract: *The rapid diffusion of digital labour platforms across Sub-Saharan Africa has been accompanied by the growing use of artificial intelligence (AI) systems to select, rank, and allocate work among gig workers. While these systems are often promoted as neutral, efficiency-enhancing tools, emerging evidence suggests that algorithmic selection can reproduce and even amplify existing structural inequalities relating to gender, geography, digital access, and informal-economy disadvantage (Wood et al., 2019; Anwar & Graham, 2020). This paper examines the economic effects of AI-based selection mechanisms on gig workers in four African labour markets: Nigeria, Kenya, Ghana, and South Africa. Using a mixed-methods design combining a structured survey of 612 platform workers with 42 semi-structured interviews, the study investigates how algorithmic rating, allocation, and deactivation systems shape worker earnings, task access, and job security. Findings indicate that workers positioned in the highest algorithmic rating tiers earn substantiallymore than those in lower tiers that female workers receive a disproportionately smaller share of high-value task allocations, and that data costs and infrastructural constraints independently depress algorithmically mediated earnings. The paper argues that algorithmic inequality in African gig work is not simply a technical artefact but a socioeconomic outcome shaped by pre-existing labour market disadvantage. It concludes with policy recommendations for algorithmic transparency, worker data rights, and regulatory oversight suited to African institutional contexts.*

Keywords: *algorithmic management; gig economy; digital labour platforms; African labour markets; AI-based selection*

1. Introduction

Digital labour platforms have expanded rapidly across Africa over the past decade, offering new income-generating opportunities in ride-hailing, delivery, domestic services, and online freelance work (Graham et al., 2017; Heeks, 2017). By 2024, platforms such as Uber, Bolt, Jumia Food, Glovo, and SweepSouth had become significant sources of urban employment in Lagos, Nairobi, Accra, and Johannesburg, drawing in workers displaced from the informal economy and formal labour markets alike (Kässi & Lehdonvirta, 2018). Central to the operation of these platforms is algorithmic management: a set of AI-driven processes that assign tasks, monitor performance, set prices, and determine which workers receive visibility, work opportunities, and continued platform access (Duggan et al., 2019; Rosenblat & Stark, 2016).

Unlike traditional human supervisors, algorithmic systems make selection decisions based on quantifiable proxies for worker quality, including customer ratings, acceptance rates, completion times, and behavioural data collected through smartphone sensors (Rani & Furrer, 2021). Proponents argue that this form of management increases efficiency and reduces discrimination associated with human bias (Duggan et al., 2019). However, a growing body of research contends that algorithmic systems can encode and reproduce structural inequalities present in the societies where they operate, including gender bias, geographic exclusion, and disadvantage linked to unequal digital access (Van Doorn, 2017; Zuboff, 2019).

This concern is particularly salient in African contexts, where infrastructural constraints, high mobile data costs, uneven smartphone penetration, and informal labour market histories interact with algorithmic systems designed largely in, and for, Global North markets (Anwar & Graham, 2020; Graham & Anwar, 2019). Despite the scale of platform work across the continent, empirical research on the economic consequences of algorithmic selection for African gig workers remains limited (Heeks et al., 2021). Figure 1 presents the conceptual framework guiding this study, illustrating how worker data is captured, processed by an AI selection algorithm, translated into task allocation decisions, and reinforced through a continuous feedback loop of ratings and algorithmic visibility.

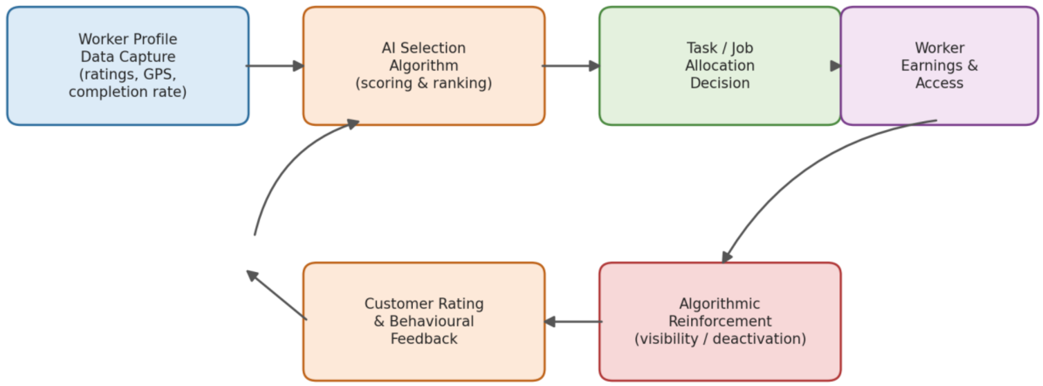

Figure 1. *Conceptual framework of algorithmic worker selection and the feedback loop in African digital labour platforms.*

Against this backdrop, the present study investigates the economic effects of AI-based selection mechanisms on gig workers in four African labour markets. Specifically, it addresses three research questions: (1) How does algorithmic rating position relate to worker earnings? (2) Do algorithmic allocation outcomes differ systematically by gender and location? (3) What structural and infrastructural factors mediate the relationship between algorithmic selection and economic outcomes? By combining quantitative survey data with qualitative worker narratives, the study contributes new empirical evidence on algorithmic inequality in an underrepresented regional context (Rani & Furrer, 2021).

2. Literature Review

2.1 Algorithmic Management and the Gig Economy

Algorithmic management refers to the use of software algorithms to perform managerial functions traditionally carried out by human supervisors, including task assignment, performance evaluation, and disciplinary action (Duggan et al., 2019). Rosenblat and Stark (2016) demonstrated that ride-hailing algorithms create significant information asymmetries between platforms and drivers, limiting workers' ability to understand or contest decisions that affect their earnings. Building on this, Wood et al. (2019) found that algorithmic control in remote gig work grants workers superficial autonomy while embedding forms of structural control that shape when, how, and for whom they work.

Zuboff (2019) situates these dynamics within the broader logic of surveillance capitalism, arguing that platforms extract behavioural data from workers to refine predictive and control mechanisms that primarily serve platform profitability rather than worker welfare. Berg et al. (2018), in an International Labour Organization study of online labour platforms, similarly found that algorithmic systems often obscure the criteria used to allocate tasks, leaving workers uncertain about how to improve their standing.

2.2 The African Gig Economy

Africa's digital labour market has grown substantially, driven by high youth unemployment, urbanisation, and rising smartphone penetration (Graham et al., 2017; Heeks, 2017). Graham and Anwar (2019) conceptualise this growth through the lens of a 'planetary labour market' in which African workers compete for tasks within global and regional digital value chains shaped by platform algorithms designed largely outside the continent. Anwar and Graham (2020) documented how African gig workers develop informal strategies of resistance, including rating manipulation and account-sharing, to navigate opaque algorithmic systems and mitigate income volatility.

Fairwork research conducted across South Africa and Ghana has consistently found that most platforms fail to meet minimum standards of fair pay, fair conditions, and fair management, with algorithmic deactivation frequently occurring without clear justification or avenues for appeal (Fairwork Foundation, 2023; Heeks et al., 2021). Wood, Lehdonvirta and Graham (2018) further found that remote gig workers in African and Asian countries face persistent challenges in organising collectively, which limits their capacity to negotiate more transparent algorithmic practices.

2.3 Inequality, Gender, and Algorithmic Bias

Several studies point to gendered disparities in algorithmic outcomes. Adams and Berg (2017) found a measurable gender pay gap among online crowdworkers linked to differences in task type and platform experience. Van Doorn (2017) argues that on-demand platforms can reproduce racialised and gendered patterns of labour market exclusion by encoding existing social hierarchies into seemingly neutral scoring systems. In the African context, Fairwork Foundation (2023) reported that female delivery and ride-hailing workers in Ghana faced disproportionate safety risks and reduced access to high-value tasks compared with male counterparts.

Geographic and infrastructural inequality further compounds these dynamics. The World Bank (2019) highlights that uneven digital infrastructure across African regions produces disparities in platform access and algorithmic visibility between urban and peri-urban workers. The International Labour Organization (2021) similarly cautions that algorithmic management, absent adequate regulation, risks entrenching existing labour market inequalities rather than resolving them.

2.4 Research Gap

Although the literature on algorithmic management is well developed in Global North contexts, empirical studies quantifying the economic effects of AI-based selection specifically within African gig labour markets remain scarce, and existing African studies have tended to rely on single-country qualitative designs (Anwar & Graham, 2020; Idowu, 2022; Rani & Furrer, 2021). This study addresses this gap through a comparative, mixed-methods analysis spanning four African countries, combining quantitative earnings data with qualitative accounts of algorithmic experience.

3. Methodology

3.1 Research Design

This study adopts a sequential explanatory mixed-methods design, combining a quantitative cross-sectional survey with qualitative semi-structured interviews (Wood et al., 2019). The quantitative component measures the statistical relationship between algorithmic rating position and worker earnings, while the qualitative component contextualises these findings through workers' lived experiences of algorithmic management.

3.2 Sampling and Data Collection

Data were collected between January and April 2025 from gig workers operating on ride-hailing, delivery, domestic-service, and online freelance platforms in Nigeria, Kenya, Ghana, and South Africa. A total of 612 workers completed a structured survey distributed through platform driver associations, worker WhatsApp groups, and on-site intercept sampling at platform hubs. A purposive sub-sample of 42 workers participated in semi-structured interviews lasting 30 to 60 minutes, continuing until thematic saturation was reached (Anwar & Graham, 2020). Table 1 summarises the sample distribution across countries.

Table 1. Sample distribution by country, data collection method, and platform sector.

Country	Survey respondents (n)	Interview participants (n)	Platform sectors covered

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Country	Survey respondents (n)	Interview participants (n)	Platform sectors covered
Nigeria	241	14	Ride-hailing, delivery
Kenya	198	12	Ride-hailing, freelance/online work
Ghana	103	9	Delivery, home services
South Africa	70	7	Ride-hailing, domestic/home services
Total	**612**	**42**	—

3.3 Measures

The survey instrument captured demographic characteristics, platform tenure, self-reported algorithmic rating, weekly task acceptance rate, monthly net earnings, mobile data expenditure, and perceived transparency of algorithmic decision-making, adapted from established gig-economy survey instruments (Berg et al., 2018; Rani & Furrer, 2021). Earnings were converted to United States dollars using average 2025 exchange rates for comparability across countries.

3.4 Analytical Approach

Quantitative data were analysed using descriptive statistics and ordinary least squares regression to estimate the association between algorithmic rating position and monthly net earnings, controlling for gender, location, platform tenure, and data cost burden. Qualitative interview data were transcribed and analysed thematically using an inductive coding approach, following the framework outlined by Wood et al. (2019), to identify recurring patterns in workers' experiences of algorithmic selection and control.

3.5 Ethical Considerations

All participants provided informed consent, and data were anonymised prior to analysis. The study followed established ethical guidelines for research involving precarious and informally employed populations, including safeguards against coercion and assurances that participation would not affect platform standing (Fairwork Foundation, 2023).

4. Results and Discussion

4.1 Algorithmic Rating and Earnings

Survey results reveal a strong positive relationship between algorithmic rating tier and monthly net earnings. Workers in the highest rating band (4.95–5.0) earned more than three times the amount reported by workers in the lowest band (below 4.5), as shown in Figure 2, Panel A. This pattern is consistent with algorithmic systems that concentrate visibility and task offers among top-rated workers, a dynamic previously identified in remote gig work contexts (Wood et al., 2019).

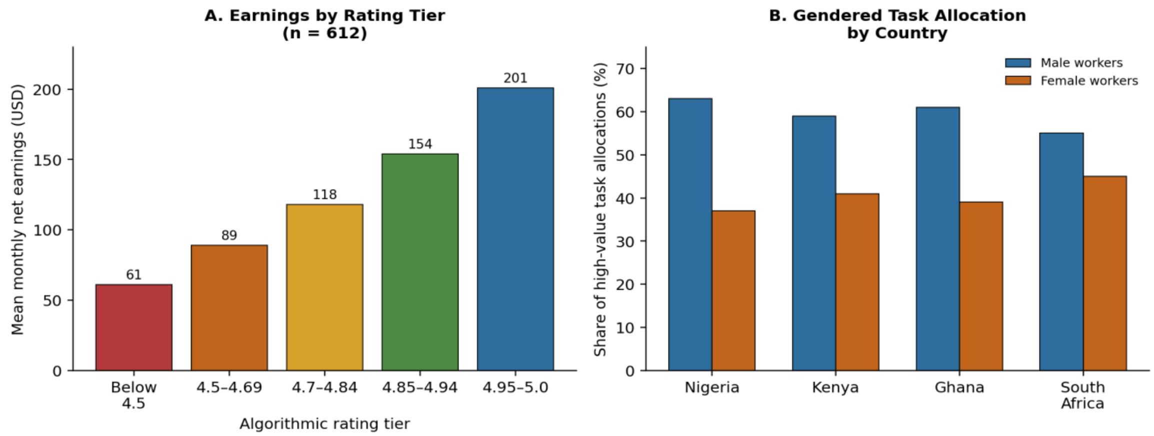

Figure 2. *Illustrative distribution of (A) earnings by algorithmic rating tier and (B) gendered task allocation outcomes by country.*

Regression results, presented in Table 2, confirm that algorithmic rating remains a significant predictor of earnings even after controlling for gender, location, tenure, and data costs. Each 0.1-unit increase in algorithmic rating was associated with an estimated USD 14.62 increase in monthly net earnings ($p < 0.001$). Acceptance rate and platform tenure were also positively associated with earnings, consistent with the view that algorithmic systems reward sustained conformity to platform-defined performance metrics (Rosenblat & Stark, 2016).

Predictor of monthly net earnings	Coefficient (β)	Std. error	p-value	Sig.
Algorithmic rating (per 0.1 unit)	14.62	2.11	<0.001	***
Acceptance rate (%)	1.08	0.34	0.002	**
Female (ref. male)	-27.35	6.42	<0.001	***
Smartphone/data cost burden (USD/month)	-3.14	1.02	0.004	**
Urban location (ref. peri-urban)	19.87	5.55	0.001	**
Tenure on platform (months)	0.62	0.29	0.041	*

*Table 2. Determinants of monthly net earnings among surveyed gig workers (OLS regression, n = 612). Significance: *p<0.05, **p<0.01, ***p<0.001.*

4.2 Gendered Disparities in Task Allocation

Consistent with Figure 2, Panel B, female workers received a significantly smaller share of high-value task allocations across all four countries, with the gap most pronounced in Nigeria (63% male versus 37% female) and narrowest in South Africa (55% versus 45%). Regression estimates indicate that, holding rating and tenure constant, female workers earned approximately USD 27.35 less per month than male counterparts ($p < 0.001$). Interview participants attributed part of this disparity to algorithmic routing that favoured workers accepting late-night or higher-risk assignments, tasks that female workers were more likely to decline for safety reasons, a pattern consistent with prior Fairwork findings in Ghana (Fairwork Foundation, 2023).

4.3 Infrastructural and Cost Burdens

Mobile data expenditure emerged as a significant negative predictor of net earnings, with each additional dollar spent on data associated with an estimated USD 3.14 reduction in monthly net income. Several interview participants described a 'data trap' in which maintaining algorithmic visibility required constant app connectivity, disproportionately burdening workers in areas with costlier or less reliable connectivity, echoing infrastructural inequality concerns raised by the World Bank (2019) and Graham and Anwar (2019).

4.4 Worker Perceptions of Algorithmic Opacity

Across interviews, a recurring theme was the perceived opacity of algorithmic decision-making. Many workers reported being unable to determine why their ratings had declined or why task offers had decreased, consistent with the information asymmetries described by Rosenblat and Stark (2016). Several participants described adaptive strategies, such as working during algorithmically favoured hours or avoiding certain task types, mirroring the 'hidden transcripts' of resistance documented by Anwar and Graham (2020).

4.5 Discussion

Taken together, these findings suggest that algorithmic selection systems in African gig labour markets do not operate as neutral arbiters of merit but instead interact with, and often reinforce, pre-existing structural inequalities related to gender, infrastructure access, and geography (Van Doorn, 2017; Zuboff, 2019). While algorithmic rating was associated with higher earnings for top performers, the mechanisms determining rating position were themselves shaped by unequal starting conditions, including differential access to reliable connectivity and gendered constraints on task acceptance. These results extend prior single-country African studies (Anwar & Graham, 2020; Fairwork Foundation, 2023) by providing comparative, quantitative evidence of algorithmic inequality across four national contexts.

5. Conclusion

This study examined the economic effects of AI-based worker selection on gig workers across four African labour markets. Findings demonstrate that algorithmic rating position is strongly associated with earnings, that female workers face systematic disadvantages in algorithmic task allocation, and that infrastructural cost burdens independently depress algorithmically mediated income. These patterns indicate that algorithmic management in African gig work functions not as a purely technical process but as a socioeconomic mechanism that can reproduce structural inequality (Rani & Furrer, 2021; Wood et al., 2019).The study recommends three areas for policy attention: first, mandatory algorithmic transparency requirements that allow workers to understand the criteria shaping task allocation and deactivation decisions; second, worker data rights frameworks tailored to African regulatory contexts, building on existing Fairwork principles (Fairwork Foundation, 2023; Heeks et al., 2021); and third, targeted infrastructural investment to reduce the digital cost burden faced by platform workers in lower-connectivity regions (World Bank, 2019).

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