International Journal of Advanced Research in Commerce, Management & Social Science (IJARCMSS)
(An International Quarterly Multidisciplinary Open Access Double Blind Peer Reviewed Refereed Journal)
ISSN :2581-7930 (Online), Impact Factor (Cosmos): 7.270 & PIF (I2OR): 5.010, Volume 09, No. 03(II), July-September, 2026, pp 78-84

Financial Precarity in the Platform Economy: An Empirical Analysis of Algorithmic Strain, Earnings Volatility and Financial Well-Being among Gig Workers

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***Citation**: Jain, M. & Vijayvargiya, S. (2026). Financial Precarity in the Platform Economy: An Empirical Analysis of Algorithmic Strain, Earnings Volatility and Financial Well-Being among Gig Workers. International Journal of Advanced Research in Commerce, Management &Amp; Social Science, 09(03(II)), 78–84. https://doi.org/10.62823/IJARCMSS/9.3(II).9291*

Abstract

The rapid expansion of platform-mediated labor has reconfigured income generation for millions of workers, yet the structural determinants of their financial well-being remain insufficiently quantified, particularly in emerging-market contexts. This study empirically examines how algorithmic work strain and earnings volatility shape the financial well-being of platform gig workers engaged in ride-hailing and delivery services. Using a quantitative, cross-sectional survey design, primary data were collected from 100 active gig workers through a structured, digitally administered questionnaire. Data were analyzed in SPSS using descriptive statistics, Principal Component Analysis, linear regression, and Pearson correlation at α = 0.05. Five latent constructs, were extracted which were productivity and daily output, financial well-being and satisfaction, operational and workplace challenges, work-related financial attitudes, and platform support and engagement. Regression analysis was also conducted to confirm the work-related financial attitudes and predict their daily productivity, indicating that financial pressure drives compensatory labor supply. Operational and workplace challenges were studied on the basis of mean score among the five constructs, closely followed by financial well-being and satisfaction, while platform sector type (ride-hailing versus delivery) relationship with financial satisfaction suggested that precarity is systemic rather than sector-specific. These findings extend the algorithmic-management literature by empirically linking financial strain to labor-supply behavior and carry direct implications for platform governance, minimum-earnings policy, and portable social-security design.

***Keywords**: Gig Economy, Financial Well-Being, Algorithmic Management, Earnings Volatility, Platform Labor.*

Introduction

The platform (or "gig") economy has become a structurally significant feature of contemporary labor markets, replacing standard, fixed-wage employment relationships with piece-rate, algorithmically mediated task allocation. Recent systematic reviews describe algorithmic management as a pervasive, hybrid control mechanism that blends autonomy-enhancing features with tight behavioral control, generating outcomes for workers that are frequently double-edged (Kadolkar, Meijerink, & Keegan, 2025). Platform-mediated ride-hailing and delivery work now underpins urban transport and logistics across both developed and developing economies, and in India alone the gig and platform workforce has grown from an estimated 7.7 million in FY21 to roughly 12 million by FY25, with continued double-digit growth projected toward 2029–30 (NITI Aayog, 2022).

Despite this scale, platform work remains structurally precarious: the absence of standardized employment contracts, fixed compensation, and institutionalized safety nets exposes gig workers to earnings volatility, unplanned operating costs, and chronic work-related anxiety (Wood, Graham, Lehdonvirta, & Hjorth, 2019). Financial well-being among this workforce is shaped by intersecting stressors — unpredictable per-task pay, opaque algorithmic rate-setting, rising fuel and maintenance costs, and the absence of employer-provided insurance, paid leave, or retirement provisions. Sector-level evidence corroborates this picture: India's 2023 Fair Work assessment found that a majority of ride-hailing and delivery workers earn below effective minimum-wage thresholds once operating hours are accounted for, with a large share reporting persistent difficulty covering routine household expenses. Continuous algorithmic surveillance and performance-rating systems compound these pressures by introducing a further, non-financial source of chronic stress (Zhang, Zhou, & Liu, 2023).

A growing body of work links this financial fragility to compensatory labor-supply behavior: because per-task earnings are volatile and often below sustainable thresholds, workers extend working hours and intensify task acceptance to stabilize household income, a dynamic that in turn elevates fatigue, reduces long-term planning capacity, and increases reliance on high-interest informal credit. Understanding precisely how algorithmic work-related perceptions and structural platform variables interact to determine financial well-being is therefore essential to shaping evidence-based platform governance, labor-protection policy, and inclusive financial-inclusion interventions. The present study contributes an India-based, multivariate empirical test of this relationship, combining factor-analytic construct validation with regression and correlation modeling of financial and productivity outcomes.

Review of Literature

Kadolkar et al. (2025) synthesize the algorithmic-management literature and argue that information asymmetries between platform algorithms and workers trigger affect-laden responses frustration and anxiety in particular because workers frequently cannot discern the rationale behind algorithmically generated decisions, a mechanism with direct downstream consequences for well-being and behavioral resistance.

Medappa (2025) documents how the speculative, capital-intensive financial logic underpinning platform businesses is transmitted downward onto cab and delivery workers in Bengaluru, generating acute financial risk, deepening household dependence on debt, and, in some cases, producing new precarious financial subjectivities among workers attempting to manage instability.

Zhang et al. (2023) show that gig workers' cognitive appraisal of algorithmic management as a hindrance stressor, rather than a challenge stressor, is a key predictor of adverse psychological and behavioral outcomes, with individual regulatory-focus traits moderating the strength of this relationship.

Moin (2021) evaluates social safety-net deficits in the informal labor sector and finds that reliance on informal credit functions as a primary coping mechanism against short-term income shortfalls, a pattern also visible in Indian survey evidence showing that a large share of gig workers report irregular earnings eroding their capacity to manage household budgets.

Apouey, Roulet, Solal, and Stabile (2020) demonstrate that income volatility among gig workers directly elevates financial anxiety and impairs subjective health outcomes through continuous exposure to market and demand-side risk.

Berger, Chen, and Frey (2019) similarly show that the absence of minimum-wage guarantees, combined with rising overhead costs borne directly by workers, impairs long-term asset accumulation among independent platform contractors. In an Indian urban context.

Wood et al. (2019) established that algorithmic management and flexible piece-rate work models generate structural precarity and high operational stress even where workers retain nominal task-level autonomy.

De Stefano (2016) argues that classifying platform workers as independent contractors systematically removes them from conventional labor protections, effectively transferring operational and financial risk from firm to worker.

Objectives of the Study

- To examine the effect of gig workers' work-related financial attitudes on their daily productivity and output levels.
- To analyse the relationship between platform sector type (ride-hailing versus delivery) and overall financial satisfaction and well-being.

Research Methodology

This study adopted a quantitative, cross-sectional survey design. Primary data were collected through a structured questionnaire administered digitally via Google Forms to active platform gig workers engaged in ride-hailing and delivery services. A sample of N = 100 respondents was obtained. Statistical analysis was conducted in SPSS, combining descriptive statistics (frequencies, percentages, means, and standard deviations) with inferential techniques like Principal Component Analysis (PCA) for latent-construct extraction, linear regression modeling, and Pearson product-moment correlation evaluated at a significance threshold of $\alpha = 0.05$. The convenience and snowball sampling technique was used for data collection.

Data Analysis and Interpretation

Table 1: Demographic Profile of Respondents (N = 100)

Background	Category	Frequency	Percentage (%)
Gender	Male	67	67.0
	Female	33	33.0
Marital status	Married	54	54.0
	Unmarried	46	46.0
Age	21–30 years	44	44.0
	31–40 years	38	38.0
	41–50 years	14	14.0
	Above 50 years	4	4.0
Operating location	Urban	50	50.0
	Semi-urban	36	36.0
	Rural / peri-urban	14	14.0
Primary platform sector	Ride-hailing (cab/bike)	57	57.0
	E-commerce / food delivery	43	43.0
Gig experience tenure	Less than 2 years	35	35.0
	2–5 years	47	47.0
	More than 5 years	18	18.0

Note. Percentages are computed within each demographic category and may not sum to exactly 100% due to rounding.

As summarized in Table 1, the sample was predominantly male (67.0%) and married (54.0%), with nearly half of respondents (44.0%) aged between 21 and 30 years consistent with national-level profiles of India's platform workforce, which show young, male, and urban (NITI Aayog, 2022). Ride-hailing accounted for the largest sectoral share (57.0%), and most respondents (50.0%) operated in urban zones with two to five years of gig tenure (47.0%), suggesting a workforce that is not merely transitional but increasingly reliant on platform work as a medium-term livelihood strategy. Figure 1 visualizes the age and sector distributions reported in Table 1.

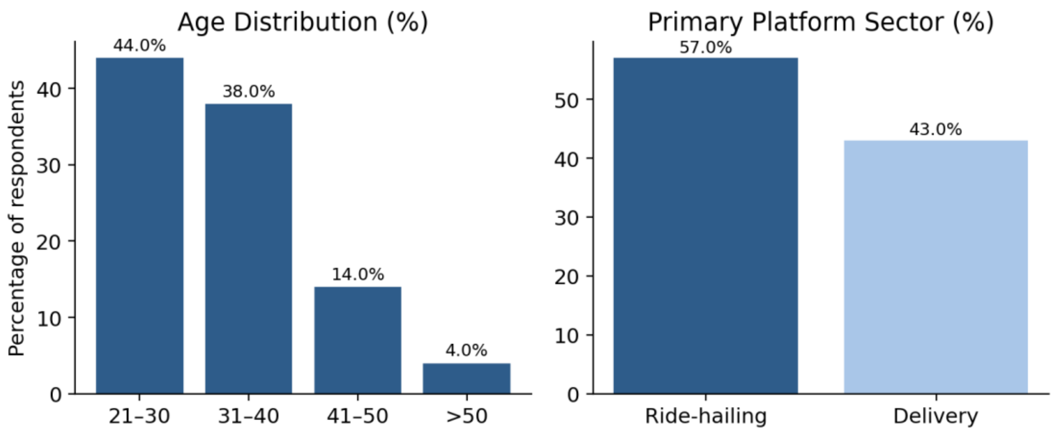

Figure 1: Age Distribution and Primary Platform Sector of Respondents

Source: Table 1.

Table 2: Instrument Reliability (Cronbach's Alpha)

Cronbach's Alpha	N of Items
.891	20

As reported in Table 2, an alpha coefficient of .891 across 20 items substantially exceeds the conventional acceptability threshold of .70, confirming strong internal consistency and supporting the reliability of the composite constructs derived from the instrument.

Table 3: Kaiser–Meyer–Olkin (KMO) and Bartlett's Test of Sphericity

Measure / Test	Value
Kaiser–Meyer–Olkin Measure of Sampling Adequacy	.823
Bartlett's Test of Sphericity (Approx. Chi-Square)	915.384
Df	190
Sig.	.000

Table 3 reports a KMO value of .823, indicating "meritorious" sampling adequacy for factor analysis, and a statistically significant Bartlett's test ($\chi^2 = 915.384$, df = 190, $p < .001$), confirming sufficient inter-item correlation to justify data reduction via PCA.

Table 4: Total Variance Explained (Principal Component Analysis)

Component	Eigenvalue (Total)	% of Variance	Cumulative %
1	6.281	31.405	31.405
2	2.241	11.206	42.611
3	1.918	9.590	52.201
4	1.496	7.479	59.680
5	1.201	6.004	65.684

Extraction method: Principal Component Analysis

As shown in Table 4 and Figure 2, five components with eigenvalues exceeding 1.0 were retained, jointly accounting for 65.68% of total variance a proportion comfortably above the 60% benchmark typically expected in social-science factor-analytic work, indicating that the five extracted dimensions meaningfully represent the underlying structure of gig workers' financial and operational experience.

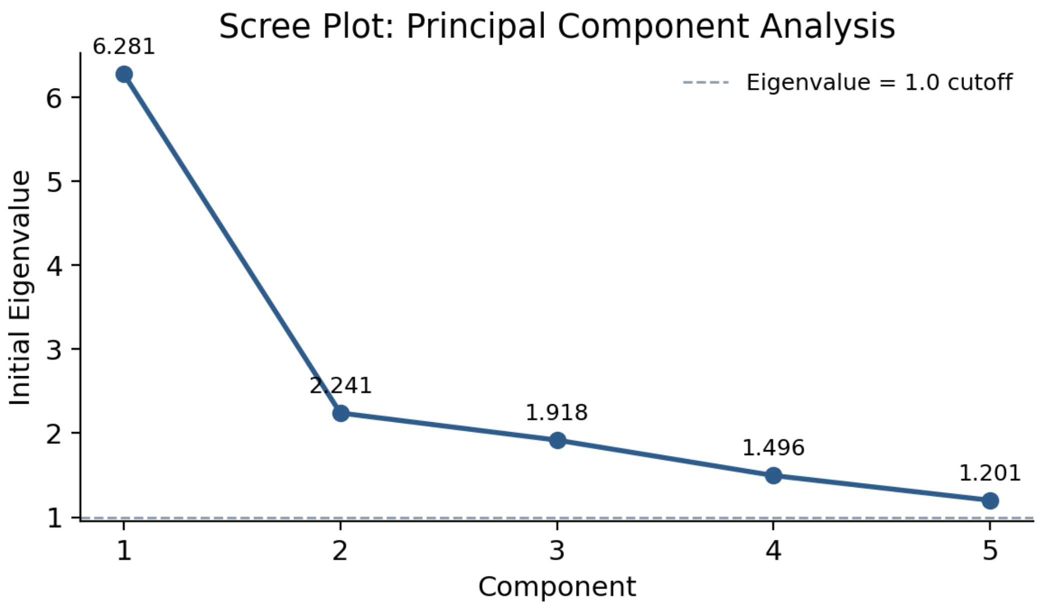

Figure 2: Scree Plot of Component Eigenvalues

Source: Table 4. The inflection ('elbow') after the fifth component supports the five-factor retention decision.

Table 5: Descriptive Statistics for Extracted Constructs

Construct Dimension	Mean	Median	SD
Productivity & Daily Output	3.84	4.00	.781
Financial Well-being & Satisfaction	3.67	3.75	.864
Operational & Workplace Challenges	3.61	3.75	.821
Work-Related Financial Attitudes	3.74	4.00	.753
Platform Support & Engagement	3.71	4.00	.891

As Table 5 and Figure 3 show, Productivity and Daily Output recorded the highest mean score (M = 3.84, SD = .781), while Operational and Workplace Challenges recorded the lowest (M = 3.61, SD = .821), closely followed by Financial Well-being and Satisfaction (M = 3.67, SD = .864). Read together, this pattern is consistent with a compensatory-effort mechanism: workers appear to sustain output through extended hours and intensified task acceptance precisely because underlying financial satisfaction and operational conditions are comparatively strained, echoing the resource-scarcity dynamics identified in algorithmic job-crafting research (job-crafting literature, 2024) and the income-volatility findings of Apouey et al. (2020).

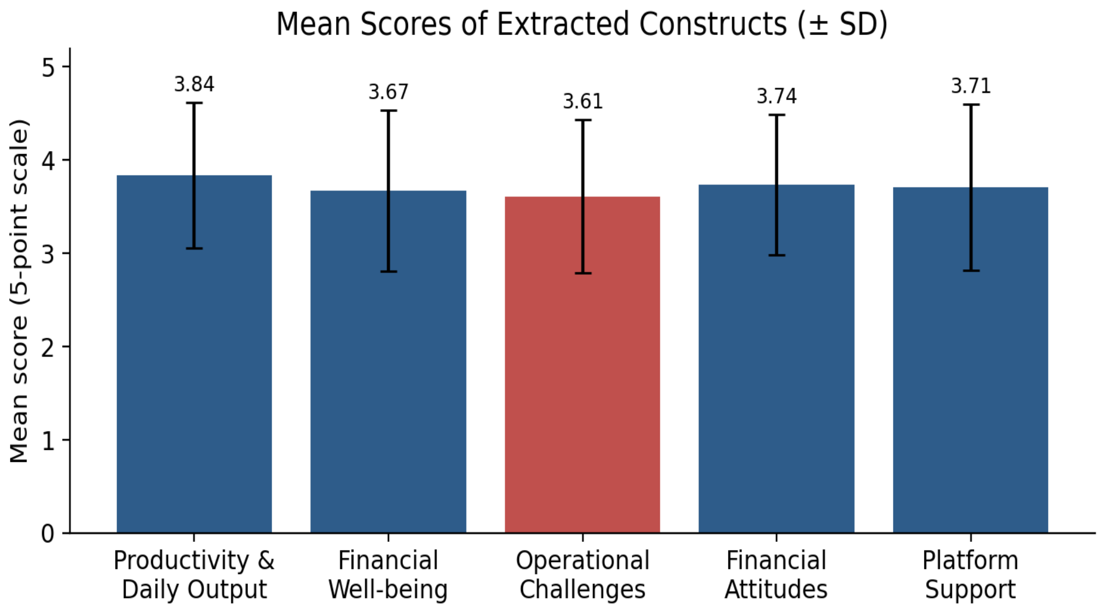

Figure 3: Mean Scores of the Five Extracted Constructs (± SD)

Source: Table 5. The lowest-scoring construct (Operational & Workplace Challenges) is highlighted in red.

Hypothesis Testing and Inferential Models

H_1: Work-related financial attitudes have a statistically significant positive effect on the daily productivity/output of gig workers.

Table 6: Regression Model Summary

Model	R	R^2	Adjusted R^2	Std. Error of Estimate
1	.431[a]	.186	.178	.712

Table 7: ANOVA

Model	Sum of Squares	Df	Mean Square	F	Sig.
Regression	12.472	1	12.472	24.592	.000
Residual	54.288	98	.554		
Total	66.760	99			

Dependent variable: Productivity & Daily Output. Predictor: Work-Related Financial Attitudes.

Table 8: Regression Coefficients

Predictor	Unstandardized B	Std. Error	Standardized β	t	Sig.
(Constant)	2.168	.331	—	6.548	.000
Work-Related Financial Attitudes	.449	.091	.431	4.959	.000

As reported in Tables 6–8, the regression model was statistically significant ($F(1, 98) = 24.592$, $p < .001$) and explained 18.6% of variance in daily productivity ($R^2 = .186$). Work-related financial attitudes emerged as a significant positive predictor ($\beta = .431$, $t = 4.959$, $p < .001$), supporting H_1. Substantively, this indicates that financial-coping orientation is not a peripheral variable but a direct behavioral driver of labor supply: workers who report more adaptive financial attitudes also report higher daily output, a pattern that plausibly reflects effort intensification undertaken to offset earnings shortfalls rather than a straightforward productivity benefit of positive financial attitudes alone. Figure 4 plots the standardized coefficient with its 95% confidence interval.

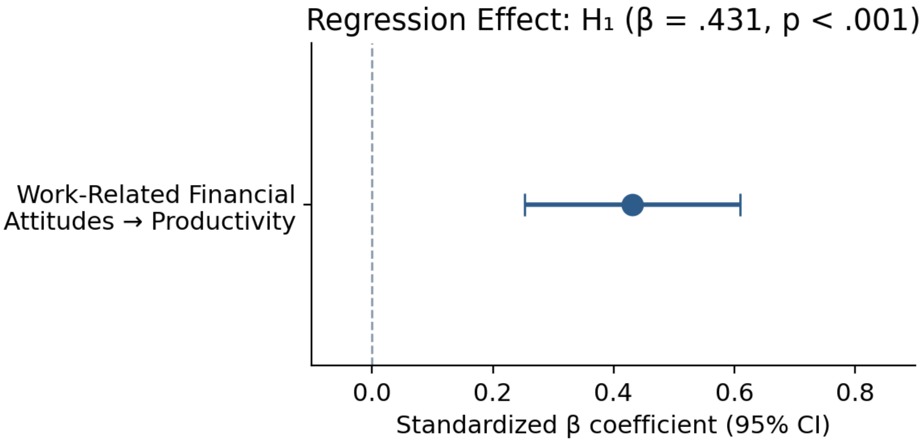

Figure 4: Standardized Regression Coefficient for H_1 (with 95% CI)

Source: Table 8.

H_2: There is a statistically significant relationship between platform sector type (ride-hailing versus delivery) and overall financial well-being and satisfaction.

Table 9: Pearson Correlation Matrix

	Platform Sector Type	Financial Well-Being & Satisfaction
Platform Sector Type — Pearson r	1	.174
Sig. (2-tailed)	—	.084
N	100	100
Financial Well-Being — Pearson r	.174	1
Sig. (2-tailed)	.084	—
N	100	100

As shown in Table 9, the correlation between platform sector type and financial well-being was weak and statistically non-significant ($r = .174$, $p = .084 > .05$); H_2 is therefore not supported, and the null hypothesis is retained. This null finding is itself substantively informative: it suggests that financial precarity in this sample is not concentrated in one sub-sector but is distributed comparably across ride-hailing and delivery work, consistent with De Stefano's (2016) argument that independent-contractor classification rather than sector-specific operational features is the primary structural driver of worker financial risk.

Findings

Factor analysis isolated five coherent dimensions of gig-work economics: Productivity Output, Financial Satisfaction, Operational Challenges, Financial Attitudes, and Platform Support, jointly explaining 65.7% of variance. High daily productivity ($M = 3.84$) appears substantially driven by compensatory labor-supply behavior, with workers extending hours to offset declining effective pay rates. Financial precarity is not alleviated by sector choice ($p = .084$): ride-hailing and delivery workers face comparable systemic financial volatility. Work-related financial coping attitudes significantly predict daily task commitment ($\beta = .431$, $p < .001$), indicating that financial stress is a direct behavioral driver of labor intensity rather than a passive background condition.

Conclusion

This study provides empirical evidence that financial precarity is a structurally embedded, cross-sectoral feature of platform gig work rather than an incidental or sector-specific outcome. While digital platforms offer low entry barriers and nominal schedule flexibility, the underlying financial architecture dynamic, often opaque pricing algorithms, uncompensated idle time, and the absence of employer-provided social protection generates measurable income variance and financial strain, which in turn drives compensatory labor intensification rather than resolving it. For platform firms and policymakers, these findings support three concrete interventions: (1) minimum-earnings guarantees indexed to active working time rather than completed-task volume alone; (2) portable, contribution-based social-security frameworks that follow the worker across platforms and sectors, consistent with emerging Indian labor-code provisions; and (3) algorithmic-transparency requirements that allow workers to anticipate and plan around rate and demand fluctuations, thereby reducing the financial-anxiety channel identified throughout this literature.

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