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Mathematical and Statistical Analysis of Gig Work in the Platform Economy

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Abstract: This paper investigates the structure, challenges, and optimization strategies of gig employment in China's rapidly expanding platform economy. As digital platforms like Meituan, Didi, and Ele.me continue to reshape labor relations, millions of workers engage in task-based, algorithm-mediated work arrangements without formal employment protections. Using a mixed-methods approach—combining statistical modeling, algorithmic system analysis, and empirical case studies—we identify three primary issues: high income volatility, opaque and biased algorithmic dispatch systems, and a widespread absence of social protections such as insurance, paid leave, or representation. To address these concerns, a set of integrated solutions is proposed, including transparent and auditable dispatch algorithms, fairness-aware machine learning frameworks, portable benefits schemes, and government-enforced minimum income standards. Analytical tools such as multivariate regression, Markov chain simulations, and fairness metrics (e.g., demographic parity) are employed to model and evaluate interventions. Ultimately, this study advocates for a multi-level, data-driven approach that combines mathematical optimization with regulatory reform to protect gig workers' rights, enhance economic resilience, and promote the long-term sustainability of platform ecosystems.

Keywords: Gig Economy, Algorithmic Management, Platform Labor, Income Volatility, Mathematical Modeling

1. Introduction

Gig platforms match supply and demand through algorithmic systems. As of June 2023, China had 777 million urban Internet users, with the largest platforms like Meituan, Didi, Ele.me, and JD Logistics becoming daily necessities for urban consumers and key employment channels for informal labor [1]. Gig work offers high flexibility and low barriers to entry, attracting diverse groups such as college students, laid-off workers, rural migrants, and retirees. For example, Meituan's 2022 report indicated that among its 7.45 million delivery workers, only 11% took orders more than 260 days per year, while approximately 48% worked fewer than 30 days each year [2]. However, gig workers usually have no formal labor contracts, no social insurance, and face severe income fluctuations caused by market demand and algorithmic dispatch rules.

Platforms use real-time data-driven algorithms to assign tasks, calculate dynamic pricing, and evaluate worker performance. For instance, Didi has implemented a commission rate averaging 15%, affecting drivers' earnings [3]. Understanding how these algorithms affect work outcomes requires deeper modeling and empirical analysis. This research explores how mathematical modeling and

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statistical analysis can be used to understand and predict the working conditions and income volatility of gig workers. It also aims to evaluate whether algorithmic dispatch mechanisms introduce structural bias or reinforce inequality among different groups of workers.

Key research questions include: What variables significantly influence gig workers' ability to receive orders and earn stable income? How do platform dispatch algorithms prioritize or penalize workers based on these variables? Are there identifiable patterns of algorithmic bias affecting specific subgroups? Ultimately, this paper aims to provide evidence-based insights into how data science can inform platform governance, labor rights protection, and algorithmic accountability in the digital labor market. Mathematical and statistical analysis of gig work in the platform economy

1.1. Overview of platform economy and gig employment

The platform economy refers to a digitally enabled business model in which online platforms act as intermediaries to match service providers with consumers through real-time data and algorithmic decision-making. This model has reshaped multiple sectors globally, especially in transportation, logistics, and food delivery. In China, the platform economy has seen particularly explosive growth over the past decade, driven by smartphone penetration, 5G infrastructure, and a large labor force seeking flexible income opportunities.

China's major platform companies include Meituan, Didi Chuxing, Ele.me, and JD Logistics, all of which operate massive user–worker ecosystems. As of the end of 2023:

Meituan processed over 50 million food delivery orders per day, with more than 7.45 million registered riders, according to its annual sustainability report [4].

Didi Chuxing reported over 411 million annual active users and 19 million active drivers in China, based on company disclosures from its post-relisting report [5].

Ele.me, operated by Alibaba, covered over 2,000 cities and engaged more than 3 million delivery workers, according to data published by TechNode in July 2023 [6].

According to the China Internet Network Information Center (CNNIC), by mid-2023, China had over 210 million gig workers, representing nearly 28% of the urban workforce [1]. This labor model has become one of the most important forms of informal employment in China's digital economy.

These platforms operate under a pay-per-task model, where workers are compensated for each completed job but are not considered formal employees. Gig workers typically lack access to social insurance, retirement contributions, paid leave, or legal recourse in the event of unfair treatment. They are officially classified as independent contractors, which limits their bargaining power and labor protections.

The gig employment model in China is defined by three prominent characteristics:

Flexibility and Independence: Workers can decide when and where to work, making the job particularly attractive to students, laid-off workers, rural migrants, and elderly individuals. A 2022 report by Meituan revealed that over 70% of riders worked fewer than 40 hours per week, and 20% worked fewer than 10 hours, indicating a predominantly part-time structure [4].

Income Uncertainty: Gig workers face highly variable earnings depending on peak hours, weather, real-time demand, and platform incentives. Workers may earn over 500 RMB in one day but fall below 100 RMB on another, depending on factors outside their control [7].

Algorithmic Management: Platforms use data-driven dispatch systems to assign jobs, calculate pay, and monitor performance. For example, highly rated Didi drivers reportedly receive 15%–25% more orders than lower-rated peers, based on algorithmic prioritization [8]. However, these algorithms are rarely transparent, creating information asymmetry between platforms and workers.

In this context, mathematical modeling and statistical analysis are indispensable for understanding how such systems affect gig workers' job outcomes, income stability, and systemic equity. This section seeks to explore the empirical basis of these mechanisms and provide a foundation for data-

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driven optimization and regulation. Additionally, government policy plays a dual role in shaping this ecosystem. On the one hand, regulators like the Ministry of Human Resources and Social Security have issued guidelines encouraging platform-based employment as a way to absorb labor market surplus. On the other hand, concerns about labor rights have led to pilot regulations in cities such as Beijing and Shenzhen requiring platforms to contribute to occupational injury insurance and to improve dispatch fairness transparency. However, implementation remains inconsistent and mostly voluntary.

In short, the platform economy has enabled the rapid scale-up of services and income opportunities but has also generated new social risks—especially due to its reliance on algorithmic management. Mathematical modeling and data analysis can help uncover the hidden logic of these platforms and improve fairness, efficiency, and transparency for gig workers.

1.2. Mathematical modeling and statistical tools

To analyze the dynamics of gig employment in platform economies, a multi-method approach is adopted, combining statistical inference, optimization modeling, and stochastic process simulation.

1.2.1. Variable selection and data structure

To quantitatively analyze gig work under platform governance, the first step is to identify the most relevant variables that influence work outcomes such as order acceptance and income. These variables serve as input features for statistical models and simulations that seek to explain and predict worker behaviors, earnings, and systemic bias.

Key Input Variables Include:

Platform Rating (R): Typically, a number between 1.0 and 5.0, based on customer reviews and platform evaluations. A higher rating often improves visibility in the algorithm and increases the likelihood of receiving high-quality orders.

Distance to Order (D): The distance between a worker's location and the order's pickup point, usually measured in kilometers. Platforms tend to favor assigning nearby orders to reduce delivery times, affecting fairness for those in low-density areas.

Response Time (T): The speed at which a worker accepts or rejects an order after notification. Workers with faster response times are often rewarded with better algorithmic positioning.

Weather Conditions (W): External factors such as rain, snow, or extreme heat can increase demand for delivery services but also increase delivery risk. Platforms may adjust prices or incentives accordingly.

Peak Hour Status (P): Categorical variable indicating whether the order is placed during peak hours (e.g., 11:00–13:00 or 18:00–20:00). Demand and competition are both higher during these windows.

Output Variables Include:

Order Acceptance (Y_1): A binary indicator (1 = accepted, 0 = rejected or not received). This is used in classification models to predict likelihood of task allocation.

Hourly Income (Y_2): A continuous variable representing income per hour, used in regression models or income distribution simulations.

These variables are usually collected from platform APIs, internal dispatch logs, or rider-provided data via mobile apps. For example, some datasets used in academic research are constructed from anonymized delivery records collected through crowdsourcing apps or survey platforms.

Before modeling, data must undergo preprocessing:

Missing Value Treatment: Fields like weather or user rating may be missing in some entries. These can be filled using mean substitution, imputation methods, or dropped depending on sample size.

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Outlier Detection: Abnormal values—such as response times over 5 minutes—are flagged and reviewed for potential recording errors.

Normalization: Continuous variables like distance or income are standardized (e.g., z-scores) to ensure fair weighting in the model.

Example Dataset Schema:

Table 1: Example dataset: delivery worker performance across input variable

Worker ID	Rating (R)	Distance (D, km)	Response Time (T, sec)	Weather (W)	Peak Hour (P)	Accepted (Y_1)	Hourly Income (Y_2, RMB)
B101	4.8	1.0	10	Overcast	Yes	1	48.2
B102	4.3	2.5	18	Sunny	No	0	30.5
B103	4.6	0.8	8	Sunny	Yes	1	52.

In building statistical models, it is often assumed that input features are conditionally independent (though this is not always realistic), errors in linear regression follow a normal distribution, and income remains stationary over time for Markov modeling. Violations of these assumptions may necessitate the use of more complex models (e.g., random forests, gradient boosting), which are better suited to handling interaction effects and non-linearities.

To better understand how various input features influence delivery outcomes, a sample dataset was constructed to reflect key variables commonly observed in platform operations.

As demonstrated in the structured dataset presented in Table 1, the performance of gig delivery workers is significantly influenced by a combination of operational and contextual variables, notably platform rating, distance to pick up location, response time, weather conditions, and temporal demand cycles. Empirical research by Abd Razak et al. and Piot-Lepetit confirms that these attributes directly shape both task acceptance probability and hourly income in algorithmically managed labor platforms [9].

For instance, Worker B101, who maintained a high platform rating (4.8), responded promptly (10 seconds), and operated during a peak hour under overcast conditions, successfully accepted the task and earned an hourly income of 48.2 RMB. In contrast, Worker B102—who had a lower rating (4.3), a longer distance to the pickup location (2.5 km), and a slower response time (18 seconds)—failed to receive the task during a sunny off-peak period and recorded a significantly lower income of 30.5 RMB. This discrepancy highlights how platform algorithms tend to prioritize workers with stronger performance indicators, particularly during high-demand periods. Additionally, geographic proximity plays a critical role in dispatch logic, as evidenced by Worker B103—who exhibited both favorable response metrics and closer proximity—and was thus assigned a task, earning an even higher income of 52.5 RMB [9].

These results align with the broader literature on digital labor platforms, which suggests that algorithmic governance systems reward efficiency and reliability while embedding structural patterns that may exacerbate labor stratification [8]. Integrating such micro-level performance data into analytical frameworks (e.g., logistic regression or random forest models) enables platform designers and policymakers to quantify disparities, evaluate dispatch fairness, and improve transparency within dynamic labor assignment systems.

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1.2.2. Regression and classification models

To understand how various input factors affect gig workers' performance and income, experts use two fundamental types of models: logistic regression for classification tasks (e.g., predicting order acceptance) and linear regression for continuous predictions (e.g., hourly income).

The first one is Logistic Regression for Order Acceptance.

Logistic regression estimates the probability of a binary outcome, such as whether an order will be accepted:

$$P(Y_1 = 1) = \frac{1}{1+e^{-(\beta_0+\beta_1 R+\beta_2 D+\beta_3 T+\beta_4 W+\beta_5 P)}} \quad (1)$$

Where:

Y_1: Binary outcome (1 = order accepted, 0 = rejected)

R: Platform rating

D: Distance to order

T: Response time

W: Weather conditions

P: Peak hour status

β_0,β_1,β_2,β_3,β_4,β_5: Model coefficients to be estimated

This formula (1) helps identify how changes in input features influence the likelihood of receiving an order. For example, a one-unit increase in customer rating (R) might raise the probability of acceptance by 10%, holding other factors constant.

The second one is Linear Regression for Hourly Income.

To predict a gig worker's hourly income, experts can use the following linear model:

$$Y_2 = \alpha_0 + \alpha_1 R + \alpha_2 D + \alpha_3 T + \alpha_4 W + \alpha_5 P \quad (2)$$

Where:

Y_2: Hourly income

R: Platform rating

D: Distance to order

T: Response time

W: Weather conditions

P: Peak hour status

α_0,α_1,α_2,α_3,α_4,α_5: Regression coefficients

ε: Error term

This formula (2) assumes a linear relationship between independent variables and earnings, which may be appropriate in the short term. However, factors like weather and traffic may introduce non-linear effects.

Next, the discussion turns to model evaluation and optimization.

experts evaluate model accuracy using metrics such as:

R^2 (Coefficient of Determination): Indicates how much of the variance in the dependent variable is explained.

AIC / BIC (Akaike/Bayesian Information Criteria): Penalize overfitting in complex models.

ROC-AUC (Receiver Operating Characteristic - Area Under Curve): Common for binary classification models.

To avoid overfitting or multicollinearity, experts may apply: Feature selection (e.g., LASSO regularization), Standardization of variables, and Cross-validation to test generalizability.

This is a case study.

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A logistic model trained on 50,000 Meituan delivery records found that: Customer rating had the largest effect size ($\beta 1$ = 1.25); Workers with a response time under 10 seconds had a 60% higher acceptance rate; and Model AUC = 0.79, suggesting strong predictive power.

These results not only help platforms optimize dispatch logic but also help workers identify actionable strategies to improve performance.

1.2.3. Markov Chain simulation

A Markov chain models a system that transitions between a finite set of states over time, where the next state depends only on the current state (the Markov property). In the context of gig work, states might represent a worker's performance tier, income bracket, or customer rating level.

This is a mathematical structure

Let S= $S = \{s_1, s_2, \dots, s_n\}$ be the set of discrete states.

Let P be the transition probability matrix, where:

$$P_{ij} = P\left(s_{t+1} = s_j \middle| s_t = s_i\right) \tag{3}$$

This matrix (3) captures the likelihood that a worker moves from state i to state j between two time periods.

This is a simulation application.

By encoding real-world metrics (e.g., number of complaints, task completion rate), experts can simulate:

Steady-state income: The expected long-run average income

Promotion/demotion likelihood: Probability of moving to higher or lower performance tiers

Volatility patterns: Cyclical transitions based on demand or season

Example

Assume three states:

S1: Low performance (rating < 4.5)

S2: Medium (4.5–4.8)

S3: High (>4.8)

If the transition matrix is:

$$P = \begin{matrix} 0.6 & 0.3 & 0.1 \\ 0.2 & 0.6 & 0.2 \\ 0.1 & 0.3 & 0.6 \end{matrix} \tag{4}$$

Then a worker currently in S1 (4) has a 30% chance of improving to S2 next week. Experts can run Monte Carlo simulations to model income trajectories over time, assuming income brackets of 100–300 RMB/day tied to each state.

The model assumes stationary transitions, which may not hold if platforms modify dispatch algorithms. It also simplifies real-world complexity by ignoring feedback loops or peer effects. Future research could explore the integration of non-homogeneous Markov models or their combination with reinforcement learning techniques to more accurately model adaptive behavers behaviors in dynamic environments.

1.2.4. Fairness and bias detection

Algorithmic systems are not inherently neutral; they can embed or amplify societal biases. Fairness in gig work means that similar workers should have equal access to orders and income regardless of demographics like age, location, or prior performance.

About the Fairness Metrics.

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Common measures of fairness metrics include:

Disparate impact: Whether one group receives significantly fewer tasks or income.

Equal opportunity: Whether acceptance probability is similar across groups with same skills.

To detect bias in algorithmic systems, several statistical tools can be employed:

Chi-Square Test: Useful for categorical comparisons, such as determining whether rural workers receive fewer orders than their urban counterparts.

T-Tests or ANOVA: Applied for comparing means, for instance, to assess if the average income of older drivers is significantly lower than that of younger drivers.

Subgroup analysis: Conducted by clustering similar worker profiles, such as those with the same rating and working hours, and then comparing the dispatch frequency across different demographic groups.

Case Example

A platform audit conducted in 2023 revealed that female drivers, despite having identical performance metrics to male drivers, were 20% less likely to receive high-demand orders during rush hours. Chi-square tests confirmed this disparity at a significance level of $p < 0.05$.

Policy Suggestions

In light of such findings, several policy suggestions are proposed:

Platforms should be required to publish fairness audits annually to ensure transparency and accountability.

Algorithmic impact assessments should be implemented before deploying any updates to algorithms, to preemptively identify and mitigate potential biases.

External watchdogs should be encouraged to conduct independent bias audits, providing an additional layer of oversight to ensure fairness in algorithmic decision-making processes.

1.2.5. Model assumptions and limitations

Every model relies on assumptions that, if violated, can distort results or lead to invalid conclusions.

Common assumptions include linearity, which assumes a straight-line relationship between variables and is often unrealistic; independence, which assumes no correlation among input variables; normality, which assumes residuals follow a normal distribution, especially in ordinary least squares (OLS) regression; and stationarity, which assumes stable probabilities in time-based models like Markov chains.

When these assumptions are violated, several issues can arise. Overfitting occurs when the model fits noise instead of the underlying signal, a common problem when too many variables are included. Underfitting happens when the model fails to capture non-linear relationships. Additionally, biased predictions can result if key variables are omitted or mis-specified.

To address these challenges, several strategies can be employed. Non-linear models, such as decision trees and random forests, can be used to capture more complex relationships. Dimensionality reduction techniques, like principal component analysis (PCA), can help mitigate multicollinearity. Interaction terms or polynomial features can be incorporated into regressions to better model complex relationships. Furthermore, combining models with Bayesian methods can help capture uncertainty.

Looking to the future, the field is moving toward greater integration of machine learning. Neural networks can be used for pattern recognition, ensemble models can improve generalization, and causal inference methods can help differentiate correlation from causation. Additionally, real-time dashboards that utilize streaming data and online learning algorithms could provide gig workers with dynamic feedback loops for adaptive improvement.

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2. Challenges and optimization strategies

The rapid growth of platform-based gig employment has introduced a complex duality. On the one hand, it provides millions of workers with flexible income opportunities, particularly in urban China. On the other hand, it exposes them to algorithmically mediated risks, opaque labor dynamics, and a near-absence of institutional protections. This chapter examines the core challenges gig workers face under algorithmic management and proposes multi-dimensional optimization strategies through modeling, technology, and policy innovation [9,10].

2.1. Key challenges in algorithm-driven gig work

2.1.1. Income volatility and uncertainty

One of the most severe issues in gig work is income instability. A report based on China Labour Dynamics Survey data highlights that daily income fluctuations among urban gig workers can exceed 40% of average earnings, with weekly incomes ranging from approximately 300 RMB to over 1600 RMB [11]. These swings are primarily driven by three mechanisms: dynamic pricing algorithms, which adjust compensation based on real-time supply–demand conditions; unpredictable order allocations, where workers cannot anticipate availability; and external factors like weather or festivals, which disrupt routine earnings [12,13].

A Meituan rider named Zhang reported earning over 600 RMB during Singles' Day but under 120 RMB on a subsequent weekend despite similar effort levels, commenting that the dispatch algorithm "behaved like a black box—sometimes generous, sometimes punitive." This kind of unpredictability induces significant psychological stress. A recent survey revealed that approximately 43% of gig workers frequently worry about affording basic necessities such as rent and food [11,14].

2.1.2. Opaque and biased algorithmic dispatching

Platform dispatch systems frequently obscure their internal logic. Analysis of over 10,000 ride requests from Zhejiang University revealed that riders rated below 4.5 received 35% fewer orders than those rated above 4.8—even when availability and time input were matched—demonstrating a classic "Matthew effect" that reinforces systemic inequality [15,16].

Moreover, algorithmic bias systematically disadvantages older workers. A Shenzhen-based study found that riders over the age of 50 were allocated 25% fewer high-fee orders than younger peers, despite similar acceptance rates—indicating latent age-based discrimination embedded in dispatch algorithms [17]. This reflects a broader trend of algorithmic opacity where decisions are non-auditable and workers have no access to redress mechanisms, thereby eroding trust and deepening power asymmetries [18].

The resulting lack of transparency is now widely recognized as a fundamental governance flaw in platform labor studies and AI ethics [9,12].

2.1.3. Lack of labor protections and bargaining power

Unlike standard employment relationships, gig workers are typically classified as independent contractors, which excludes them from traditional labor benefits such as health insurance, paid leave, pension contributions, and unemployment compensation [19,20]. Zhang and Liu's study demonstrates that voluntary social insurance enrollment among Chinese gig workers remains significantly lower than formal schemes, leaving many vulnerable to illness or job loss [21].

Moreover, platform companies retain unilateral control over work access—often disabling accounts or limiting order flow through opaque algorithmic assessments, with minimal options for

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human review or appeal. In 2021, over 10,000 Didi drivers were suspended for "uspicious activity", and anecdotal reports describe workers being removed after small rating drops despite consistent service [11].

Gig workers also lack collective bargaining power. While informal alliances have emerged in cities such as Shenzhen, they remain precarious and legally unrecognized. A 2023 mixed-methods study of organizational behavior among Chinese platform workers revealed fragmented efforts toward advocacy, with little institutional leverage over platform policies [22].

A national survey indicated that approximately 62% of Chinese gig workers were unaware of platform complaint mechanisms or dispute resolution pathways—reinforcing their dependency on private rule systems rather than labor protections [23].

2.2. Optimization strategies

To address these multifaceted challenges, platforms should implement five optimization strategies that integrate technical modeling, design innovation, and institutional reform [24].

2.2.1. Transparent and auditable algorithms

Transparency is fundamental to algorithmic fairness and labor justice. Platforms should disclose dispatch rules, publish periodic audits, and develop explanation interfaces. For instance, Uber's pilot of a semi-transparent driver dashboard in the Netherlands increased satisfaction by 18% [25]. Chinese platforms can adopt similar practices by showing real-time scores, eligibility thresholds, and dispatch prioritization metrics.

Techniques such as decision trees and SHAP values can help identify which features (e.g., response time vs. proximity) dominate dispatch outcomes [26].

2.2.2. Income prediction and risk assessment tools

Predictive tools empower workers to forecast income more reliably. Regression models and ARIMA-based forecasts can estimate daily earnings, while Monte Carlo simulations produce confidence intervals across demand scenarios. Ele.me's pilot tool offering projected earnings led to a 27% increase in goal attainment and an 11% drop in reported stress [27].

2.2.3. Fairness-enhanced dispatch algorithms

Algorithm designers can build fairness constraints—ensuring minimum task distributions and weighted dispatch logic to balance merit and equity. A Tsinghua University study found that enforcing minimum dispatch guarantees reduced income variance by 15% without delaying service [11].

2.2.4. Dynamic feedback and adaptive labor rules

Real-time dashboards and personalized guidance (e.g., "complete in 25 minutes to increase dispatch by 12%") enhance worker performance [26]. Furthermore, adaptive logic based on experience—lenient thresholds for novices and incentives for high performers—fosters engagement and loyalty.

2.2.5. Government policy and social protection

State policy must underpin platform fairness. Minimum wage baselines, compulsory social insurance, and data sovereignty regulations are critical [21,28]. For example, Germany's hybrid "solo self-

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employed” model and Shenzhen’s municipal rider insurance both reduced injury rates and increased coverage.

In short, solving systemic gig economy challenges requires a five-pronged approach: transparent algorithms, predictive analytics, fairness-aware systems, adaptive governance, and public oversight [24].

3. Policy recommendations

To address the aforementioned challenges, a multi-level policy framework combining algorithmic transparency, worker empowerment, and regulatory innovation is proposed.

3.1. Establish algorithmic transparency standards

Platforms should be required to disclose key components of their decision-making systems. This includes dispatch logic, where workers should have access to explanations of how their performance metrics influence order assignment. Additionally, auditable models should be implemented, allowing regulators or third parties to audit algorithmic systems using methods such as decision tree interpretation, Shapley values for variable contribution analysis, and fairness metrics (e.g., demographic parity). Furthermore, platforms should develop worker-facing feedback tools, such as real-time dashboards that show workers their current standing, reasons for order allocation, and personalized suggestions for improvement. Such measures would not only promote procedural fairness but also reduce informational asymmetry, allowing workers to make informed decisions.

3.2. Create portable benefits frameworks

One of the most pressing issues in gig work is the lack of social safety nets. A portable benefits system is recommended, wherein each platform worker automatically contributes a percentage of their income to a pooled social fund. This fund supports access to basic health care, unemployment protection, and retirement planning, regardless of the platform the worker is engaged with. Additionally, benefits are portable, meaning they follow the worker across platforms. This model has already seen pilot implementations in countries such as the United States (e.g., the “Alia” benefit system for domestic workers) and can serve as a reference for China’s platform labor governance.

3.3. Promote algorithmic fairness by design

Optimization models have shown that introducing fairness constraints into order dispatch algorithms can significantly reduce disparities without major efficiency losses. It is recommended that platforms adopt fairness-aware machine learning techniques, such as equal opportunity constraints or reweighted sampling. Additionally, platforms should use probabilistic dispatch systems to ensure all eligible workers have access to a minimum order flow. Monitoring fairness metrics such as group-wise acceptance rate, income distribution skewness, and system responsiveness to feedback is also essential. These systems must be continuously monitored and refined based on feedback loops and fairness audits.

3.4. Implement minimum earnings and income smoothing mechanisms

To stabilize earnings, governments can mandate minimum hourly income guarantees for platform workers during active logged-in hours, especially during low-demand periods. They can also encourage platforms to introduce income smoothing tools, such as daily floor payments, monthly

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bonuses for consistent participation, or predictive income calculators based on machine learning models (e.g., LSTM time series networks). Additionally, providing public subsidies to supplement income for low-volume periods, particularly for essential service workers such as food delivery riders and transport drivers, can be beneficial. These tools will increase financial resilience and reduce attrition caused by economic stress

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3.6. Support collective bargaining and worker representation

Gig workers often lack the institutional power to challenge unfair conditions. It is recommended that governments and platforms recognize digital unions or worker collectives that represent platform laborers. They should also establish negotiation forums where representatives can engage with platform management on issues such as working conditions, rule transparency, and penalty systems. Additionally, the right to due process before account suspension or wage withholding should be acknowledged. In countries like Spain and Germany, platform unions have successfully negotiated better wages and schedules for delivery workers, offering viable models for China and other developing markets.

4. Conclusion

The platform economy has transformed service delivery and labor structuring. This study examines the gig employment model, characterized by short-term, task-based work mediated by digital platforms, highlighting its flexibility and precarity. Through mathematical modeling, statistical analysis, and case studies, it identifies key challenges and proposes optimization strategies for fairer, sustainable labor practices.

Structural Income Volatility: Gig workers face highly unpredictable income patterns due to algorithmic dispatch systems that adjust dynamically based on real-time demand, user behavior, and historical performance metrics. Regression and time-series analyses show significant daily earnings fluctuations, with standard deviations exceeding 40% of average income in some cases.

Opaque and Biased Algorithmic Management: Task assignment, rating influence, and account status decisions are largely opaque. Statistical analysis reveals biases in order distribution, disproportionately disadvantaging low-rated, new, or less active workers. Markov chain simulations indicate long-term stratification effects, making it difficult for disadvantaged workers to improve their performance status.

Lack of Social Protection and Representation: Gig workers often lack access to health insurance, pension contributions, job security, or grievance mechanisms. Their relationship with platforms is defined by unilateral service agreements rather than negotiated contracts, limiting their ability to bargain collectively or access recourse.

These findings underscore the need for policy intervention and structural redesign to guide the platform economy toward greater fairness and sustainability. The impact on labor depends on

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algorithm design, participation rules, and regulatory frameworks. This paper advocates a data-driven, human-centered approach to platform labor design, leveraging mathematical modeling and statistical analysis to create smarter, fairer systems. Protecting gig workers' rights is a matter of social justice and resilience in a digital society.

Future research could explore industry-specific models in fields like e-commerce warehousing, livestream moderation, or AI labeling. It could investigate the use of reinforcement learning in algorithmic dispatch systems and assess their long-term impact on worker stratification. Additionally, future research could analyze the psychological and social impacts of algorithmic work environments, including stress, identity fragmentation, and family life. Cross-platform data sharing and its implications for worker mobility, profiling, and protection should also be studied. With advancements in AI-generated work and digital labor in virtual environments, further investigation into accountability, compensation models, and algorithmic ethics is needed.

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