

Human-Centred Information Systems in the Gig Economy: How Personal Resources Buffer Algorithmic Stressors among Female Platform Workers

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Abstract: Gender-agnostic algorithmic management on digital platforms creates severe psychological stressors for frontline service workers. Grounded in Human-Centred Information Systems (HCIS) and the Job Demands-Resources (JD-R) framework, this study examines how app-based demands (algorithmic tracking, rating pressure, physical safety hazards, and economic precarity) affect the psychological well-being and job performance of female gig service partners in Delhi-NCR, India. It also tests whether psychological resilience (an internal resource) and perceived social support (an external resource) buffer these effects. Data were collected from 385 female platform workers in the beauty, domestic, and care sectors on platforms such as Urban Company and Housejoy, using the CD-RISC-10, the Multidimensional Scale of Perceived Social Support, and Ryff's Psychological Well-Being Scale, and analysed with Structural Equation Modelling (SEM). Rigid app tracking, rating pressure, and fear of being blocked significantly reduced well-being and job performance. Moderation analysis revealed a two-way buffering effect: resilience weakened the negative effect of algorithmic control on well-being, while social support protected against rating pressure and loneliness. The findings identify key human-computer interaction (HCI) friction points and support three design recommendations: human-in-the-loop recourse for automated deactivation, transparent algorithmic rules, and stress-aware, micro-flexible interfaces.

Keywords: Human-Centred Information Systems (HCIS); App-based Management; Human-Computer Interaction (HCI); Female Gig Workers; Job Demands-Resources (JD-R) Framework

1. Introduction

Digital labour platforms have shifted employment away from traditional employer-employee contracts toward task-based, algorithmically mediated work (Memon et al., 2025). Although early narratives celebrated gig work as a "boss-free" route to flexibility, autonomy, and low-barrier income (Hunt & Samman, 2019; Memon et al., 2025), platform capitalism routinely transfers organisational, financial, and operational risks onto individual workers. In India, platforms such as Urban Company and Housejoy have entered the beauty, domestic, and care services sectors, providing income to socio-economically marginalised workers (Anjali Anwar et al., 2022). Yet they operate amid inequality, income volatility, and weak legal protection (Memon et al., 2025).

At the core of these platforms is app-based management: automated systems that assign tasks, track workers via GPS, evaluate them based on customer ratings, and deactivate accounts with almost no human oversight (Duggan et al., 2020). This "algocracy" (Aneesh, 2009) replaces managerial judgement with opaque rules. Although the interfaces are presented as neutral, they are designed without regard to gender and overlook the lived realities of women workers (Churchill et al., 2026; Scheuerman, 2023). Women often join gig work to balance paid work with housework and caregiving (Churchill et al., 2026), yet strict tracking, continuous rating pressure, and the fear of being blocked clash with their fragmented routines and keep them alert. They also face client harassment, safety risks during



home visits and late-night travel, and low ratings when they reject inappropriate behaviour. Because ratings govern visibility and task assignment, women absorb sustained distress to protect their livelihoods, and breaks for pregnancy, illness, or caregiving can trigger ranking penalties known as "dropping out of the algorithm" (Raj & Yadav, 2026).

This study combines Human-Centred Information Systems (HCIS) with the Job Demands-Resources (JD-R) framework (Bakker & Demerouti, 2024; Militaru & Breaban, 2026). JD-R distinguishes job demands, which require sustained effort and drain energy, from job resources, which support growth and buffer strain (Watson et al., 2021). On platforms, strict tracking, rating pressure, fear of blocking, safety hazards, and unstable income act as demands that harm well-being and performance (Billah & Khan, 2026). Because platforms externalise healthcare, safety, and career support onto workers (Anjali Anwar et al., 2022), well-being depends heavily on personal resources (Agarwal et al., 2024). We examine two: psychological resilience, the internal capacity to adapt and recover from stressors (Watson et al., 2021), and perceived social support, the emotional, practical, and informational backing from family, peers, and informal worker networks (Memon et al., 2025). Under the JD-R buffering hypothesis, such resources can weaken the effect of demands on strain (Bakker & Demerouti, 2024). However, Information Systems and Human-Computer Interaction (HCI) research has rarely examined how resilience and social support jointly moderate the effects of algorithmic stressors among marginalised female service workers in developing economies (Hou et al., 2019; Memon et al., 2025).

To address this gap, we test the buffering roles of resilience and social support in the effects of algorithmic stressors on well-being and job performance (Ali & Sivasubramanian, 2024; Wang et al., 2020), using Structural Equation Modelling (SEM) on data from 385 female platform workers in Delhi-NCR. The study contributes in three ways: it extends JD-R to algorithmically managed service work (Watson et al., 2021); it provides quantitative evidence on female gig workers in the Global South (Raj & Yadav, 2026); and it translates the findings into design recommendations for stress-aware interfaces, transparent algorithmic rules, and human-in-the-loop appeals of automated deactivation (Green & Chen, 2019).

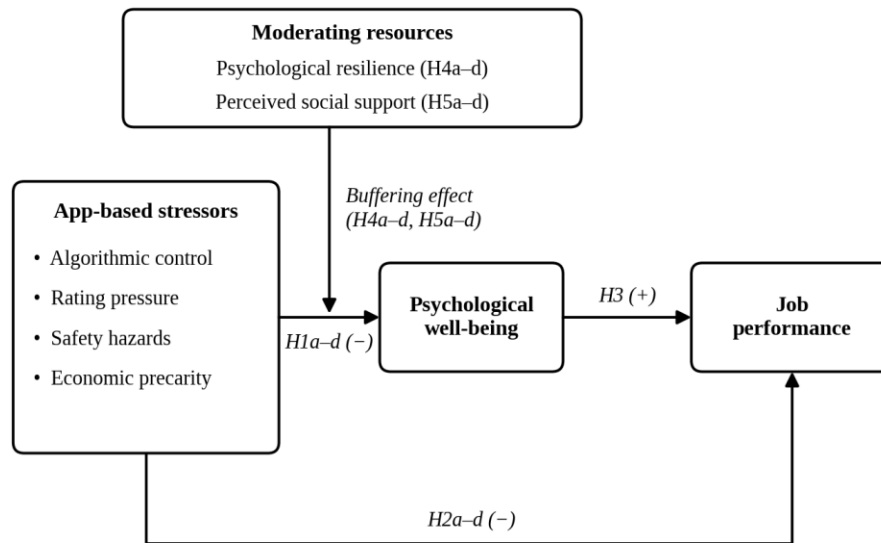
2. Literature Review and Hypotheses

2.1 Theoretical Foundations

Human-Centred Information Systems (HCIS) and the Job Demands-Resources (JD-R) framework together link technology design to worker well-being (Bakker & Demerouti, 2024; Li & Li, 2026). Whereas traditional Information Systems research prioritises efficiency, adoption, and throughput (Kellogg et al., 2020), HCIS asks how software interfaces affect dignity, psychological safety, and health (Raj & Yadav, 2026). When software is the primary manager, understanding how computational architectures generate psychosocial strain is required (Bajwa et al., 2018). JD-R divides work characteristics into demands, which require sustained effort and deplete energy, leading to strain, exhaustion, and weaker performance, and resources, which meet psychological needs, foster engagement, and buffer strain (Bakker & Demerouti, 2024; Demerouti & Bakker, 2023). Platform workers are classified as "independent contractors" and so lack supportive supervisors, career pathways, and formal benefits; their well-being, therefore, depends on the balance between algorithmic stressors and personal and social support (Russell & Halbesleben, 2026). Figure 1 presents the research model.

Figure 1

Conceptual Research Model: App-Based Stressors, Psychological Well-Being, Job Performance, and Moderating Resources



Note. App-based stressors (algorithmic control, rating pressure, safety hazards, and economic precarity) are hypothesised to reduce psychological well-being (H1) and job performance (H2), and to increase well-being (H3), which in turn is hypothesised to increase job performance. Psychological resilience (H4) and perceived social support (H5) are hypothesised to weaken the negative effect of each stressor on well-being.

2.2 App-based Stressors as Job Demands

Algorithmic control and tracking. App-based management uses algorithms to track, evaluate, and discipline labour without human intervention (Duggan et al., 2020), through restricting choices, recommending behaviours, recording metrics, rating, deactivating, and rewarding compliance (Kellogg et al., 2020). GPS tracking and automatic task allocation create an "invisible digital cage" in home-based services, where workers fear being blocked for missing response windows, failing to meet acceptance thresholds, or taking breaks (Bajwa et al., 2018). Without human managers or channels of appeal, workers experience information asymmetry and helplessness.

Rating pressure. Oversight is crowdsourced to customers, and because dispatch and bonuses depend on star ratings, feedback becomes a high-stakes disciplinary tool (Churchill et al., 2026). Women in intimate home-service settings must manage delicate boundaries under scrutiny (James, 2024), and clients who are rebuffed after harassment often retaliate with low ratings that algorithms penalise without checking context. Workers respond with defensive emotional labour to avoid "dropping out of the algorithm" (Churchill et al., 2026).

Safety hazards. Door-to-door work exposes women to gender-specific risks, including abuse, physical attacks, and stalking during late-night travel and visits (Memon et al., 2025). Apps offer little emergency support or customer screening, and algorithmic penalties for refusing unsafe jobs force a choice between safety and income (Galperin, 2021).

Economic precarity. Platforms shift equipment, fuel, and data costs and income swings onto workers, and women face unstable per-task rates, arbitrary deductions, and no paid maternity leave, health insurance, or injury compensation (Bajwa et al., 2018). Unpaid preparatory work, such as checking the app, soliciting tasks, and vetting customers, collides with domestic caregiving and intensifies work-family conflict (Billah & Khan, 2026).

2.3 Well-Being and Job Performance

Under the JD-R health-impairment process, prolonged demands without resources exhaust psychological reserves, causing burnout, anxiety, and depressive symptoms (Dollard & Bakker, 2010). On platforms, tracking, rating pressure, safety threats, and financial instability harm well-being (Singh et al., 2024). Distress in turn impairs performance through reduced focus, slower task execution, and poorer customer communication, whereas well-being supports emotional regulation, initiative, and service quality (Demerouti & Bakker, 2023).

H1: Algorithmic control (a), rating pressure (b), safety hazards (c), and economic precarity (d) are negatively related to psychological well-being.

H2: Stressors (a)-(d) are negatively related to job performance.

H3: Psychological well-being is positively related to job performance.

2.4 Moderating Role of Personal and Social Resources

Psychological resilience. Resilience is the ability to adapt, recover, and regulate emotions in the face of adversity. According to the Conservation of Resources theory and the JD-R buffering proposition, strong personal resources alter how stressors are appraised and encourage problem-solving rather than loss spirals (Demerouti & Bakker, 2023; Kan et al., 2026). Resilient workers can detach from harsh ratings, reframe tracking, and sustain self-efficacy amid income swings.

H4: Resilience moderates the negative relationship between stressors (a)-(d) and well-being, such that the relationship is weaker at high resilience.

Perceived social support. This external resource comprises emotional, practical, and informational help from family, peers, and informal worker networks (Russell & Halbesleben, 2026). Women form informal peer messaging groups to warn each other about unsafe customers and offer emotional support. Such support reduces isolation, buffers against anxiety, and eases work-family conflict, preventing acute demands from becoming chronic strain.

H5: Perceived social support moderates the negative relationship between stressors (a)-(d) and well-being, such that the relationship is weaker at high support.

3. Methodology

3.1 Research Design and Sampling

This study used a quantitative, cross-sectional design (Mishra & Malla, 2026). The target population was female platform service partners in home-based beauty, wellness, domestic care, and home maintenance in Delhi-NCR, which has a high concentration of on-demand platforms such as Urban Company and Housejoy, as well as considerable socio-economic diversity among workers (Ahmad, 2026). Because no formal sampling frame exists for algorithmically managed workforces, stratified convenience sampling with direct field interaction was used across New Delhi, Gurgaon, Noida, and Ghaziabad over several months (Singh et al., 2024). Respondents had at least three months of platform tenure and completed at least 15 appointments per month, ensuring familiarity with dispatch, ratings, and deactivation rules. Cochran's formula ($z = 1.96$, $p = 0.50$, $e = 0.05$) gives a minimum of 384.16 (Gujamagadi & Sarangamath, n.d.), so the final sample of $N = 385$ meets requirements for SEM (Mazhar et al., 2026; Memon et al., 2025). Table 1 profiles the sample.

Table 1*Sample Profile (N = 385)*

Category	Classification	<i>n</i>	%
Age	18–25 years	68	17.7
	26–35 years	204	53.0
	36–45 years	92	23.9
	Above 45 years	21	5.4
Marital status	Married	254	65.7
	Single / Unmarried	71	18.4
	Widowed / Divorced / Separated	60	15.6
Education	Up to Class 10	135	35.1
	Class 12	142	36.9
	Diploma / Vocational	68	17.7
	Undergraduate or higher	40	10.3
Service sector	Home beauty & salon	212	55.1
	Caregiving & elderly care	98	25.5
	Domestic maintenance & cleaning	75	19.4
Monthly earnings	Below ₹15,000	127	33.0
	₹15,000–₹25,000	173	44.9
	Above ₹25,000	85	22.1
Income dependency	Primary/sole income	238	61.8
	Supplementary income	147	38.2

3.2 Measures

All constructs were measured on 7-point Likert scales (1 = strongly disagree, 7 = strongly agree) (Agarwal et al., 2024). The instrument was translated into Hindi using back-translation and pilot-tested with 30 female gig partners. App-based stressors were measured with five items each: algorithmic control and tracking (Kellogg et al., 2020; Duggan et al., 2020), rating pressure (Möhlmann & Zalmanson, 2017), physical safety hazards (Cox et al., 2024), and economic precarity (Anwar & Graham, 2021). Psychological resilience was measured using the 10-item CD-RISC-10 (Connor & Davidson, 2003), and perceived social support was measured using the 12-item MSPSS (Zimet et al., 1988). Psychological well-being was measured using an adapted 8-item version of Ryff's scale (Ryff, 1989), and job performance was measured using a 5-item self-report scale covering service quality, protocol adherence, accuracy, and initiative (Demerouti & Bakker, 2023).

3.3 Common Method Bias

Because all constructs were self-reported by a single respondent, procedural and statistical controls were implemented (Atobishi & Nosratabadi, 2026; Memon et al., 2025). Respondents were anonymous, item blocks were shuffled to separate stressors from outcomes, and ambiguous or double-barreled wording was removed during piloting. In Harman's single-factor test, the first unrotated factor explained 31.4% of variance, below the 50% threshold (Brennan et al., 2024; Lissaneddine et al., 2026). Full-collinearity VIFs ranged from 1.18 to 2.45, below 3.3 (Henseler et al., 2015; Shariatzadeh et al., 2026). Adjusting for an unrelated marker variable (Digital Device Preference) changed path coefficients negligibly ($\Delta\beta < 0.02$, $p > 0.05$) (Agarwal et al., 2024). CMB, therefore, did not appear to distort the results.

3.4 Estimation Strategy

Data were analysed with PLS-SEM in SmartPLS 4 (Chin, 1998), chosen over CB-SEM because the model is complex, includes interaction terms, extends JD-R to a new context, does not require multivariate normality, and prioritises explained variance in well-being and performance. Bootstrapping with 5,000 resamples produced path coefficients (β), t-statistics, and 95% bias-corrected confidence intervals (Abdalla et al., 2026; Memon et al., 2025). Moderation (H4 and H5) was tested with the two-stage product-indicator approach, multiplying standardised stressor indicators by standardised resource indicators (Bakker et al., 2023). A significant positive interaction coefficient ($p < 0.05$) indicates buffering (Bakker & Demerouti, 2024). Model quality was assessed through R^2 (≥ 0.26 = substantial), effect size f^2 (0.02 small, 0.15 medium, 0.35 large), and Stone-Geisser Q^2 (> 0 = predictive relevance).

3.5 Measurement Model Validation

The reflective measurement model was assessed for reliability and validity (He et al., 2026). All indicator loadings exceeded 0.70 ($p < 0.001$) (Agarwal et al., 2024; Lissaneddine et al., 2026; Memon et al., 2025). As Table 2 shows, Cronbach's α and composite reliability exceeded 0.70 for every construct (Wu et al., 2026), and AVE exceeded 0.50, supporting convergent validity (Othman et al., 2017; Zahoory & Hameed, 2026). Discriminant validity was supported by the Fornell-Larcker criterion and by HTMT ratios below 0.85 (highest = 0.724, between economic precarity and rating pressure) (Memon et al., 2025; Pala, 2026); the full HTMT matrix is available in the supplementary material.

Table 2

Reliability and Convergent Validity

Construct	Items	α	CR	AVE
Algorithmic Control (AC)	5	0.842	0.887	0.612
Rating Pressure (RP)	5	0.865	0.902	0.648
Safety Hazards (SH)	5	0.821	0.874	0.583
Economic Precarity (EP)	5	0.854	0.895	0.625
Resilience (PR)	10	0.912	0.928	0.564
Social Support (SS)	12	0.898	0.915	0.582
Well-Being (PWB)	8	0.876	0.904	0.543
Job Performance (JP)	5	0.835	0.881	0.598

Note. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted.

4. Results

4.1 Structural Model Assessment

The model was estimated with PLS-SEM in SmartPLS 4, using 5,000 bootstrap resamples for path coefficients (β), t-statistics, and 95% bias-corrected confidence intervals (Agarwal et al., 2024; Abdalla et al., 2026). Inner VIF values ranged from 1.21 to 2.38, below 3.0, indicating no collinearity problems. The model explained 54.8% of the variance in psychological well-being ($R^2 = 0.548$, adjusted $R^2 = 0.536$) and 42.3% of the variance in job performance ($R^2 = 0.423$, adjusted $R^2 = 0.411$), both exceeding the 0.26 benchmark for substantial explanatory power. Blindfolding (omission distance = 7) yielded Q^2 values of 0.292 for well-being and 0.241 for job performance, confirming predictive relevance (Kayalı et al., 2026). Model fit was acceptable (SRMR = 0.058, threshold < 0.08).

4.2 Direct Effects (H1-H3)

Table 3 shows that all four stressors significantly and negatively predicted well-being, supporting H1a-d and the JD-R health-impairment process (Bakker et al., 2023). Rating pressure had the strongest effect ($\beta = -0.315$, $p <$

.001), followed by algorithmic control ($\beta = -0.242$), economic precarity ($\beta = -0.211$), and safety hazards ($\beta = -0.184$; all $p < .001$). All four stressors also had significant negative direct effects on job performance, supporting H2a-d, with the strongest effect for rating pressure ($\beta = -0.198$, $p < .001$) and the weakest for safety hazards ($\beta = -0.138$, $p = .006$). Well-being was positively related to job performance ($\beta = 0.384$, $p < .001$), supporting H3.

Table 3

Direct Path Coefficients (H1–H3)

Path	β	<i>SE</i>	<i>t</i>	<i>p</i>
H1a: Algorithmic Control → Well-Being	−0.242	0.050	4.812	< .001
H1b: Rating Pressure → Well-Being	−0.315	0.050	6.241	< .001
H1c: Safety Hazards → Well-Being	−0.184	0.047	3.915	< .001
H1d: Economic Precarity → Well-Being	−0.211	0.049	4.302	< .001
H2a: Algorithmic Control → Job Performance	−0.152	0.051	2.981	.003
H2b: Rating Pressure → Job Performance	−0.198	0.052	3.824	< .001
H2c: Safety Hazards → Job Performance	−0.138	0.050	2.745	.006
H2d: Economic Precarity → Job Performance	−0.165	0.053	3.112	.002
H3: Well-Being → Job Performance	0.384	0.054	7.152	< .001

Note. All hypotheses supported; two-tailed tests.

4.3 Moderation Analysis (H4 and H5)

Interaction terms were built with the two-stage product-indicator method. As Table 4 shows, all eight interactions were positive and significant, so resilience (H4a-d) and social support (H5a-d) each weakened the negative effect of every stressor on well-being. The strongest buffers were resilience for rating pressure ($\beta = +0.168$, $p < .001$) and social support for rating pressure ($\beta = +0.185$, $p < .001$). The effect sizes were small ($f^2 = 0.024$ to 0.061), so the buffering is real but modest in magnitude.

Table 4

Moderation Path Coefficients (H4 and H5)

Stressor × Resource → Well-Being	β	<i>t</i>	<i>p</i>	<i>f</i> ²
H4a: Algorithmic Control × Resilience	+0.142	3.125	.002	0.038
H4b: Rating Pressure × Resilience	+0.168	3.841	< .001	0.052
H4c: Safety Hazards × Resilience	+0.112	2.415	.016	0.024
H4d: Economic Precarity × Resilience	+0.135	2.948	.003	0.033
H5a: Algorithmic Control × Social Support	+0.118	2.612	.009	0.028
H5b: Rating Pressure × Social Support	+0.185	4.102	< .001	0.061
H5c: Safety Hazards × Social Support	+0.154	3.321	.001	0.042
H5d: Economic Precarity × Social Support	+0.126	2.784	.005	0.031

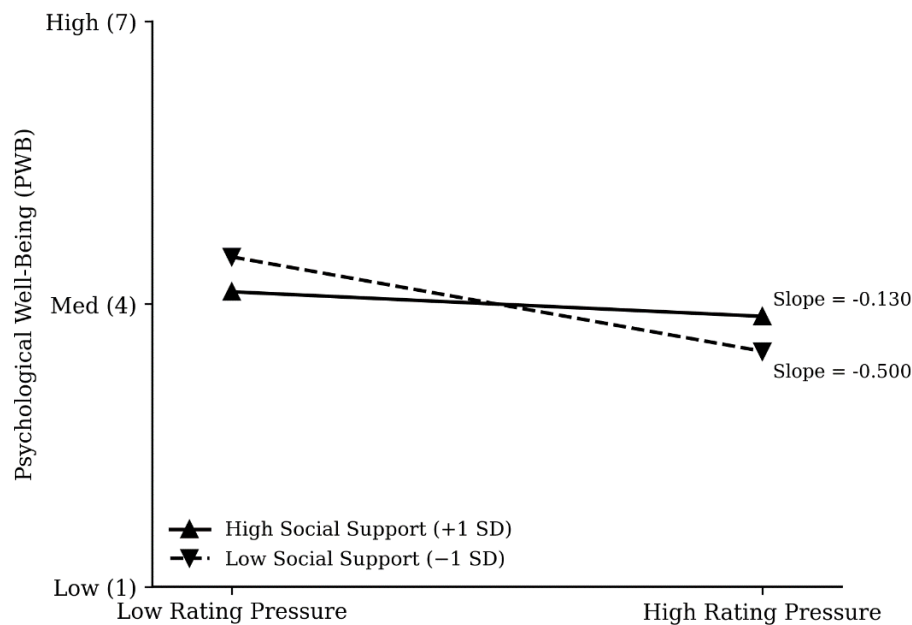
Note. All hypotheses supported; f^2 : 0.02 = small, 0.15 = medium, 0.35 = large.

4.4 Simple Slope Analysis

Simple slopes were examined at -1 SD, the mean, and $+1$ SD of each resource. Figure 2 shows that for workers with low social support, rating pressure sharply reduced well-being ($b = -0.500$, $p < .001$), whereas at high social support the effect was much weaker ($b = -0.130$, $p = .035$), consistent with informal peer networks cushioning rating-related anxiety (Cui & Wang, 2024). Similarly, algorithmic control reduced well-being strongly for workers with low resilience ($b = -0.384$, $p < .001$) but far less for those with high resilience ($b = -0.100$, $p = .048$).

Figure 2

Simple Slope Plot: Rating Pressure $\times$ Social Support $\rightarrow$ Well-Being



Note. Slopes at -1 SD and $+1$ SD of social support: low, $b = -0.500$, $p < .001$; high, $b = -0.130$, $p = .035$.

5. Discussion and Design Recommendations

5.1 Interpretation of Findings

The results show that app-based stressors impair the well-being and performance of female platform workers, and that resilience and social support moderately buffer these effects. This supports the JD-R health-impairment process in platform-mediated, location-based service work. Rating pressure ($\beta = -0.315$) and algorithmic control ($\beta = -0.242$) had the largest effects on well-being. This fits Kellogg et al.'s (2020) account of how platforms direct workers by restricting and recommending, evaluating them by recording and rating, and disciplining them by replacing and rewarding. Because customer ratings serve as crowdsourced supervision governing future dispatch, workers may tolerate inappropriate client behaviour to avoid the account deactivation that a low, unverified rating can trigger. The effect of algorithmic control is consistent with the "autonomy paradox": platforms advertise flexibility, yet real-time GPS monitoring, fixed response windows, and acceptance-rate tracking create the "invisible digital cage" that drains energy and fosters burnout.

Safety hazards ($\beta = -0.184$) and economic precarity ($\beta = -0.211$) reflect the intersecting vulnerabilities of women in India's platform economy. Women in domestic care and home beauty often combine platform work with unpaid caregiving and spend additional unpaid preparatory time checking the app, vetting customers, and managing expectations (Billah & Khan, 2026). Penalties for declining tasks in unsafe areas or late at night force a trade-off between safety and visibility, while opaque fee structures and automatic deductions erode net income.

The moderation results support a double-support pattern (H4 and H5). Where platforms replace HR managers, grievance procedures, and career channels, workers rely on inner capacities and outer networks. Resilience, in line with the Conservation of Resources theory, appears to help workers reframe tracking and detach from unfair reviews. Social support buffered rating pressure ($\beta = +0.185$) and safety hazards ($\beta = +0.154$), consistent with the informal peer messaging groups in which women share warnings about abusive clients and offer emotional backing. The buffering effects were modest ($f^2 \leq 0.061$), so personal resources should complement, not replace, better system design.

5.2 HCIS Design Recommendations

Because these stressors arise from system design, the following principles aim to reduce them at source. They are proposals derived from the findings and remain to be tested.

Principle 1: Human-in-the-loop recourse. To counter deactivation anxiety and one-sided rating systems, potential suspensions should trigger a provisional flag rather than immediate termination. An appeals dashboard should let workers submit evidence such as photos, audio, or location timestamps, with disputes reviewed by human staff or an independent ombudsperson. Rating systems should filter retaliatory ratings, such as those following a worker's rejection of inappropriate advances or a safety-related cancellation.

Principle 2: Transparent algorithmic rules. To reduce information asymmetry and precarity, task allocation screens should explain their rationale (for example, "assigned by proximity and certified skill"). Earnings screens should itemise gross fare, commission, loan recovery, and kit fees before a task is accepted. Changes to allocation, rating thresholds, or pricing should be announced in advance, for example, 14 days, to prevent algorithmic shocks.

Principle 3: Stress-aware, micro-flexible scheduling. To ease the clash between rigid tracking and caregiving, apps should offer short booking windows of two to three hours, realistic time estimates based on local conditions, and automatic unpenalised rest buffers after prolonged activity. A one-touch "caregiving pause" should let workers go offline without a ranking demotion.

Principle 4: Safety-centric architecture and peer support. Platforms should verify customer identity before home bookings and provide a one-tap SOS linked to GPS and an emergency response team. Workers should be able to cancel unsafe jobs without penalty. Given the buffering role of social support (H5), platforms should also host moderated peer communities in-app so workers do not rely on unmonitored external chat groups.

5.3 Managerial and Policy Implications

Platforms that rely on monetary incentives and algorithmic discipline risk turnover, mental strain, and poorer service quality. Investing in transparent fees, recourse channels, and welfare provisions such as group accident and health insurance can build trust and retention. In terms of policy, India's Code on Social Security (2020) recognises gig and platform workers, but its implementation remains incomplete. Regulators could require aggregators to contribute a fixed share of turnover to a social security fund covering healthcare, maternity, and injury; mandate independent algorithmic audits to detect gender-biased allocation, hidden pay penalties, and discriminatory deactivation, as under the EU Directive on Platform Work; and adopt a "dependent contractor" status with minimum earnings guarantees.

6. Conclusion, Limitations and Future Research

6.1 Conclusion

Integrating Human-Centred Information Systems (HCIS) with the Job Demands-Resources (JD-R) framework, this study examined how app-based stressors affect the well-being and job performance of 385 female platform workers in Delhi-NCR. Algorithmic control, rating pressure, safety hazards, and economic precarity each significantly reduced well-being and performance, with rating pressure having the strongest effect. Psychological resilience and perceived social support both buffered the effect of every stressor on well-being, though the effects were modest.

Based on these findings, we proposed four design principles: human-in-the-loop recourse, transparent and explainable algorithmic rules, stress-aware micro-flexible scheduling, and safety-centric architecture with peer support.

6.2 Limitations

First, the cross-sectional survey limits causal inference, and longitudinal designs are needed to establish direction. Second, the sample was drawn by stratified convenience sampling from Delhi-NCR home-service platforms, so the findings may not generalise to rural or semi-urban settings, other sectors, or remote platforms such as Upwork or Amazon Mechanical Turk, where mobility and safety risks differ. Third, all measures were self-reported; although the diagnostic tests suggested that common method bias was not a serious concern, objective platform data, such as acceptance rates or GPS pause times, would strengthen future work. Fourth, the design recommendations are derived from the findings and have not been tested with users.

6.3 Future Research

Future studies could (1) use panel or daily-diary designs to track how weekly variation in tracking and ratings affects burnout and coping; (2) examine how caste, religion, education, and single motherhood intersect with algorithmic management; (3) test the design principles through field experiments or A/B tests comparing standard and human-centred interfaces; (4) compare workers across welfare regimes in the Global South, such as India, Bangladesh, Kenya, and Brazil; and (5) study platform cooperatives as alternatives to capital-driven platform design.

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