

Algorithmic Control, Digital Labour and Economic Vulnerability: A Propensity Score Matching Analysis of Gig and Non-Gig Workers in Ranchi City
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Abstract

The rapid expansion of the digital labour market has fundamentally transformed employment relations through the rise of platform-based gig work governed by algorithmic management systems. While these systems enhance efficiency, flexibility, and task optimization, they simultaneously generate new forms of economic vulnerability, reflected in income instability, extended working hours, and limited access to social protection. In this context, the present study examines the economic impact of algorithmic control on workers by undertaking a comparative analysis of gig and non-gig workers in Ranchi city, Jharkhand. The analysis is based on primary survey data collected from workers across different employment categories, ensuring comparability through similar observable characteristics. To address potential selection bias and enhance the validity of comparisons between gig and non-gig workers, the study employs Propensity Score Matching (PSM) to construct an appropriate counterfactual framework. Multiple matching techniques, including Nearest Neighbor Matching and Kernel Matching, are utilized to estimate treatment effects. In addition, sensitivity analysis is conducted to assess the robustness of the results and the reliability of the estimated causal relationships. The findings indicate that although gig workers earn moderately higher incomes, they experience significantly greater economic vulnerability in terms of longer working hours, lower job security, and reduced access to social protection compared to their non-gig counterparts. These results highlight the dual nature of platform-based employment, where income gains are accompanied by increased labour risks under algorithmic control. This study contributes to the growing literature on digital labour by providing causal evidence from a non-metropolitan context, which remains relatively underexplored. It further offers important policy insights for regulating platform-based work, strengthening social security mechanisms, and improving labour conditions in the evolving gig economy in India.

Keywords ; Gig Economy; Algorithmic Control; Economic Vulnerability; Propensity Score Matching; Digital Labour; India

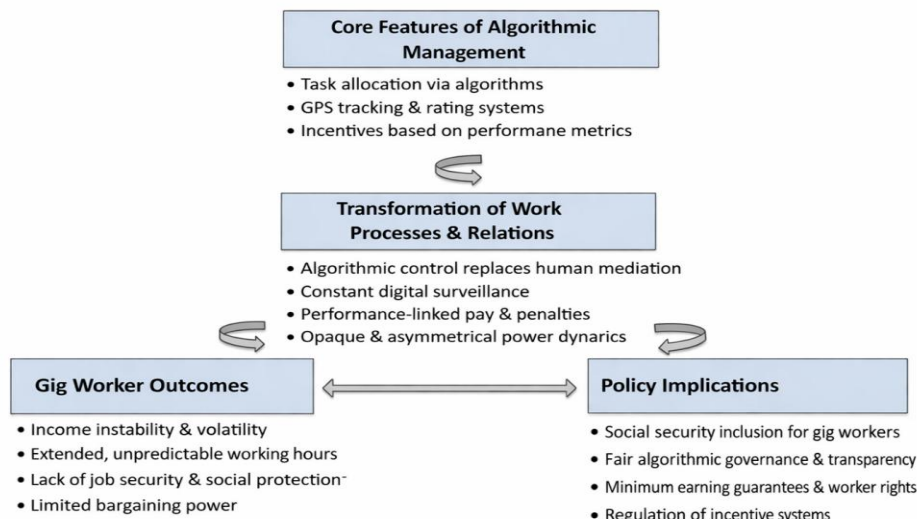
Introduction

India has emerged as one of the fastest-growing digital economies, driven by rapid urbanization, widespread smartphone adoption, and the expansion of digital payment systems. The digital labour market has expanded significantly, with millions engaged in platform-based work across sectors such as transportation, food delivery, e-commerce, and online services. This expansion reflects a broader structural shift in the labour market, marked by increasing reliance on digital platforms and flexible work arrangements. Importantly, this transformation now extends beyond metropolitan centres to Tier-II and Tier-III cities such as Ranchi. In these regions, platform-based work is driven not only by technological diffusion but also by structural constraints such as high unemployment, limited industrialization, and scarce formal job opportunities. Consequently, gig work has become a crucial livelihood strategy, although its associated vulnerabilities—income instability, lack of social protection, and dependence on opaque algorithmic systems—are often more pronounced due to weaker institutional support.

Platform-based work in India broadly takes two forms: location-based work and online platform work. Location-based work includes services such as ride-hailing, food delivery, and home-based services that require physical presence and depend on real-time coordination through digital applications. In contrast, online platform work encompasses freelancing, digital education, and other knowledge-based services that can be performed remotely. Despite these differences, both forms share a common institutional feature—algorithmic management, wherein data-driven systems are used to allocate tasks, monitor performance, and determine rewards and penalties.

At its core, algorithmic management operates through features such as automated task allocation, GPS-enabled tracking, rating and feedback mechanisms, and performance-linked incentives. These systems fundamentally reshape work processes by replacing direct human supervision with platform-mediated control, emphasizing outcome-based evaluation, and generating information asymmetry between platforms and workers. Consequently, work becomes increasingly fragmented, continuously monitored, and detached from traditional employer–employee relationships. Chart 1 illustrates how algorithmic management, through data-driven task allocation and monitoring, transforms work processes and employment relations in the gig economy.

Chart 1: Algorithmic Control and Economic Vulnerability in Digital Labour -MarketsConceptual Framework



The conceptual framework illustrates the mechanism through which algorithmic control shapes labour outcomes in the digital economy. It begins with the core features of algorithmic management, including algorithm-driven task allocation, real-time monitoring, rating systems, and performance-based incentives. These features operate through an intermediate mechanism of algorithmic task allocation, wherein workers are matched, ranked, and assigned tasks based on data-driven criteria such as location, performance, and availability. This process leads to a transformation of work processes and employment relations, characterized by the replacement of human supervision with algorithmic control, continuous digital surveillance, performance-linked compensation, and increasing information asymmetry between platforms and workers.

Workers operate under continuous digital surveillance, where GPS tracking, customer ratings, and platform-generated performance metrics determine task allocation, earnings, and continued access to work.

As a result, algorithmic control gives rise to a labour regime that is fragmented, data-driven, and structurally asymmetrical, where flexibility coexists with reduced autonomy and heightened economic risk. This transformation reflects the emergence of “digital Taylorism,” wherein continuous monitoring and performance optimization enhance efficiency but frequently come at the cost of longer working hours, income instability, and diminished worker well-being.

Review of Literature

The gig economy has gained significant attention across labour economics, sociology, and development studies, primarily due to its dual nature of offering flexibility while generating precarity. It lowers entry barriers and creates income opportunities, especially in developing economies (De Stefano, 2016), but is often associated with income instability, job insecurity, and lack of social protection (Wood et al., 2019).

A key feature of platform work is algorithmic management, where digital systems allocate tasks, monitor performance, and enforce discipline. These algorithms act as “invisible managers,” controlling workers through ratings, incentives, and penalties, often with limited transparency (Rosenblat & Stark, 2016). This reduces worker autonomy and intensifies performance pressure (Kellogg et al., 2020).

Labour precarity—defined by insecure employment, uncertain income, and absence of social security (Standing, 2011)—is a central concern in gig work. In India, gig workers commonly face irregular earnings, long working hours, and occupational risks, particularly in platform-based sectors (Sundararajan, 2016).

Recent studies indicate that gig work is expanding beyond metropolitan areas into smaller cities due to rising unemployment and technological diffusion (NITI Aayog, 2022). However, vulnerabilities may be more severe in these regions due to weaker institutional support and limited employment alternatives.

Methodologically, existing research is largely descriptive or qualitative, often overlooking selection bias. Propensity Score Matching (PSM) addresses this limitation by enabling causal inference through matching comparable groups (Rosenbaum & Rubin, 1983). It has been widely applied in labour economics (Caliendo & Kopeinig, 2008), but its use in analyzing algorithmic management and precarity—especially in India—remains limited.

Research Gap : This study fills the gap by applying PSM to estimate the causal impact of algorithmic control on labour precarity, offering a rigorous comparison between gig and non-gig workers.

Objectives of the Study

The study aims to:

- To examine the extent and nature of algorithmic management in platform-based gig work.
- To compare the socio-economic conditions of gig and non-gig workers.
- To estimate the causal impact of gig employment on labour outcomes—namely income, job security, working hours, and access to social protection—using Propensity Score Matching (PSM).
- To propose policy recommendations for regulating platform-based work and improving labour conditions.

Research Questions

- What is the extent and nature of algorithmic management in platform-based gig work?
- Are there significant differences in the socio-economic conditions of gig and non-gig workers?
- What policy measures are required to regulate platform-based work and improve labour conditions?

Hypotheses

To study the impact of Algorithmic management on work allocation, monitoring, and performance evaluation among gig workers, following hypotheses have been framed

- **H02 :** Gig employment has no significant impact on workers’ income.
- **H03:** Gig employment has no significant impact on job security.
- **H04:**Gig employment has no significant impact on access to social protection.

Research Methodology

Research Design and Study Area

This study adopts a mixed-methods research design, combining quantitative and qualitative approaches to capture both measurable labour outcomes and the lived experiences of workers in the digital economy. The empirical analysis is conducted in Ranchi city, Jharkhand, with a focus on urban areas where platform-based labour markets are actively operational. The integration of quantitative and qualitative methods enables a comprehensive assessment of both the outcomes and underlying mechanisms of algorithmic labour control.

A stratified purposive sampling strategy is employed to ensure comparability between gig and non-gig workers with similar socio-economic characteristics. The final sample comprises 200 respondents, including 100 gig workers engaged in platform-based employment (such as ride-hailing and delivery services) and 100 non-gig workers in comparable traditional occupations.

Chart 2: Sample Selection Framework Showing Matched Occupational Categories between Digital and Traditional Labour

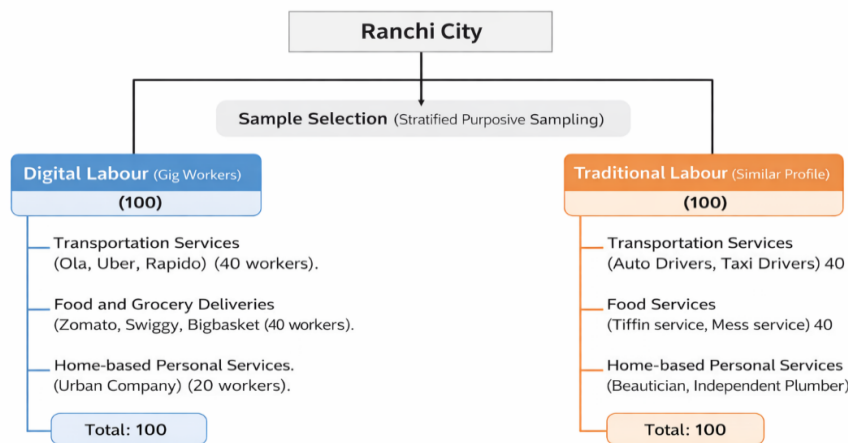


Figure 1: Sample Selection Framework Showing Matched Occupational Categories between Digital and Traditional

Primary Data : Primary data are collected through:

- A structured survey questionnaire capturing demographic characteristics, income, working hours, job security, and access to social protection
- Semi-structured interviews to explore worker experiences, perceptions of algorithmic management, and working conditions

Secondary Data : Secondary data are obtained from:

- Government reports (e.g., NITI Aayog, Periodic Labour Force Survey)
- Academic literature on digital labour and platform economies
- Reports from organizations such as the International Labour Organization (ILO)
- Policy documents, credible websites, and relevant publications

Analytical Framework: Propensity Score Matching (PSM)

To estimate the causal impact of platform-based gig employment on labour outcomes, this study employs Propensity Score Matching (PSM), a widely used method for causal inference in observational settings (Rosenbaum & Rubin, 1983). Since individuals self-select into gig work based on observable characteristics—such as age, education, gender, work experience, and household size—direct comparisons between gig and non-gig workers may produce biased estimates. PSM addresses this issue by constructing a statistically comparable control group and approximating a counterfactual outcome.

Let $T_i \in \{0,1\}$ denote the treatment indicator, where $T_i = 1$ if individual i is a gig worker and $T_i = 0$ otherwise. Let $Y_i(1)$ and $Y_i(0)$ represent the potential outcomes under treatment and control, respectively. Since only one of these outcomes is observed for each individual, the missing counterfactual is estimated through matching techniques.

The parameter of interest is the Average Treatment Effect on the Treated (ATT), defined as:

$$ATT = E[Y_i(1) - Y_i(0) | T_i = 1]$$

Estimation of Propensity Score

The propensity score is defined as the conditional probability of participation in gig employment given a set of observed characteristics X_i :

$$p(X_i) = P(T_i = 1 | X_i)$$

where X_i includes age, education, gender, work experience, and household size. The propensity scores are estimated using a logistic regression model:

$$P(T_i = 1 | X_i) = \frac{e^{\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \dots + \beta_k X_{ki}}}{1 + e^{\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \dots + \beta_k X_{ki}}}$$

Matching Procedure

To ensure robustness and improve the quality of matches, multiple matching algorithms are employed:

- **Nearest Neighbor Matching (NNM):** Matches each treated unit with one or more control units having the closest propensity score
- **Radius Matching (RM):** Matches observations within a specified propensity score radius
- **Kernel Matching (KM):** Uses weighted averages of all control units, with weights inversely related to distance in propensity scores
- **Stratification Matching (SM):** Divides the sample into blocks based on propensity score intervals and estimates treatment effects within each block

Assumptions for Identification

The validity of the PSM approach relies on two key assumptions:

- **Conditional Independence Assumption (CIA):**

$$(Y_i(1), Y_i(0)) \perp T_i | X_i$$

This implies that, conditional on observed covariates, treatment assignment is independent of potential outcomes.

- **Common Support Condition:**

$$0 < P(T_i = 1 | X_i) < 1$$

This ensures sufficient overlap in the distribution of propensity scores between treatment and control groups.

Estimation of Treatment Effects

The ATT is estimated using matched samples as:

$$ATT = \frac{1}{N_T} \sum_{i \in T} \left[Y_i - \sum_{j \in C} w(i, j) Y_j \right]$$

where:

- N_T = number of treated units (gig workers)
- $w(i, j)$ = weight assigned to control unit j matched with treated unit i
- Y_i and Y_j represent observed outcomes

This formulation captures the average difference between observed outcomes of gig workers and their estimated counterfactual outcomes.

Outcome Variables and Covariates

The analysis focuses on key labour outcomes reflecting economic vulnerability, including:

- Monthly income
- Job security
- Working hours
- Access to social protection

The covariates used in estimating propensity scores—age, education, gender, work experience, and household size—are selected based on their relevance in influencing both participation in gig work and labour outcomes.

Model Validation and Robustness

To ensure the reliability of the estimates, several validation procedures are implemented. Balancing tests are conducted to assess whether the distribution of covariates is similar between matched treatment and control groups. A successful match significantly reduces differences in observable characteristics.

Robustness checks are performed using alternative matching specifications, particularly Kernel Matching. In addition, sensitivity analysis (Rosenbaum bounds) is employed to evaluate the potential influence of unobserved factors on the estimated treatment effects.

All empirical analyses are conducted using Stata, which provides standard procedures for estimating propensity scores, implementing matching algorithms, and computing treatment effects.

Results

Descriptive Profile of Respondents

The study compares 100 gig workers and 100 non-gig workers in Ranchi across matched occupational categories, namely transportation, food-related services, and home-based personal services. The descriptive statistics indicate that the two groups are broadly comparable in socio-demographic characteristics, although some differences are evident in age, education, and work experience.

Table 1. Descriptive Statistics of Gig and Non-Gig Workers

Variable	Gig Workers (n=100) Mean / %	Non-Gig Workers (n=100) Mean / %
Age (years)	29.4	33.1
Education (years of schooling)	11.8	10.9
Male (%)	82.0	79.0
Work experience (years)	4.6	7.1
Household size	4.9	5.2
Monthly income (₹)	18,750	16,480
Weekly working hours	61.3	51.7
Job security index (0–10)	3.4	6.8
Social protection index (0–10)	2.1	5.9

The descriptive results suggest that gig workers are relatively younger and less experienced than non-gig workers. They report somewhat higher average monthly income, but this is accompanied by substantially longer working hours. In contrast, non-gig workers report better job security and greater access to social protection. These preliminary differences indicate that while gig work may provide immediate earnings opportunities, it is associated with less stable and less protected employment conditions.

Mean Difference Test

To assess whether the observed differences between the two groups are statistically significant, independent sample t-tests were conducted for major outcome variables.

Table 2. Difference in Means between Gig and Non-Gig Workers

Variable	Mean Difference	t-value	p-value
Monthly income (₹)	2,270	2.21	0.028
Weekly working hours	9.6	4.08	0.000
Job security index	-3.4	-8.17	0.000
Social protection index	-3.8	-8.92	0.000

The mean difference test indicates statistically significant differences across all major outcome variables. Gig workers earn, on average, more than non-gig workers, but they also work significantly longer hours. At the same time, they experience markedly lower job security and reduced access to social protection. These results provide initial evidence that gig employment is associated with a trade-off between higher short-term earnings and greater labour precarity.

Propensity Score Estimation

Since participation in gig work is not random, a logistic regression model was estimated to generate propensity scores based on observable characteristics. The treatment variable takes the value 1 for gig workers and 0 for non-gig workers.

Table 3. Logit Estimates for Participation in Gig Work

Covariate	Coefficient	Std. Error	z-value	p-value
Age	-0.051**	0.021	-2.43	0.015
Education	0.118**	0.049	2.41	0.016
Gender (Male=1)	0.267	0.392	0.68	0.496
Work experience	-0.144**	0.038	-3.79	0.000
Household size	-0.063	0.081	-0.78	0.436
Constant	1.924**	0.887	2.17	0.030

Pseudo R² = 0.184; LR chi² = 31.72; Prob > chi² = 0.000

Note: ** p < 0.05, * p < 0.10

The logit results show that younger and less experienced individuals are significantly more likely to participate in gig work, while education has a positive and significant association with gig employment. Gender and household size are not statistically significant predictors in this specification. These results support the argument that gig workers differ systematically from non-gig workers, thereby justifying the use of PSM.

Balancing Property and Common Support

Before matching, meaningful differences existed between treatment and control groups in terms of age, education, and work experience. After matching, the standardized mean differences declined substantially, indicating improved comparability.

Table 4. Covariate Balance before and after Matching

Covariate	Standardized Bias Before Matching (%)	Standardized Bias After Matching (%)
Age	28.4	6.1
Education	21.7	5.3
Gender	6.0	2.4
Work experience	34.8	7.0
Household size	9.5	3.2

The balancing test confirms that the matching procedure substantially reduces observable differences between gig and non-gig workers. All matched covariates fall within acceptable bias limits, suggesting that the common support condition is satisfied and that the matched sample is suitable for treatment effect estimation.

Average Treatment Effect on the Treated (ATT)

The impact of gig work on labour precarity was estimated using multiple matching techniques. The ATT results are reported below.

Table 5. ATT Estimates Using Propensity Score Matching

Outcome Variable	Nearest Neighbor Matching	Radius Matching	Kernel Matching	Stratification Matching
Monthly income (₹)	1,980**	2,110**	2,045**	1,924**
Weekly working hours	8.7**	9.1**	8.9**	8.3**
Job security index	-3.1**	-3.3**	-3.2**	-3.0**
Social protection index	-3.5**	-3.7**	-3.6**	-3.4**

Note: ** p < 0.05, * p < 0.10

The ATT estimates consistently show that gig work has a positive effect on monthly income, with gig workers earning approximately ₹1,900–₹2,100 more than comparable non-gig workers. However, this gain is accompanied by significantly longer working hours. More importantly, gig work has a strong negative effect on job security and social protection, indicating that algorithmically managed work intensifies labour precarity even after controlling for observable worker characteristics.

Robustness Check: Kernel Matching

Kernel matching was used as an alternative specification to test the stability of the treatment effects. The results remain substantively unchanged, confirming the robustness of the main findings.

Table 6. Kernel Matching Results

Outcome Variable	ATT	Std. Error	t-value	p-value
Monthly income (₹)	2,045	846	2.42	0.016
Weekly working hours	8.9	2.11	4.22	0.000
Job security index	-3.2	0.46	-6.96	0.000
Social protection index	-3.6	0.51	-7.06	0.000

The consistency of the kernel matching estimates with the nearest-neighbor and radius matching results indicates that the estimated treatment effects are not sensitive to the choice of matching algorithm.

Sensitivity Analysis

To assess whether the results are vulnerable to hidden bias arising from unobserved characteristics, Rosenbaum bounds were applied. The findings remained significant up to moderate levels of hidden bias, suggesting that the main results are reasonably robust.

Table 7. Rosenbaum Bounds Sensitivity Analysis

Outcome Variable	Critical Gamma (Γ)
Monthly income	1.5
Weekly working hours	1.8
Job security index	2.0
Social protection index	2.1

The sensitivity analysis suggests that the negative effects of gig work on job security and social protection are especially robust, while the income effect is somewhat more sensitive to unobserved heterogeneity. Even so, the overall direction of the findings remains stable.

Summary of Findings

The findings of this study provide strong empirical evidence on the relationship between **algorithmic control and labour precarity** in the context of the gig economy in Ranchi. By applying Propensity Score Matching (PSM), the study isolates the causal effect of gig work from observable individual characteristics, thereby offering a more robust understanding of labour outcomes in platform-based employment.

The results demonstrate that algorithmically managed gig work in Ranchi is associated with a mixed outcome structure. On the positive side, gig workers earn modestly higher monthly income than comparable non-gig workers. On the negative side, they work substantially longer hours and face significantly lower job security and social protection. Thus, the results support the argument that platform-based gig work generates immediate income opportunities but does so within a labour regime marked by precarity, insecurity, and weak institutional protection.

Conclusion and Policy Implications

This study examines the impact of algorithmic control on labour precarity in the gig economy by comparing gig and non-gig workers in Ranchi using Propensity Score Matching (PSM). By addressing selection bias and constructing a counterfactual framework, the analysis provides robust causal evidence on how platform-based work shapes labour outcomes., this advantage is accompanied by significantly longer working hours, lower job security, and limited access to social protection. The results suggest that algorithmic management—through mechanisms such as task allocation, performance monitoring, and rating systems—plays a central role in intensifying labour precarity.

Overall, the study confirms that the gig economy, while offering flexibility and income opportunities, operates within a labour regime characterized by insecurity, asymmetry of power, and weak institutional protection. Thus, algorithmic management emerges as a double-edged phenomenon—enhancing efficiency while simultaneously deepening precarity.

Policy Implications

The findings of this study have significant implications for labour policy and the regulation of platform-based work in India. As algorithmic management reshapes employment relations, there is a growing need for institutional frameworks that balance flexibility with worker protection.

1. Inclusion of Gig Workers in Social Security Frameworks: There is an urgent need to extend social protection measures—such as health insurance, accident coverage, and pension benefits—to gig workers. Integrating gig workers into existing schemes under the Code on Social Security can help mitigate economic vulnerability and provide a basic safety net.

2. Regulation of Algorithmic Management: Policy interventions should promote greater transparency and accountability in algorithmic decision-making. Platforms must disclose key criteria related to task allocation, rating systems, and incentive structures to reduce information asymmetry and ensure fair treatment of workers.

3. Minimum Earnings and Income Stability Mechanisms: Introducing minimum earning guarantees or floor wages can help address income volatility among gig workers. This is particularly relevant in sectors such as ride-hailing and food delivery, where earnings are highly dependent on fluctuating demand conditions.

4. Legal Recognition of Gig Workers as a Distinct Labour Category: Recognizing gig workers as a distinct category—separate from traditional employees and independent contractors—can enable the formulation of targeted regulatory frameworks. Such recognition would facilitate the design of policies that preserve flexibility while ensuring minimum labour standards.

5. Strengthening Worker Voice and Grievance Redressal Mechanisms: Platforms should establish formal grievance redressal systems that allow workers to contest algorithmic decisions, unfair ratings, or payment disputes. Encouraging collective representation and worker participation can further enhance accountability and improve working conditions.

6. Data Governance and Worker Rights: Given the central role of data in algorithmic management, policies should ensure that workers have access to their performance data and are protected against misuse. Establishing data rights and safeguards can reduce asymmetries between platforms and workers.

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