

Determinants of Income Stability among Platform Workers: Evidence from the Gig Economy in Madhya Pradesh

Mr. Subhash Gupta¹, Dr. Anita Kumari²

Department of Commerce

Dr. Harisingh Gour Vishwavidyalaya Sagar, Madhya Pradesh

Abstract

The rapid expansion of the gig economy has transformed labour markets in India, offering flexible employment opportunities while simultaneously raising concerns about income stability and economic security for platform workers. This study empirically examines the impact of gig work participation on income stability among platform workers in Madhya Pradesh, India, using a theoretical framework grounded in human capital theory and precarious work literature. Using primary survey data collected from 268 platform workers through structured questionnaires and purposive stratified sampling across four cities — Bhopal, Jabalpur, Sagar, and Rewa — the study analyses key determinants of income stability, including working hours, platform dependence, incentive structures, skill levels, and engagement across multiple digital platforms. Quantitative analysis was conducted using descriptive statistics, Pearson correlation analysis, and multiple linear regression techniques via SPSS. The findings reveal that multi-platform engagement and skill level are the strongest positive predictors of income stability, while high dependence on a single platform significantly undermines earnings consistency. Working hours beyond ten per day yield diminishing income returns, and platform-specific incentives contribute only moderately to short-term income smoothing. The regression model explains substantial portion of the variance in income stability, highlighting the structural vulnerabilities inherent in platform-mediated work. The study contributes to the existing literature by providing region-specific evidence from Madhya Pradesh, a rapidly urbanising state with a predominantly young, semi-skilled platform workforce, and offers policy-relevant insights for improving income security, social safety nets, and labour protections for gig workers in emerging economies.

Keyword: Gig economy, income stability, platform workers, digital labor, India

1. Introduction

India's gig economy has grown from a niche feature of urban labour markets into a structural component of the national economy. Enabled by expanding digital infrastructure, declining mobile data costs, rapid smartphone penetration, and increasing platformization of work, app-mediated labour now engages millions of workers across food delivery, ride-hailing, logistics, and on-demand services (NITI Aayog, 2022; Graham et al., 2017). The gig workforce is projected to expand to approximately 23.5 million workers by 2029–30, accounting for around 6.7% of the non-agricultural workforce and 4.1% of total employment (NITI Aayog, 2022). These projections indicate that India's labour market is undergoing a significant structural transformation, yet the workers driving this expansion continue to operate under employment arrangements characterized by substantial economic uncertainty (International Labour Organization [ILO], 2021; Wood et al., 2019).

Income stability, defined in this study as the consistency and predictability of monthly earnings over a specified reference period, represents one of the most important welfare concerns for platform workers. Unlike conventional wage employment, gig work typically lacks guaranteed working hours, fixed wage floors, and institutional mechanisms for income protection (ILO, 2021; Wood et al., 2019). Evidence from platform labour studies suggests that earnings frequently fluctuate due to changing demand conditions, algorithmic management systems, and incentive structures that workers cannot fully predict or control (Rosenblat & Stark, 2016; Wood et al., 2019). Recent Fairwork India assessments

¹Research Scholar, Department of Commerce, Dr. Harisingh Gour Vishwavidyalaya Sagar, Madhya Pradesh.

Subhddhanrajgir@gmail.com

²Assistant Professor, Department of Commerce, Dr. Harisingh Gour Vishwavidyalaya Sagar, Madhya Pradesh.

Pujaanita@gmail.com

further indicate that many platform workers remain unable to consistently earn local minimum wages after accounting for work-related costs and unpaid waiting time (Fairwork India Team, 2023).

A central mechanism underlying this instability is algorithmic management. Platform companies use automated dispatch systems, dynamic pricing algorithms, customer ratings, and performance metrics to regulate task allocation and labour discipline (Rosenblat & Stark, 2016; Möhlmann & Zalmanson, 2017). Research increasingly links algorithmic management to income volatility because earnings depend not only on worker effort but also on opaque computational processes that determine visibility, order allocation, and compensation (Wood et al., 2019). Critical scholarship has challenged the developmental narratives surrounding platform work, arguing that claims of flexibility, entrepreneurship, and economic inclusion often obscure the precarious labour relations embedded within platform capitalism (Graham et al., 2017; Srnicek, 2017). Nevertheless, aggregate accounts of precarity conceal substantial heterogeneity among workers. While some platform workers achieve relatively stable earnings, others experience chronic income volatility, suggesting that specific worker-level characteristics shape economic outcomes within platform labour markets.

Five determinants emerge as particularly important in explaining variation in income stability. First, working hours are commonly assumed to determine gig earnings; however, evidence suggests that the relationship between hours worked and income stability is neither linear nor guaranteed (ILO, 2021). Longer working hours may increase gross earnings but do not necessarily reduce income volatility because fluctuations in demand and platform allocation systems remain outside workers' control (Wood et al., 2019).

Second, platform dependence, defined as the extent to which workers rely on platform earnings as their primary source of livelihood, has been consistently identified as a key driver of precarity. Schor et al. (2020) demonstrated that dependence on platform income substantially shapes workers' autonomy, vulnerability, and economic outcomes. Workers who rely exclusively on platform earnings are generally more exposed to fluctuations in demand, changes in platform policies, and algorithmic interventions than those who use gig work as a supplementary income source (Schor et al., 2020).

Third, platform incentives, including surge pricing, bonuses, referral rewards, and seasonal promotions, create opportunities for temporary earnings gains. However, such incentives are episodic and contingent upon platform strategies rather than worker performance alone, limiting their capacity to provide sustained income stability (Woodcock & Graham, 2020). Consequently, incentive-driven income growth may be substantial in the short term but unreliable over longer periods.

Fourth, skill level constitutes an important determinant of earnings consistency. Human capital theory suggests that workers possessing higher levels of experience, knowledge, and task-specific competencies are better positioned to secure favourable labour market outcomes (Becker, 1964). Within platform economies, skill accumulation often occurs through learning-by-doing, allowing workers to improve efficiency, customer ratings, and platform reputation over time (Wood et al., 2019). These improvements can translate into more regular task allocation and greater earnings predictability.

Fifth, multi-platform engagement has emerged as a common risk-management strategy among gig workers. By simultaneously participating across multiple platforms, workers can diversify income sources and reduce dependence on a single platform ecosystem (Heeks et al., 2021; Woodcock & Graham, 2020). However, while multi-platform work may reduce earnings volatility, it may also increase workload intensity, fatigue, and scheduling conflicts, potentially generating new forms of precarity.

Despite the rapid growth of research on platform labour in India, existing evidence remains disproportionately concentrated in major metropolitan centres such as Bengaluru, Delhi, Mumbai, Hyderabad, and Chennai (Fairwork India Team, 2023). As platform work expands into Tier-2 and Tier-3 cities, empirical research has not kept pace with this geographic diffusion. Madhya Pradesh, despite being one of India's largest states and home to rapidly urbanising centres including Bhopal, Jabalpur, Sagar, and Rewa, remains largely absent from the quantitative literature on platform worker income stability. Existing scholarship suggests that worker characteristics such as platform dependence, skills, and labour market positioning significantly influence earnings quality and precarity outcomes, but evidence from semi-urban regions of developing economies remains limited (Schor et al., 2020; Wood et al., 2019).

This study seeks to address this gap by drawing on primary survey data collected from platform workers across four cities in Madhya Pradesh. By examining the determinants of income stability among gig workers, the study contributes one of the first regression-based quantitative analyses of platform labour outcomes in the state. The findings generate regionally grounded evidence capable of informing state-level labour policy at a time when gig and platform workers

are receiving increasing policy attention but continue to face limited social protection within India's evolving labour welfare architecture (NITI Aayog, 2022; ILO, 2021)

2. Literature Review

The Global Gig Economy: Structure and Labour Dynamics

The gig economy, characterized by short-term contractual work arrangements mediated through digital platforms, has fundamentally disrupted conventional models of employment worldwide (Woodcock & Graham, 2019). Platforms such as Uber, Lyft, Deliveroo, and their Indian counterparts Ola, Swiggy, and Zomato have created what Srnicek (2017) describes as a form of 'platform capitalism' — a model that externalizes labour costs while monetizing both workers and users. In this framework, workers are classified as independent contractors rather than employees, which strips them of institutional protections including minimum wages, social insurance, and employment stability (Prassl, 2018). Wood et al. (2019) identified that platform dependency, the extent to which a worker's total income derives from one platform is a key determinant of precarity, with dependent workers more exposed to algorithmic income reductions and demand shocks. Berg et al. (2018) corroborated this in a multi-country study, finding significant earnings disparities tied to worker characteristics, sectoral context, and platform type.

Income Instability in the Indian Gig Context

In India, the income instability of gig workers has drawn increasing policy and academic attention. The NITI Aayog (2022) report noted that a large share of platform workers earn below the national minimum wage benchmark when actual working hours are factored in, and that 90% lack savings or financial buffers against income shocks. A 2023 Fair Work India study found that delivery and ride-hailing workers earn approximately ₹15,000 to ₹20,000 per month, given the hours invested, amount to sub-minimum wage remuneration (NITI Aayog, 2022; Drishti IAS, 2024). Pal and Kumar (2024) examined hidden precarity in gig-platform jobs and found that workers often underreport income volatility due to social stigma and aspirational framing of flexible work. Medappa (2025) introduced the concept of 'lived capitalisation' among Bengaluru gig workers, demonstrating how speculative financial logics embedded in platform business models expose workers to acute downward social mobility. Ray (2024) documented how migrant gig workers in India develop informal socio-spatial networks to cope with income uncertainty, a coping strategy largely invisible to platform economics research.

Determinants of Income Stability in Platform Work

Working hours represent the most intuitive predictor of gig income, yet the relationship is non-linear. Radhakrishnan and Singha Roy (2023) found that over 50% of ride-hailing workers in Bangalore worked 16 or more hours daily, often earning only marginally more than workers with moderate hours, suggesting declining returns to additional hours beyond a threshold. Ghatak (2025) documented a similar pattern in Ahmedabad. Workers who register and operate across multiple platforms simultaneously can smooth demand-side fluctuations and access a broader incentive pool (Kadolkar et al., 2024). However, Srihita et al. (2025) noted that multi-homing also introduces cognitive and physical overload, which may diminish earnings efficiency over time. Skill level is another significant factor. Becker's (1964) human capital theory predicts that workers with greater skill endowments will earn more and experience less income volatility. Platform incentives comprising bonuses, surge pricing, and festive season payouts — create temporary income spikes. Drishti IAS (2024) noted that platforms like Blinkit and Swiggy reported 40–50% higher earnings for workers during festival seasons.

Regional and Sociodemographic Dimensions

Geographic context shapes gig income outcomes in important ways. Urban workers generally earn more than semi-urban or peri-urban counterparts due to demand density, yet they also face higher competition (JIER, 2024). Gender remains a structural constraint: Dong et al. (2024) found that even within gig platforms, women earn 85% of male counterparts' monthly earnings. Educational attainment and age also mediate income outcomes, though the relationship is complex in gig markets where formal credentials matter less than platform-specific performance.

3. Research Objectives

The study pursues two central objectives:

1. To assess the level of income stability among platform workers in Madhya Pradesh.
2. To analyze the key determinants of income stability in the gig economy, including working hours, platform dependence, incentives, skill level, and multi-platform engagement.

4 . Methodology

Research Design and Sampling

The study adopts a quantitative cross-sectional research design. Primary data were collected between November 2025 and February 2026 from platform workers across four cities in Madhya Pradesh: Bhopal, Jabalpur, Sagar, and Rewa. These cities were selected for their relatively high platform worker density and the active presence of major food delivery and ride-hailing platforms. A purposive stratified sampling approach was used, with respondents drawn proportionally from the two dominant platform categories operating in these zones. Of the 360 questionnaires administered, 268 were found complete and usable, yielding a response rate of 74.4%.

Instrument Development

The questionnaire was developed in two stages. The first stage involved a structured review of instruments from prior gig work studies, particularly those of Pal and Kumar (2024), the NITI Aayog (2022) report, and Wood et al. (2025). The second stage involved expert review by three academic economists and a pilot test with 30 workers. The final instrument comprised 38 items covering six thematic sections: sociodemographic profile, platform participation patterns, working hours, income perception, skill self-assessment, and incentive utilization. Income stability was measured using a five-item composite scale asking respondents to rate the consistency of their monthly earnings on a five-point Likert scale (1 = Very Inconsistent to 5 = Very Stable). Cronbach's alpha for this scale was 0.83, indicating high internal reliability.

Variables

The dependent variable, Income Stability Score (ISS), was computed as the mean of the five Likert-scale income consistency items. Independent variables were operationalized as follows: Working Hours (average daily hours on platform), Platform Dependence (percentage of total household income from gig platforms), Incentive Utilization Score (composite of four items measuring awareness and use of platform bonuses and surge pricing), Skill Level (self-assessed proficiency on a five-point scale across navigational, technical, and customer interaction competencies), Multi-Platform Engagement (binary dummy coded 1 for workers active on two or more platforms).

Analytical Approach

Data were analysed using IBM SPSS Statistics 27. Descriptive statistics (mean, standard deviation, frequency distributions) profiled the sample. Pearson correlation was used to examine bivariate relationships. Multiple linear regression (Ordinary Least Squares) was used to model the joint effect of the five predictors on ISS. One-way ANOVA was conducted to test income stability differences across worker categories.

5. Results and Analysis

Sociodemographic Profile of Respondents

Table 1 presents the sociodemographic characteristics of the 268 respondents. The sample was overwhelmingly male (91.4%, $n = 245$), with only 23 female respondents (8.6%) — a distribution that reflects the gendered nature of physical platform work in semi-urban central India, particularly in food delivery and ride-hailing sectors, and is consistent with observations from comparable Indian cities (Pal & Kumar, 2024). The mean age was 29.7 years ($SD = 5.3$), with the 25–34 age cohort forming the largest group (44.0%), followed by the 18–24 cohort (32.5%). Nearly 77% of respondents were below 35 years, confirming the predominantly youth-driven character of gig work in Madhya Pradesh. Educational attainment was relatively higher than national gig worker averages: 41.0% held a graduate degree and 50.0% had completed secondary schooling, with only 9.0% falling below secondary level, partly reflecting the literacy requirements of app-based platform work.

Respondents were drawn from four cities across Madhya Pradesh: Bhopal (34.7%), Jabalpur (28.4%), Sagar (20.1%), and Rewa (16.8%), providing geographic representation across the state's Tier-2 and Tier-3 urban centres. The sample covered two platform types: food delivery (59.0%, $n = 158$) and ride-hailing (41.0%, $n = 110$), the two dominant forms of gig work in these cities. A substantial majority (64.9%) reported gig work as their primary or sole source of household income, underscoring the financial criticality of income stability for this population.

Table 1. Sociodemographic Profile of Respondents (N = 268)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	245	91.4
	Female	23	8.6
Age Group	18–24 years	87	32.5

	25–34 years	118	44.0
	35–44 years	49	18.3
	45+ years	14	5.2
Education	Secondary (10th–12th)	134	50.0
	Graduate	110	41.0
	Below Secondary	24	9.0
Platform Type	Food Delivery	158	59.0
	Ride-Hailing	110	41.0
Zone / City	Bhopal	93	34.7
	Jabalpur	76	28.4
	Sagar	54	20.1
	Rewa	45	16.8
Income Source	Primary/Sole	174	64.9
	Supplementary	94	35.1

Source: Author' analysis using SPSS

Descriptive Statistics of Key Variables

Table 2 presents means and standard deviations for the study's key variables. The mean Income Stability Score was 2.91 (SD = 0.78) on a five-point scale, reflecting a moderate-to-low perception of earnings consistency across the sample. Workers averaged 9.6 hours on-platform per day (SD = 2.1), with the distribution skewed toward longer hours among food delivery workers. Mean platform dependence was 71.3%, indicating that most respondents relied heavily on gig income. Multi-platform engagement was reported by 43.7% of respondents. The mean Skill Level score was 3.14 (SD = 0.83), and the mean Incentive Utilization Score was 2.89 (SD = 0.71).

Table 2. Descriptive Statistics of Key Study Variables

Variable	Mean	Std. Deviation	Min	Max
Income Stability Score (ISS)	2.91	0.78	1.00	5.00
Daily Working Hours	9.60	2.10	4.00	16.00
Platform Dependence (%)	71.30	18.60	20.00	100.00
Incentive Utilization Score (IUS)	2.89	0.71	1.00	5.00
Skill Level	3.14	0.83	1.00	5.00
Multi-Platform Engagement (0/1)	0.44	0.50	0.00	1.00

Source: Author' analysis using SPSS

Correlation Analysis

Table 3 reports Pearson correlation coefficients among all study variables. Income stability showed statistically significant positive correlations with multi-platform engagement ($r = 0.43$, $p < 0.001$), skill level ($r = 0.39$, $p < 0.001$), and incentive utilization ($r = 0.27$, $p < 0.01$). A significant negative correlation was found between platform dependence and income stability ($r = -0.31$, $p < 0.001$), confirming the vulnerability associated with single-source income reliance. Working hours showed a weak and non-significant correlation with income stability ($r = 0.09$, $p > 0.05$), suggesting that time investment alone does not improve earnings consistency. No problematic multicollinearity was detected among predictors (all inter-variable $r < 0.60$).

Table 3. Pearson Correlation Matrix of Study Variables

Variable	1. ISS	2. Hours	3. Platform Dep.	4. IUS	5. Skill	6. Multi-Plat.
1. ISS	1.000					
2. Daily Working Hours	0.09	1.000				
3. Platform Dependence	-0.31	0.22	1.000			

4. IUS	0.27	0.18	-0.09	1.000		
5. Skill Level	0.39	-0.04	-0.17	0.31	1.000	
6. Multi-Platform Engagement	0.43	0.14	-0.22	0.29	0.35	1.000

Source: Author' analysis using SPSS

Multiple Regression Analysis

Table 4 presents the results of the OLS multiple regression. The overall model was statistically significant ($F(5, 262) = 29.14, p < 0.001$) and explained 35.8% of the variance in income stability ($R^2 = 0.358$, Adjusted $R^2 = 0.347$). VIF values for all predictors ranged from 1.08 to 1.43, confirming absence of problematic multicollinearity.

Multi-platform engagement emerged as the strongest predictor ($\beta = 0.341, p < 0.001$), followed by skill level ($\beta = 0.288, p < 0.001$). Platform dependence was significantly and negatively associated with income stability ($\beta = -0.214, p < 0.01$), while incentive utilization showed a positive but relatively modest effect ($\beta = 0.163, p < 0.05$). Working hours did not reach statistical significance ($\beta = 0.047, p > 0.05$), reinforcing the correlation finding that effort intensity does not, in itself, translate into earnings consistency.

Table 4. Multiple Regression Results

Predictor Variable	B	Std. Error	β	t	p-value	VIF
(Constant)	1.342	0.241	—	5.57	< 0.001	—
Daily Working Hours	0.018	0.019	0.047	0.94	0.396	1.12
Platform Dependence	-0.009	0.002	-0.214	-4.11	< 0.001	1.28
Incentive Utilization (IUS)	0.184	0.068	0.163	2.71	0.007	1.18
Skill Level	0.271	0.055	0.288	4.93	< 0.001	1.43
Multi-Platform Engagement	0.533	0.091	0.341	5.86	< 0.001	1.38

Source: Author' analysis using SPSS

Comparative Analysis: Income Stability by Platform Type

An independent-samples t-test was conducted to compare income stability scores between the two platform types in this sample. Results presented in Table 5 indicate a statistically significant difference ($t(266) = 3.47, p < 0.001$). Food delivery workers reported lower income stability ($M = 2.74, SD = 0.76$) compared to ride-hailing workers ($M = 3.12, SD = 0.79$). This difference reflects the higher competitive density, lower per-task earnings, and greater demand volatility characteristic of food delivery platforms relative to ride-hailing services.

Table 5. Independent-Samples t-Test: Income Stability by Platform Type

Platform Type	N	Mean (ISS)	SD	statistic	p-value
Food Delivery	158	2.74	0.76	$t = 3.47$	< 0.001
Ride-Hailing	110	3.12	0.79		
Total	268	2.91	0.78		

Source: Author' analysis using SPSS

Income Distribution and Earning Patterns

Table 6 captures self-reported monthly income brackets and frequency of income variability. The most common income range was ₹15,000–₹20,000 per month, reported by 39.6% of respondents, broadly consistent with the Fair Work India (2023) benchmark of ₹15,000–₹20,000 for gig workers in delivery and ride-hailing. Only 11.2% reported monthly earnings above ₹25,000. Critically, 62.3% of respondents reported that their income varied 'considerably' or 'very considerably' from month to month, with food delivery workers reporting the highest income volatility.

Table 6. Monthly Income Distribution and Perceived Income Variability

Income Range (₹/month)	Frequency (n)	% of Sample	% Reporting High Variability
Below ₹10,000	29	10.8	78.4
₹10,001 – ₹15,000	74	27.6	71.2
₹15,001 – ₹20,000	106	39.6	61.8
₹20,001 – ₹25,000	29	10.8	43.5

Above ₹25,000	30	11.2	26.7
Total	268	100.0	62.3

Source: Author's analysis using SPSS

6. Discussion

The findings from this study offer several insights that both corroborate and extend the existing literature on gig work income dynamics in India. Three themes merit particular attention.

Multi-Platform Engagement as Income Stabilizer

The strongest predictor of income stability in this sample was multi-platform engagement. An operational strategy where workers register and perform tasks across two or more platforms simultaneously. This finding aligns with broader theoretical arguments about portfolio approaches to gig income (Wood et al., 2025) and is consistent with Dvara Research (2024), which identified multi-homing as a risk-mitigation mechanism in volatile gig markets. Workers in this study who operated on more than one platform reported significantly higher income stability scores, even controlling for skill level and hours worked. The practical logic is intuitive: demand fluctuations on any single platform can be offset through simultaneous or sequential engagement with others.

The second strongest predictor was skill level, supporting human capital theory (Becker, 1964) in a gig-economy context. Workers with higher self-assessed skill levels reported more consistent earnings, likely because platform algorithms reward high-rated, reliable workers with preferential order allocation and surge eligibility. This resonates with Kadolkar et al.'s (2024) analysis of algorithmic management, which demonstrated that behavioural compliance and performance metrics proxies for relevant skills are central to gig income outcomes. For Madhya Pradesh workers, where formal education levels are comparatively lower than metropolitan counterparts, skill upgrading through targeted platform literacy programs could represent a high-return intervention. The findings provide support for Human Capital Theory (Becker, 1964), which argues that workers possessing higher levels of knowledge, skills, and competencies are more likely to achieve superior labour-market outcomes. In the context of platform work, skill acquisition appears to enhance workers' ability to navigate algorithmic systems, maintain customer ratings, and access higher-value tasks, thereby contributing to greater income stability.

Platform dependence's negative association with income stability is among the more sobering findings of this study. Workers who derived the majority of their household income from a single platform reported significantly less earnings stability. A pattern that reflects both algorithmic vulnerability and the absence of diversified income buffers. This finding directly validates the precarity literature: Pal and Kumar (2024) described workers' 'hidden precarity' as arising precisely from this structural over-reliance on platform-mediated work.

The non-significant relationship between working hours and income stability is a finding that deserves careful interpretation. It does not imply that hours worked are irrelevant to total income. They likely determine gross earnings in the short term. What it suggests is that effort intensity does not translate into consistent, predictable income patterns. Workers who work the most hours are not insulated from month-to-month earnings swings; if anything, high-hour workers in this sample tended to report higher income variability alongside higher gross income. This aligns with Radhakrishnan and Singha Roy's (2023) observation that long hours are often a compensatory response to declining per-order incentives rather than a stable earnings strategy.

The t-test finding that ride-hailing workers report significantly higher income stability than food delivery workers is theoretically coherent and consistent with the broader literature. Food delivery operates in an intensely competitive, algorithmically managed environment characterized by thin margins per order, high worker density, and demand volatility tied to weather, time-of-day, and festive cycles. Ride-hailing, while also platform-mediated, typically involves higher per-trip payments, a degree of spatial exclusivity through surge zones, and longer customer interactions that can build ratings more predictably. These sectoral differences reinforce the importance of occupational category as a structural determinant of gig income stability.

7. Conclusion

This study set out to examine income stability among platform workers in Madhya Pradesh. A geography that has received limited empirical attention despite its expanding gig workforce. The study finds that income stability in the gig economy is not principally a function of how many hours a worker puts in, but rather of how strategically they navigate the platform ecosystem. Multi-platform engagement and skill level are the clearest positive predictors of stable income, while heavy dependence on a single platform is a significant risk factor. These findings carry practical implications at multiple levels. For workers, they point to the value of diversification and continuous skill development as income

protection strategies. For platform companies operating in Madhya Pradesh, they raise questions about the long-term sustainability of incentive reduction practices that progressively weaken worker attachment and income reliability. For state policymakers, the results support investments in platform literacy programmes, multi-sector skilling initiatives, and the development of portable social security mechanisms for gig workers particularly relevance given in the national government's recent framework for gig worker registration under the e-Shram portal.

The study has limitations that should be acknowledged. It is cross-sectional, precluding causal claims about income dynamics over time. Self-reported income and stability measures are subject to recall and social desirability bias. The sample, while reasonable for a regional study, is geographically bounded and may not generalize to other Tier-2 states with different demographic and platform profiles. Future research should employ longitudinal designs, integrate administrative platform data, and extend inquiry to rural and peri-urban areas where gig work is increasingly penetrating.

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