

FACTORS INFLUENCING THE MENTAL WELL-BEING OF LOCATION-BASED GIG WORKERS IN KARACHI

Dr Ammad Zafar^{*1}, Dr Sobia Iqbal², Dr Shahid Raza Mir³

^{1,2}Associate Professor, Department of Management Sciences, DHA Suffa University

³Assistant Professor, Department of Management Sciences, DHA Suffa University

¹ammad.zafar@dsu.edu.pk, ²sobia.iqbal@dsu.edu.pk, ³shahid.raza@dsu.edu.pk

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Corresponding Author: *

Dr Ammad Zafar

Abstract

The expansion of the gig economy introduced new forms of employment that particularly benefit location-based gig workers situated in Karachi's urban areas. The flexible nature of gig work exposes workers to insecure employment due to automation systems and unpredictable working schedules that jeopardize mental well-being. This research investigates which factors affect the mental health of location-based gig workers operating in Karachi. A study utilized quantitative methodology to evaluate results from 396 workers selected through convenience sampling who delivered rides or performed deliveries. The study analyzed data using SPSS and found that algorithm-based decisions and fair treatment, along with workloads, have a significant positive impact on mental well-being. Moreover, it reveals that the combination of sophisticated task allocation programs and unclear execution algorithms caused serious mental pressure among workers, as shown by the study's analytic evidence. A few workers valued the ability to work independently on these platforms as well as the flexibility that they provided. The research establishes that immediate financial benefits from gig work coexist with substantial psychological risks because regulatory measures and mental health assistance are non-existent. Digital platforms, together with algorithmic management, have enabled a fast-growing gig economy that fundamentally changes how work exists globally.

INTRODUCTION

Digital platforms paired with algorithmic management tools function as rapid agents that modify work practices across global societies. Gig platforms like Bykea, Foodpanda, and Indrive, along with other services, have gained popularity as income sources in Pakistan among urban youth. However, the flexibility and autonomy often associated with gig work come at a cost—workers are frequently exposed to algorithm-driven decision-making processes, inconsistent workloads, and opaque performance evaluations that may negatively impact their mental well-being (Wood et al., 2019).

The combination of computerized data analysis and machine learning models under algorithmic management shows limited transparency and few ways to keep managers accountable (Meijerink & Bondarouk, 2021). The challenge of understanding and challenging automated systems in task allocation-based payment methods leads to equal treatment problems for workers. Unpredictable workloads in gig work lead to emotional exhaustion and stress for workers, according to Bérastégui (2021).

Research now views mental health as an essential health element that requires further attention throughout the developing gig economy sector. According to De Stefano et al. (2022), the work environment with limited employee power, perceived injustice, and excessive job requirements leads to significant psychological challenges for workers. Research in South Asian locations with minimal labor protection fails to produce sufficient understanding about platform-based labor despite global acknowledgment of these problems.

Problem Statement

The rapid expansion of Bykea, together with Foodpanda and Indrive operating in the Karachi platform economy, relies on algorithmic systems for worker assignment tasks. Flexibility in worker earnings from gig work stands alongside job instability, which generates psychological pressure. Workers who receive flexible pay through gig work experience mental stress because the payment systems lack uniformity and unpredictability. Limited academic investigations examine how the advancement of digital platforms in Pakistan interacts with labor law changes and affects the psychological health of platform workers. There is a critical need to understand how factors such as algorithmic decision-making, perceived fairness, and workload influence the mental well-being of these workers.

Research Objectives

1. To examine the impact of algorithmic decision-making on the mental well-being of gig workers in Karachi.
2. To evaluate how perceived fairness in the gig work environment affects the mental well-being of workers.
3. To assess the influence of perceived workload on the mental well-being of gig workers.

Literature Review

Algorithmic Management and Psychological Control

The algorithmic management system implemented by Gig platforms modifies the operational structure of their ride-hailing and food delivery services. These systems allocate work tasks, track employee

performance, and calculate payment amounts (Wood et al., 2019). Kellogg et al. (2020) revealed that systems using hidden algorithms produce unpredictable conditions that reduce worker control before workers start experiencing burnout symptoms. Kellogg et al. According to Ivanova et al. Ivanova et al. (2018) identify how algorithmic management implements digital Taylorism through its elimination of worker autonomy to produce psychological impacts. Research by Ivanova et al. demonstrates findings. Similar findings are demonstrated by Ivanova et al. The removal of worker autonomy through algorithmic management forms digital Taylorism and produces mental health issues, according to Ivanova et al. (2018). Research by Colquitt et al. (2001) has shown that organizational justice creates quantifiable psychological effects. Gig work struggles with unfair treatment because algorithms control major decisions, yet users face challenges with official complaint submission systems.

Most published literature points to algorithmic systems inducing mental health decline because they conduct perpetual monitoring and generate substantial stress on workers (Rosenblat & Stark, 2016; Mateescu & Nguyen, 2019).

Perceived Fairness and Emotional Well-being

A worker's mental health state depends primarily on their perception of fair earnings distribution, procedural interactions, and work environment responses. Colquitt et al. According to Colquitt et al., ride-hailing service workers (Dubal, 2022) consider ratings and customer feedback through algorithms to be unjust since they must operate without review process control. The combination of automated decision systems and inadequate complaint channels causes frequent fairness problems in gig work.

Dubal (2022) reports that ride-hailing workers consider algorithms and consumer ratings unfair because they have no influence on review processes. Almost all platform bonuses target established full-time or high-rated contributors, which creates social divisions between workers (Goods et al., 2021). Bérastégui (2021) found that workers who perceive greater fairness show higher job satisfaction and emotional stability in a gig worker environment.

Workload, Emotional Burnout, and Psychological Strain

Workload is a proven indicator of occupational stress and mental fatigue. According to Peticca-Harris et al. (2020), gig workers face uncertain work hours with demanding shifts that alternate between periods of high demand and periods of low work. Workload variability generates financial stress, which causes workers to overextend themselves during busy periods while skipping periods of rest (Veen et al., 2020).

According to Lehdonvirta (2018), performance ratings based on deliverables and minimal workload restrictions push workers to maintain excess effort levels. The lack of labor protections beyond paid leave, combined with insufficient emotional support systems, creates severe mental stress for gig workers (ILO, 2021).

Kellner et al. Low-income workers dedicate from 10 to 14 hours of their day to their employment, according to Anwar and Graham (2021). Anwar and Graham (2021) found that workdays in resource-constrained nations commonly exceed 10–14 hours for their workers. The way gig workers experience mental challenges in their work depends on demographic factors and social characteristics. The feeling of being replaceable and invisible causes workers' mental fatigue to deepen, according to their descriptions.

Intersectionality and Vulnerability

Mental health outcomes for gig workers emerge from the way different population groups and social characteristics combine. Women need to perform two tasks simultaneously: they must work through

platform services and care for their family members without pay, which creates excessive emotional distress (Ticona & Mateescu, 2018). Working-class employees and marginalized members of society face the most risk because economic instability in platform-based work intensifies their stress levels (Graham et al., 2020).

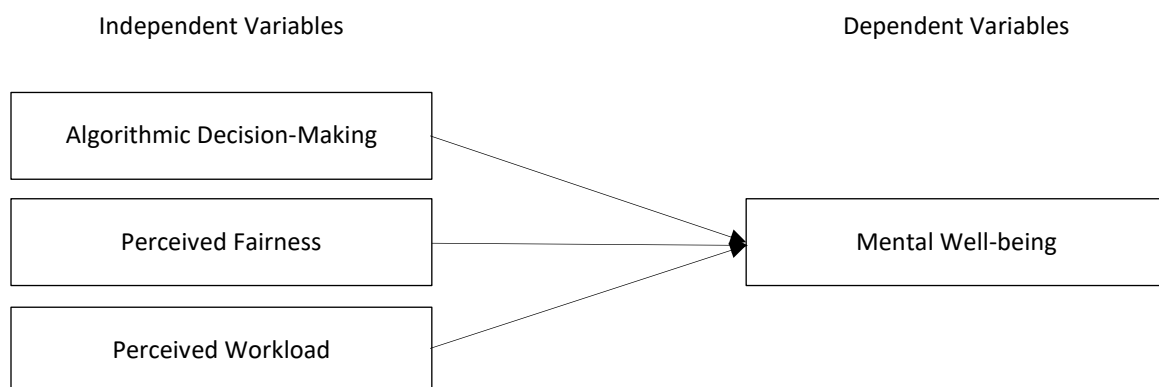
Understanding these intersectional dimensions is crucial for contextualizing mental health challenges within broader socioeconomic and gender-based inequalities.

Theoretical Framework

Job Demands-Resources (JD-R) Theory provides the foundation for this research to explain how specific job demands (e.g., workload, pressure) and job resources (e.g., autonomy, fairness) influence employee stress and well-being (Demerouti et al., 2001). The study classifies algorithmic management along with fairness perceptions as job resources or demands according to worker experience, while workload maintains its primary job demand status. The JD-R model helps explain how these factors influence mental well-being, especially in precarious work environments like the gig economy (Bakker & Demerouti, 2017).

Conceptual Framework

The research design combines algorithmic decision-making with workforce perceptions of fairness and workload to measure their effects on mental well-being. Each independent variable is hypothesized to have a direct impact on the dependent variable, the mental well-being of gig workers.



The framework is illustrated as follows:

These relationships are derived from the literature on platform labor and occupational health psychology (Wood et al., 2019).

Study Hypotheses

H₁: Algorithmic decision-making has a significant impact on Mental Well-being.

H₂: Perceived fairness in the work environment has a significant impact on Mental Well-being.

H₃: Perceived workload has a significant impact on Mental Well-being.

Research Methodology

Research Approach

A quantitative research methodology is used to analyze how algorithmic decision-making, together with workers' sense of fairness and their workload, interacts with their mental health. Quantitative analysis provides optimal conditions for studying measurable variables together with their statistical relationships (Creswell & Creswell, 2018).

Research Design

Two research methods allowed investigators to obtain data through a point-in-time survey. This design is appropriate for assessing the current perceptions and experiences of gig workers, and for exploring causal relationships between the independent variables (algorithmic management, perceived fairness, and workload) and the dependent variable (mental well-being).

Population and Sample

The research subject population consisted of gig workers operating ride-hailing and delivery platforms within Karachi, Pakistan's Bykea, Foodpanda, and Indrive systems. Because this workforce is distributed and easy to access, researchers used convenience sampling as their technique. Data were collected from 396 respondents, ensuring a sufficiently large sample for robust statistical analysis.

Instrument Development

The researcher developed the questionnaire using a combination of validated scales, which contained content that matched the findings from existing literature. The questionnaire contained five-point Likert scale items that operated from Strongly

Disagree (1) to Strongly Agree (5). It was divided into five sections: demographics, algorithmic management, perceived fairness, workload, and mental well-being.

Variables and Measurement

- Algorithmic Decision-Making: Measured using 3 items evaluating algorithm transparency, fairness, and equal opportunity.

- Perceived Fairness: Measured through 3 items covering task assignment criteria, pay fairness, and workload distribution.

- Perceived Workload: Assessed with 3 items relating to stress levels, consistency, and manageability of tasks.

- Mental Well-being: Captured using 4 items examining emotional exhaustion, mental stress, and fulfillment.

Cronbach's alpha values demonstrated acceptable to good internal consistency since they ranged from 0.717 to 0.845.

Pilot Testing

A preliminary analysis in Karachi tested questionnaire items for clarity before conducting the full survey. The small-scale test survey recruited a manageable number of workers from the selected online platforms. Participants' feedback enabled researchers to adapt survey elements so they became clear and minimally ambiguous. The study's main function and design were explained to participants before they provided their consent. The study followed all ethical protocols, which emphasized both the protection of participant privacy and their voluntary willingness to take part.

Data Collection Procedure

Data collection spanned across a month using physical surveys and online forms to achieve participant diversity. The researchers provided participants with information about the study's purpose before obtaining consent from willing participants. Strict ethical standards governed the research process through guaranteed anonymity and data privacy for participants.

Data Collection Sources

- **Primary Data:** Obtained through the structured questionnaire administered to gig workers in Karachi.
- **Secondary Data:** Derived from a comprehensive literature review of scholarly articles and prior empirical studies. This helped in formulating the theoretical framework and hypotheses.

Data Analysis Techniques

The data were analyzed using SPSS (Statistical Package for the Social Sciences). The following statistical methods were applied:

- **Descriptive Statistics** to summarize demographic information.

Analyses and Interpretation**Demographic Summary Table****Table 01: Demographics Analysis**

Category	Sub-Category	Frequency	Valid Percent
Age	18-25	180	45.5%
	26-35	168	42.4%
	36 and Above	48	12.1%
Gender	Male	312	78.8%
	Female	84	21.2%
Education	Matric or Below	84	21.2%
	Intermediate	156	39.4%
	Graduation or Higher	156	39.4%
Employment Status	Full Time	228	57.6%
	Part Time	84	21.2%
	Freelancer	84	21.2%
Organization Worked For	Bykea	132	33.3%
	Foodpanda	132	33.3%
	Indrive	132	33.3%

This table provides a summary of the demographic profile of the respondents. The age distribution shows that the majority (45.5%) fall within the 18-25 age group, followed by 42.4% in the 26-35 bracket, and a smaller segment (12.1%) aged 36 and above. Gender representation reveals that males overwhelmingly dominate the sample, with 78.8%, while females make up only 21.2%. In terms of educational background, respondents are equally

- **Reliability Analysis (Cronbach's Alpha)** is used to test the internal consistency of scales.
- **ANOVA** to identify differences in mental well-being across organizations.

- **Binary Logistic Regression** to evaluate the impact of algorithmic management, perceived fairness, and workload on mental well-being.

Ethical Considerations

The study followed ethical research practices. All participants were **informed of their rights**, and **no identifiable data** were collected. Participants had the freedom to withdraw at any stage without any consequences. Informed consent was obtained prior to data collection, ensuring voluntary participation and confidentiality.

split between those with intermediate qualifications and those holding graduation degrees or higher, both at 39.4%, whereas 21.2% possess matriculation-level education or below. Regarding employment status, most respondents (57.6%) are working full-time, while part-time workers and freelancers each account for 21.2%. Lastly, the participants are evenly distributed among three organizations—Bykea, Foodpanda, and Indrive—each contributing 33.3% to the total sample.

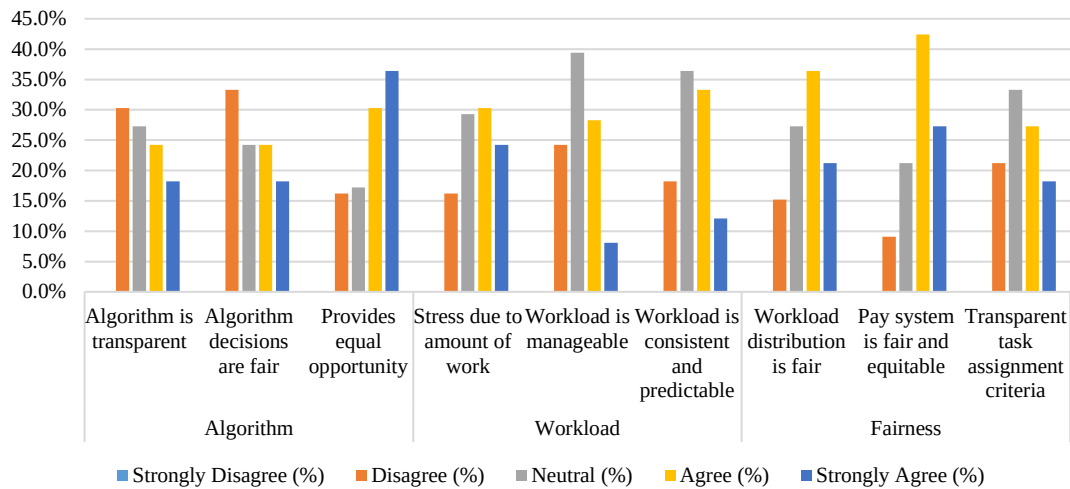
Figure 01: Construct of Independent Variables

Figure 01 summarizes employee perceptions across three categories—Algorithm, Workload, and Fairness—based on a five-point Likert scale. In the **Algorithm** category, responses indicate mixed views. While only a small percentage strongly agree that algorithms are transparent (18.2%), a notable 30.3% disagree, showing a lack of confidence in algorithmic clarity. Similarly, 33.3% disagree that algorithmic decisions are fair, with just 18.2% strongly agreeing, suggesting concerns about fairness. However, views improve regarding equal opportunity, where a combined 66.7% agree or strongly agree, showing optimism in this area. For **Workload**, 54.5% of

respondents agree or strongly agree that they feel stress due to their workload, while only 36.4% agree it is manageable. Additionally, only 12.1% strongly agree that their workload is consistent and predictable, indicating some dissatisfaction with workload management. In the **Fairness** section, 57.6% agree or strongly agree that workload distribution is fair, and a strong 69.7% believe the pay system is fair. However, only 45.5% feel task assignments are transparently distributed. Overall, while fairness in pay and opportunity is relatively well-perceived, concerns remain around algorithmic transparency and workload predictability.

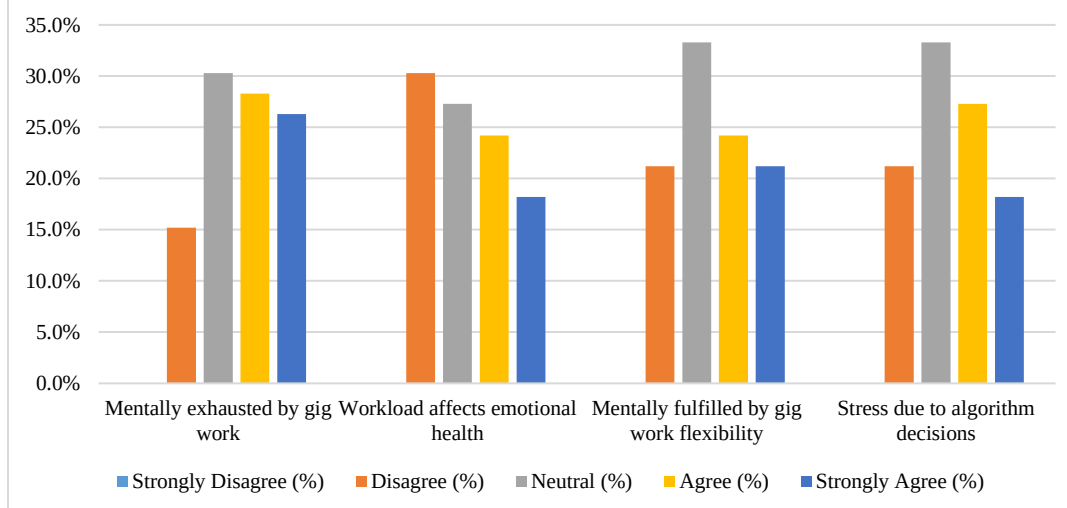
Figure 02: Constrcut of Dependent Variable: Mental Well-being

Figure 02 reflects respondents' views on mental well-being in the context of gig work. A significant number (54.6%) agree or strongly agree that gig work leaves them mentally exhausted, indicating that psychological strain is a real concern. When asked whether workload affects emotional health, responses are more dispersed, while 42.4% disagree or remain neutral, 42.4% agree or strongly agree, showing a divided perception. Regarding mental fulfillment from the flexibility offered by gig work, 45.4% hold a neutral or negative stance, whereas

45.4% agree or strongly agree, suggesting that flexibility is appreciated by some but not universally experienced as fulfilling. Finally, stress due to algorithmic decision-making also shows mixed reactions, with 45.5% agreeing or strongly agreeing and 33.3% remaining neutral. These results highlight the emotional complexity faced by gig workers, with clear evidence of mental fatigue and stress, tempered by a moderate level of appreciation for job flexibility.

Reliability Analysis

Table 02: Cronbach's Alpha

Variables	No of Items	Cronbach Alpha
Algorithm	03	0.831
Fairness	03	0.845
Workload	03	0.733
Mental Well-being	04	0.717

Table 02 presents the internal consistency of the scales used to measure four variables: Algorithm, Fairness, Workload, and Mental Well-being. Each construct is measured through multiple items, and the Cronbach's Alpha value indicates how reliably these items capture the intended concept. The Algorithm scale, comprising three items, has a high reliability score of 0.831, suggesting strong internal

consistency. Similarly, the Fairness scale, also with three items, shows a slightly higher alpha of 0.845, reflecting excellent reliability. The Workload scale, although still acceptable, records a lower alpha of 0.733. The Mental Well-being scale, which consists of four items, shows the lowest but acceptable reliability at 0.717, still within the threshold for psychological and social science research.

Table 03: ANOVA for the Current Organization of respondents

		Sum of Squares	df	Mean Square	F	Sig.
Algorithm	Between Groups	0.283	2	0.141	0.197	0.821
	Within Groups	139.758	195	0.717		
	Total	140.040	197			
Fairness	Between Groups	0.768	2	0.384	0.566	0.569
	Within Groups	132.242	195	0.678		
	Total	133.010	197			
Workload	Between Groups	6.909	2	3.455	3.551	0.031
	Within Groups	189.697	195	0.973		
	Total	196.606	197			
Mental Wellbeing	Between Groups	2.465	2	1.232	1.963	0.143
	Within Groups	122.424	195	0.628		
	Total	124.889	197			

Table 03 displays the results of one-way ANOVA tests to determine whether respondents' current organization (Bykea, Foodpanda, or Indrive)

significantly influences their perceptions of Algorithm, Fairness, Workload, and Mental Well-being. The p-values indicate statistical significance.

The results show that perceptions of Workload differ significantly across organizations ($p = 0.031$), implying that where respondents work may affect how they perceive their workload. However, no statistically significant differences are found for

Algorithm ($p = 0.821$), Fairness ($p = 0.569$), or Mental Well-being ($p = 0.143$). This suggests that while workload perceptions vary, other variables appear consistent regardless of the organization.

Table 04: Model Summary for Binary Logistic Regression Analysis

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	156.538 ^a	0.272	0.406

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than 0.001.

Table 04 summarizes the goodness-of-fit for a binary logistic regression model assessing the impact of Algorithm, Fairness, and Workload on a binary outcome (likely a satisfaction or mental health-related variable). The model's fit is evaluated using

the -2 Log Likelihood value, which is 156.538. Two pseudo R-square values are also provided: Cox & Snell R^2 is 0.272, and Nagelkerke R^2 is 0.406. These indicate that the model explains between 27.2% and 40.6% of the variance in the outcome variable, reflecting a moderate level of explanatory power.

Table 05: Variables in the Equation for Binary Logistic Regression Analysis

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1 ^a	Algorithm(1)	1.521	0.504	9.118	1	0.003	4.576
	Fairness(1)	1.118	0.534	4.387	1	0.036	3.058
	Workload(1)	1.867	0.436	18.292	1	0.000	6.468
	Constant	-2.007	0.523	14.721	1	0.000	0.134

a. Variable(s) entered on step 1: AG, FR, WL.

Table 05 presents the logistic regression coefficients for each predictor variable—Algorithm, Fairness, and Workload. All predictors are statistically significant. The Algorithm variable has a positive coefficient ($B = 1.521$) and a p-value of 0.003, indicating a strong and significant positive effect on the outcome. Fairness is also significant ($p = 0.036$) with an odds ratio ($\text{Exp}(B)$) of 3.058, suggesting that a one-unit increase in perceived fairness increases the odds of the outcome occurring by over three times. Workload shows the strongest effect with the highest coefficient ($B = 1.867$) and a highly significant p-value ($p = 0.000$), indicating that perceived workload significantly affects the outcome. The constant term is also significant, reinforcing the robustness of the model.

Discussion

Research results reveal essential knowledge about the interplay between algorithmic management systems, fairness judgments, and workload on mental health

for platform workers in Pakistan's freelance industry. To validate results with greater robustness, both ANOVA and logistic regression testing were applied to each hypothesis.

H₁: Algorithmic decision-making has a significant impact on Mental Well-being.

The findings of logistic regression establish a significant positive relationship between algorithmic decision-making and mental well-being at a 0.003 p-value and with an odds ratio of 4.576. Such workers show a statistically significant improvement in their mental well-being based on their understanding of algorithmic process transparency and fairness. ANOVA results indicate no significant relationship between team perception differences ($p = 0.821$), but individual exposure to algorithmic design significantly influences psychological responses. Research published by Kellogg et al. (2020) and Möhlmann et al. (2021) confirms how opaque

algorithmic systems in gig work environments can lead to stress and anxiety among workers.

H₂: Perceived fairness in the work environment has a significant impact on Mental Well-being.

The regression analysis data showed meaningful psychological effects from superficial fairness judgments despite showing no statistical significance ($p = 0.569$, ANOVA). Subjective perceived fairness judgment analysis through regression demonstrated significant psychological relevance, but ANOVA statistical findings yielded nonsignificant results at $p = 0.569$. Prior studies have emphasized the importance of procedural fairness in organizational settings, particularly in non-traditional work arrangements where job security and worker autonomy are low (Berkhout & Richardson, 2022).

H₃: Perceived workload has a significant impact on Mental Well-being.

The statistical tests of mental well-being reveal workload as the main contributing factor because workers with improved workload control show positive mental health outcomes about 6.5 times more frequently. ANOVA analysis ($p = 0.031$) demonstrates that workload variations between different groups have a substantial effect on mental health outcomes. Gig-based workers experience burnout and emotional exhaustion because of excessive or irregular workloads, which contradict the promised flexibility (Wood et al., 2019; Dubal, 2021).

Despite similar group-level measurements according to ANOVA, logistic regression delivers additional details about how variables affect mental health status in the population. The practical implications are substantial: gig platforms and policy-makers must prioritize algorithm transparency, fair treatment, and sustainable workloads to enhance the psychological resilience of workers in this emerging labor sector.

Conclusion

The study analyzed interaction patterns between platform algorithms and worker perceptions of equity and workload responsibilities impacting mental health outcomes for Pakistani ride-hailing platform workers. Data obtained from logistic regression confirmed that algorithmic management,

together with fairness and workload metrics, significantly affected mental well-being among participants. Workload emerged as the variable with the greatest predictive ability from among the study variables. ANOVA findings showed that algorithmic management combined with fairness did not produce significant group differences, although the research data indicates these elements directly affect the mental health of workers. New research about algorithmic labor and platform-based employment receives valuable contributions from these findings.

Recommendations

According to the evidence gathered, platform companies need to prioritize the transparency and fairness of their algorithmic systems. Disclosure of decision-making processes enables gig workers to feel less stressed and uncertain. Systems should include techniques for workload distribution to prevent overwhelming individuals while also making tasks both achievable and predictable. Organizations that practice fair compensation systems alongside fair work assignment methods will likely benefit their workforce by improving mental health and job satisfaction. Legislators should create laws that protect the mental health of gig workers through requirements for fair labor practices and ethical algorithm regulation.

Limitations of the Study

The study contains multiple constraints. This research's convenience sampling method weakens the ability to share the study's identified results across different settings. The collected data focused on Karachi's gig workers, resulting in limited information about the experience of workers in other locations or international regions. The cross-sectional design of the study limits researchers from establishing causal connections between variables. The study collected data through questionnaire-based self-reporting, which potentially introduced social desirability bias and subjective response interpretation from participants.

Significance of the Study

The research findings have practical implications and academic consequences. They add to the sparse body of evidence focusing on South Asian gig workers in

algorithmically managed platforms. The study shows that workers in the gig economy need immediate solutions for algorithmic pressure, workplace inequality, and excessive workload management. By identifying key psychological risks in the gig economy, the study offers actionable insights for platform designers, HR practitioners, and policymakers aiming to create healthier and more sustainable digital labor systems.

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