

Algorithmic Management, Perceived Algorithmic Injustice, and Gig Worker Outcomes in Pakistan: A Time-Lagged, Moderated-Mediation Analysis

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Abstract

While algorithmic management (AM) has emerged as the dominant form of workforce coordination on digital labor platforms, there is limited empirical evidence from South Asian gig economies, where norms of informal labor dominate and regulations are weak. This study builds and tests a moderated-mediation model that champions the concept of organizational justice theory and the concept of conservation of resources (COR) theory, with the moderating effect of psychological capital (PsyCap) and the mediating effect of perceived algorithmic injustice between AM and two worker outcomes: emotional exhaustion and resistance behavior. A three-wave, time-lagged research design was used, recruiting 438 ride-hailing and delivery gig workers across five cities of Punjab, Pakistan: Lahore, Faisalabad, Multan, Rawalpindi and Gujranwala. The results for PLS SEM (SmartPLS 4) revealed that AM was significantly and positively associated with perceived algorithmic injustice, which subsequently could predict emotional exhaustion and resistance, supported by PLS-Predict (out-of-sample) and importance-performance map analysis. Bootstrapped indirect effects confirmed the mediating effect of perceived injustice. Results from the moderated-mediation analysis using the PROCESS macro (Model 7) indicated that the indirect effects of AM on both outcomes were significantly lower for workers with high PsyCap. The results contribute to the algorithmic management literature because they empirically address the input-process-output logic that was proposed in the recent systematic reviews and show the protective relationship between psychological resources and work in an under-investigated, high power-distance context. Theoretical and practical implications for platform design, labor policy and worker training to Pakistan and similar emerging gig economies are discussed.

Keywords: algorithmic management, gig economy, organizational justice theory, conservation of resources theory, psychological capital, moderated mediation, Pakistan,

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PLS-SEM, PROCESS macro

1 Introduction

Digital labor platforms like Uber, Careem, InDriver, Foodpanda, or Bykea have reshaped the allocation, monitoring, evaluation, and compensation of work all over the world, replacing human supervisors with machine learning algorithms that are performing what used to be considered managerial work (Duggan et al., 2020; Kellogg et al., 2020). Algorithmic management (AM) is a form of workforce coordination that is often referred to as the automation of monitoring, directing, evaluating and disciplining human workers by using machine learning algorithms, with limited, if any, human intervention (Kadolkar et al., 2025; Möhlmann et al., 2021). Despite the tremendous increase in research on AM in the last decade, recent systematic reviews show that the literature is still highly fragmented, characterized by qualitative and conceptual studies, and, crucially, largely non-theoretical, with only a few quantitative tests of specific theoretical mechanisms linking AM to worker outcomes (Kadolkar et al., 2025; Wu & Huang, 2024).

This is especially significant if we consider that much empirical AM research has been done in countries outside of North America and Europe. Over the last few years, there has been a rapid expansion of app-based ride-hailing and delivery services in Pakistan, including in Punjab province, which have attracted many underemployed young males to platform mediated livelihoods (Duggan et al., 2020). Pakistan is distinguished from the institutional context analyzed in previous AM studies by the presence of relatively lax labor market regulation on digital platforms, strong power distance and collectivist cultural norms, and a mostly informal pre-gig labor market in which gig work is being integrated (Rani & Furrer, 2021). These contextual elements are likely to influence the interpretation and reactions of workers to algorithmic control, and thus far these elements have been virtually ignored in empirical, theory-driven research.

The present study aims to fill this void by making each of the hypothesized relationships explicit in one of two complementary theoretical lenses: organizational justice theory (Colquitt, 2001) and conservation of resources theory (Hobfoll, 1989; Hobfoll et al., 2018) instead of atheoretical, purely empirical relationships. Following the input-process-output (IPO) integration proposed by Kadolkar et al. (2025), we suggest that algorithmic (in)justice is an input that influences gig workers' perceptions of algorithmic (in)justice, which in turn leads to two different classes of output: internalized (exhaustion) and externalized (resistance). We propose in this article, based on a COR approach to resources (Hobfoll et al., 2018), that such an input-process-output mechanism is not uniform but rather depends upon higher-order psychological resources: psychological capital (PsyCap) of workers, which involves hope, efficacy, resilience, and optimism (Luthans & Youssef-Morgan, 2017).

There are four contributions to this study. First, it is one of the first quantitative, dual-theory assessments of the AM → process → outcome pathway that has been recommended in recent systematic reviews, directly challenging the call to open the black box of AM (Kadolkar et al., 2025, p. 1070) by explicitly stating the theoretical pathways underlying each hypothesis within the model rather than the model itself. Second, it adopts a three-wave time-lagged design, which takes place in different waves at different time points, addressing a design limitation that pervades the existing literature, which is that the majority of studies rely on cross-sectional, single-source data (Cropanzano et al., 2023). Third, the analysis is explicitly designed to be rigorous: In addition to the standard reflective measurement and structural-path analysis, a complete heterotrait–monotrait (HTMT) discriminant-validity matrix is reported, out-of-sample predictive assessment via PLSpredict (Shmueli et al., 2019), a moderated-mediation analysis with triangulation between SmartPLS and the PROCESS macro, and an importance-performance map analysis (IPMA; Ringle & Sarstedt, 2016) to determine which dimension of AM is most predictive of perceived injustice. Fourthly, the research moves beyond the typical context of AM research, placing it in the Pakistani

context of Punjab, where gig work is quickly replacing informal wage labor in an emerging-economy setting.

2. Literature Review, Theoretical Lenses, and Hypothesis Development

2.1 Theoretical Lenses: Organizational Justice Theory and Conservation of Resources Theory

This research does not consider AM as a generic stressor, but rather draws all of the hypotheses from two strong and complementary theoretical frameworks. Organizational justice theory (Colquitt, 2001; Greenberg, 1987) suggests that employees assess the fairness of the process of decision-making on procedural (consistency, accuracy, correctability, and voice) and informational (adequacy and truthfulness of explanations) dimensions regardless of the outcomes of the decision-making. This lens is applied to the derivation of the AM → perceived injustice relationship (H1) because algorithmic decision systems themselves are a type of procedural and informational authority that is opaque and that must be evaluated by workers for its fairness (Rahman, 2021; Shin et al., 2022).

Conservation of resources (COR) theory (Hobfoll, 1989; Hobfoll et al., 2018) suggests that when a valued resource is threatened, lost, or not adequately replenished, psychological strain occurs, and people are motivated to acquire, retain, and protect valued resources. COR theory also defines the movement of resources as “resource caravans”—as a package of psychological, social and material resources that collectively represent the capacity to cope with demands (Hobfoll et al., 2018). This lens was employed to derive the perceived-injustice → outcome relationships (H2, H3) because of the internalized (exhaustion) and externalized (resistance) forms of perceived injustice, and (b) the moderating role of PsyCap (H5, H6) because of the role of PsyCap as a resource caravan that determines the extent to which a given stressor is experienced as a loss of resources. Each path from the full hypothesis set and the theoretical perspective underlying each is summarized at the end of this section in Figure 1.

2.2 Algorithmic Management and Perceived Algorithmic Injustice: An Organizational Justice Theory Lens

Through HRM, algorithms have been found to do the same functions as a human HRM which include selection, task allocation, scheduling, performance assessment, compensation, and discipline, tasks that were once the exclusive domain of human HRM (Duggan et al., 2023; Parent-Rocheleau et al., 2024). Gig workers do not generally have visibility into the criteria, weightings, and logic used to come up with algorithmic decisions (Rosenblat & Stark, 2016; Shapiro, 2018). This opacity creates what Kadolkar et al. (2025) call information, power and calculative asymmetries between platforms and workers – platforms hold detailed information about worker behaviour; workers have little feedback on or influence over the system that affects their livelihood (Cutolo & Kenney, 2021).

Algorithmic decisions are often viewed as unfair when employees are not able to understand why a rating, deactivation or fare has been assigned (informational injustice) or provide a consistently fair process to challenge (procedural injustice) (Colquitt, 2001; Rahman, 2021; Shin et al., 2022). This perception is reinforced by the constant algorithmic monitoring, which implies a constant assessment for workers, but with few indications on how this assessment is being translated into consequences (Newlands, 2021; Wood et al., 2019). We therefore anticipate that the more algorithmic monitoring, direction, evaluation and compensation-setting a worker undergoes, the more unjust the worker will feel the platform's decision processes are.

Hypothesis 1 (H1) — Organizational Justice Theory lens: Algorithmic management is positively related to gig workers' perceived algorithmic injustice.

2.3 Perceived Algorithmic Injustice and Gig Worker Outcomes: A Conservation of Resources Theory Lens

According to the COR theory, people are motivated to maintain their psychological resources and feel strained when those resources are threatened, depleted or not sufficiently replenished (Hobfoll, 1989; Hobfoll et al., 2018). Injury is exactly one of these resource-depleting stressors: When workers feel the system of where they are earning their income and how they continue to access work is arbitrary, unaccountable, they have to use some cognitive and emotional resources to make sense of, anticipate, and navigate through unpredictable algorithmic decisions (Möhlmann et al., 2023). This chronic resource drain is likely to result in emotional exhaustion (Maslach & Jackson, 1981) which is the central component of burnout, and involves feeling emotionally overextended and depleted by their work. Previous qualitative and survey research has established associations between aspects of algorithmic monitoring, opacity and asymmetries, and worker stress, helplessness and exhaustion (Cheng & Foley, 2019; Kadolkar et al., 2025; Sayre, 2023).

Hypothesis 2 (H2) — COR Theory lens: Perceived algorithmic injustice is positively related to gig workers' emotional exhaustion.

COR theory also assumes that resource loss inspires compensatory, protective action to address the loss spiral to stop or reverse it (Hobfoll et al., 2018). Workers can also try to save any remaining resources and restore a sense of control by reacting to the source of the threat. In line with Edwards' (1979) contested terrain approach, extended by Kellogg et al. (2020) and Kadolkar et al. (2025), workers who perceive the ruling algorithmic system as illegitimate and threatening to their resources try to gain back control through manipulation, subversion or disruption (Ferrari & Graham, 2021). We also assume that perceived algorithmic injustice has a positive connection to resistance behavior, which we operationalize as a set of quotidian resistance tactics (rule circumvention, strategic non-cooperation and willingness to engage in collective action) that gig workers use to challenge platform control (Bucher et al., 2021; Cameron & Rahman, 2022).

Hypothesis 3 (H3) — COR Theory lens: Perceived algorithmic injustice is positively related to gig workers' resistance behavior.

Perceived algorithmic injustice, as a first step in an organizational-justice appraisal, is followed by a second step in a COR-theoretic resource-loss process that transmits the effects of AM to both the well-being-relevant and the behavioral output domains proposed in the IPO framework of Kadolkar et al. (2025).

Hypothesis 4 (H4) — Integrated Organizational Justice / COR Theory lens: Perceived algorithmic injustice mediates the positive relationship between algorithmic management and (a) emotional exhaustion and (b) resistance behavior.

2.4 The Moderating Role of Psychological Capital: A COR Theory (Resource Caravan) Lens

Interpretation and response to AM is not the same for all workers. Psychological capital (PsyCap) is a higher order state-like resource that consists of four components: hope (goal-directed persistence and pathways thinking), efficacy (confidence in ability to succeed), resilience (capacity to bounce back from setbacks), and optimism (positive attributional style about the future) (Luthans & Youssef-Morgan, 2017). In COR theory, the idea of PsyCap is best conceptualized as a personal resource caravan that refers to those who have more resources to draw upon to appraise potentially threatening situations as manageable challenges instead of uncontrollable stressors and thus are less likely to experience resource loss spirals when confronted with an ambiguous stressor like AM (Avey et al., 2010; Hobfoll et al., 2018).

In the case of the gig context, workers with high PsyCap might be more inclined to be engaged in

active sensemaking from algorithmic outputs (Möhlmann et al., 2023), to interpret nebulous ratings or scheduling decisions favourably, and to feel good about their chances of success even in the face of a less transparent framework of evaluation (a first-stage moderation effect, in line with the logic of resource-caravan passageways, in COR theory). On the other hand, workers with low PsyCap may not have the interpretive and coping resources to deal with the ambiguity and unpredictability of AM, and are therefore likely to judge algocontrol as relatively less just.

Hypothesis 5 (H5) — COR Theory (resource caravan) lens: Psychological capital moderates the relationship between algorithmic management and perceived algorithmic injustice, such that this relationship is weaker among workers with higher psychological capital.

Further to the moderation and mediation hypothesis, we predict a moderated-mediation effect that involves the strength of the latter pathway (perceived algorithmic injustice to emotional exhaustion and resistance) moderated by the worker's PsyCap.

Hypothesis 6 (H6) — COR Theory (resource caravan) lens: The indirect effects of algorithmic management on (a) emotional exhaustion and (b) resistance behavior, through perceived algorithmic injustice, are conditional on psychological capital, such that the indirect effects are weaker among workers with higher psychological capital.

2.5 Integrated Theoretical Framework

In the following, Hypotheses 1 to 6 are combined into a single conceptual model, which is shown in Figure 1, with the theoretical perspective used to derive each path indicated. In accordance with the resource-caravan logic of COR theory, algorithmic management at Time 1 is modeled as a second order input construct predicting perceived algorithmic injustice at Time 2, which in turn is the process/mediating mechanism, which predicts emotional exhaustion and resistance behavior at Time 3 (the outputs). The controls for age, gender, tenure, platform type, and monthly income are included as these factors have been documented to be associated with attitudes and behavior of gig workers (Sessions et al., 2023).

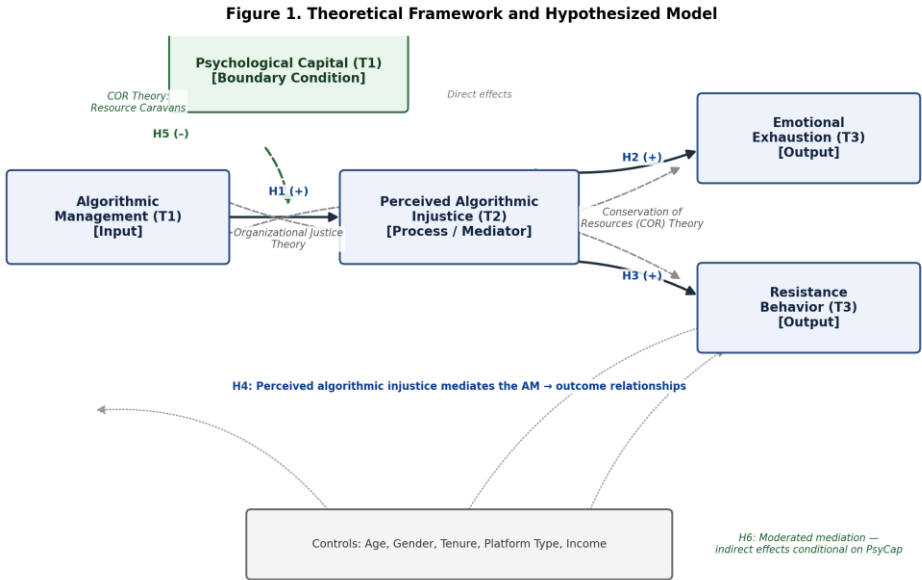


Figure 1. Theoretical framework and hypothesized model. Solid arrows denote the hypothesized

directional paths (H1–H4); the dashed arrow from Psychological Capital denotes the hypothesized first-stage moderation effect (H5–H6). Each path is labeled with its governing theoretical lens.

2 Method

3.1 Research Context

In the study, data were gathered in five urban centers, having significant platform-work activity, namely Lahore, Faisalabad, Multan, Rawalpindi and Gujranwala, in the province of Punjab, the most populated province in Pakistan. Participants were active gig workers from ride-hailing platforms (such as Careem, Uber) and food and parcel delivery platforms (such as Foodpanda, Bykea). Pakistan offers a context that is both theoretically informative for AM research, since platform work is swiftly being absorbed into the informal sector of Pakistan's employment market which is dominated by low regulation, and because collectivist, high power-distance cultural norms may lead to a different interpretation of impersonal, algorithmically mediated authority than in the contexts from where most AM theory has been developed in the West (Rani & Furrer, 2021).

3.2 Sample and Procedure

Recommendations for time-lagged organizational research (Podsakoff et al., 2003) were followed by having the study variables measured in 3 waves spaced about 3 to 4 weeks apart from one another to establish temporal precedence among the study variables and to minimize common method bias. All of the algorithmic management, psychological capital and demographic/control variables were assessed at Time 1 (T1). Measuring perceived algorithmic injustice was done at Time 2 (T2), which occurred around three weeks later. Emotional exhaustion and resistance behavior were assessed at Time 3 (T3), 3–4 weeks after that. Two independent bilingual management researchers used a translation/back-translation method to assure semantic equivalence (Brislin, 1970) to administer the surveys in a bilingual (Urdu–English) format. The respondents were selected by using a combination of convenience sampling and snowball sampling for the population that has no centralized sampling frame, gig workers at the platform's WhatsApp groups, rider and delivery hubs, and intercept sampling at fuel stations and waiting areas at food courts.

The last 4 digits of the participant's mobile number and birth month were used to create a unique matching code, which was self-generated by the participants to allow linkage across waves and to maintain the anonymity of the participants. A total of 750 questionnaires were distributed at T1 and 620 were returned (82.7% response rate) and usable. Of these, 512 respondents returned for the T2 survey (82.6% retention), and 438 of those respondents returned for the T3 survey (85.5% retention) resulting in a final matched, three-wave sample of 438 (70.6% of the original T1 sample). No differences were found between the T1 age, gender, platform type, or T1 study variables between respondents who completed all three waves and those who did not (all $ps > .10$), so it is unlikely that attrition is biasing results.

The final sample consisted mainly of males (93.6%) and the mean age was 28.4 years ($SD = 6.1$), similar to the gender balance and age distribution of the platform workforce in Pakistan. As far as education is concerned, 21.0% completed the matriculation or lower level of education, 34.0% completed intermediate level education, 32.0% completed the bachelor's level education and 13.0% completed the master's level education. With respect to the platform type, 44.7% mainly worked in ride-hailing and 55.3% mainly worked in food or parcels delivery. The mean time on the platform was 15.2 months ($SD = 9.8$). The respondents were spread across Lahore (38%), Faisalabad (19%), Multan (16%), Rawalpindi (15%) and Gujranwala (12%).

3.3 Measures

All items used a five-point Likert-type response scale (1 = strongly disagree, 5 = strongly agree) unless otherwise noted. Once more, the scales were adapted to the context of gig-work by replacing the terms 'supervisor' or 'organization' with 'the app' or 'the platform' as in previous algorithmic-management investigations (Cram et al., 2022; Zhang et al., 2023).

3.3.1 Algorithmic Management (Time 1)

Algorithmic management was assessed by the Parent-Rocheleau et al. (2024) developed and validated Algorithmic Management Questionnaire (AMQ), consisting of five higher-order dimensions (Higher-order AM construct modeling, Type II) of the first-order dimensions (Higher-order construct modeling, Type I): monitoring (4 items), goal setting (5 items), scheduling (4 items), performance rating (3 items), and compensation (4 items). Examples of sample items: An automated system tracks me carefully to make sure that I do the right tasks, my daily tasks are determined by an automated system, an automated system decides when I work and when I don't, the way I am evaluated for my work is through an electronic system, a large portion of my compensation is tied to an automated system. The internal consistency at T1 for the overall scale was .91.

3.3.2 Perceived Algorithmic Injustice (Time 2)

To examine algorithmic injustice, eight items were adapted from Colquitt's (2001) procedural and informational justice subscale items, which were recently used to rephrase organizational justice items related to algorithmic decision-making in the platform (Shin et al., 2022). The reverse wording was used to elicit a sense of injustice directly (e.g., "The app's decisions about my ratings and earnings are not applied consistently," "The app doesn't provide explanations about what it decides, I have no way of finding out why the app made a particular decision about me"). Scores were higher the more the respondents felt the injustice. Cronbach's alpha was .89.

3.3.3 Psychological Capital (Time 1)

The original PCQ (Luthans et al., 2000) was shortened to 12 items, the Psychological Capital Questionnaire (PCQ-12; Avey et al., 2010); the three items for each of the four psychological capital constructs were: hope (e.g., "Right now I see myself as being pretty successful at my gig work"), efficacy (e.g., "I can think of many ways to reach my current income goals"), resilience (e.g., "Over the past few years, I have faced a lot of setbacks and frustrations but I eventually overcame them"), and optimism (e.g., "In the past few years, I have had a lot of setbacks and frustrations, but I'm getting through."). Following previous PsyCap research which conceptualized the construct as a higher-order psychological resource (Luthans & Youssef-Morgan, 2017), the items were collapsed into a single composite PsyCap score. Cronbach's alpha was .90.

3.3.4 Emotional Exhaustion (Time 3)

Emotional exhaustion was assessed using the 5-item emotional exhaustion subscale of the Maslach Burnout Inventory (Maslach & Jackson, 1981, e.g., "I feel emotionally drained from my work on the platform," "Working on this app all day is really a strain for me"). Cronbach's alpha was .88.

3.3.5 Resistance Behavior (Time 3)

The resistance behavior was assessed using a six-item scale created for this research, which is based on the qualitative typology of gig-worker resistance tactics (manipulation, subversion, and disruption) identified by Ferrari and Graham (2021) and Cameron and Rahman (2022). Responses range from "I purposely act in ways that the algorithm does not know about to protect my interests" to "I have deliberately refused or withdrawn from jobs I was assigned by the app" to "I have thought about joining other gig workers to challenge platform rules." Cronbach's alpha was .85.

3.4 Control Variables

Prior gig-economy research found that age (years), gender (0 = female, 1 = male), organizational tenure (months on the platform), platform type (0 = delivery, 1 = ride-hailing), and monthly income (Pakistani rupees, log transformed) were associated with attitudes and behaviors of workers (Sessions et al., 2023), and were therefore included as controls in all structural models.

3.5 Common Method Bias

This three-wave temporal separation of predictor, mediator, and outcome variables was the major procedural solution to common method bias (CMBI) of the Podsakoff et al. (2003) study. Furthermore, all the substantive items loaded on one test (Harman's single factor test) explained only 31.4% of the total variance, which is below the usual 50% criterion of concern. A full collinearity test based on variance inflation factors (VIFs) from a full collinearity assessment of PLS-SEM (Kock, 2015) showed a maximum VIF of 2.41, which is below the conservative limit of 3.3, indicating that the associations found were not likely due to common method bias.

3.6 Analytical Strategy

For the analysis of the data, variance-based structural equation modeling (SEM) was employed using the software of SmartPLS 4 (Hair et al., 2019; Ringle et al., 2022) with a two-step analysis approach, which is assessment of measurement model followed by assessment of structural model. The second-order, reflective-formative approach to operationalizing algorithmic management was employed and PLS-SEM was chosen as it can handle such second-order constructs, is well suited for the rather moderate complexity of the nomological network investigated, and is suitable for the rather moderate size of the sample and the rather non-normal distribution of the items, which is typical for a field study in an under-researched group such as informal-sector workers (Hair et al., 2019). The significance of path coefficients and indirect effects were evaluated using bias-corrected and accelerated (BCa) 95% confidence intervals and bootstrapping with 5,000 subsamples.

Three additional procedures were performed to enhance the rigor of structural analysis, in addition to the conventional fit indices of the in-sample models. First, the full heterotrait–monotrait ratio (HTMT) matrix was used to assess discriminant validity instead of just a single summary statistic (Henseler et al., 2015). Second, out-of-sample predictive power was tested using the PLSpredict k-fold cross validation procedure, which was compared to an out-of-sample naive linear-model (LM) predictive power benchmark for each indicator of the key endogenous constructs (Shmueli et al., 2019). Third, an importance-performance map analysis (IPMA) was used to gain action-oriented diagnostic insights beyond the standardized path coefficients (Ringle & Sarstedt, 2016) by analyzing the five first-order AM dimensions to identify which specific AM dimension has the largest total effect (“importance”) on the perceived degree of algorithmic injustice, given its average performance score.

To complement this variable-centered analysis, we also created a moderated-mediation model using the PROCESS macro (Version 4.2) for SPSS (Model 7, Hayes, 2013) as a robustness check and estimated a first-stage moderated mediation model in which the moderator (PsyCap) moderates the relationship between the predictor (AM) and the mediator (perceived algorithmic injustice). A total of 10,000 bootstrap resamples were generated and 95% confidence intervals were created for the moderated-mediation model's index (Preacher et al., 2007). A two-part analytical approach, first using PLS-SEM for the full measurement and structural model of the proposed model, and second, using PROCESS for a focused, regression-based test of the conditional indirect effects, follows recommended practice by Hayes (2013) to triangulate moderated-mediation hypotheses in organizational research.

4. Results

4.1 Descriptive Statistics and Correlations

Table 1 presents sample demographic characteristics, and Table 2 presents means, standard deviations, reliability coefficients, and zero-order correlations among study variables. Algorithmic management was positively correlated with perceived algorithmic injustice ($r = .46, p < .001$), which was in turn positively correlated with emotional exhaustion ($r = .41, p < .001$) and resistance behavior ($r = .36, p < .001$). Psychological capital was negatively correlated with perceived algorithmic injustice ($r = -.33, p < .001$), emotional exhaustion ($r = -.38, p < .001$), and resistance behavior ($r = -.24, p < .001$), consistent with its hypothesized buffering role.

Table 1. Sample Demographic Profile

Variable	n	%
Gender: Male	410	93.6
Gender: Female	28	6.4
Platform: Ride-hailing	196	44.7
Platform: Delivery	242	55.3
Education: Matric or below	92	21.0
Education: Intermediate	149	34.0
Education: Bachelor's	140	32.0
Education: Master's	57	13.0
City: Lahore	166	38
City: Faisalabad	83	19
City: Multan	70	16
City: Rawalpindi	66	15
City: Gujranwala	53	12

Table 1. Sample Demographic Profile (N = 438). Note: Mean age = 28.4 years (SD = 6.1); mean platform tenure = 15.2 months (SD = 9.8).

Table 2. Descriptive Statistic

Variable	M	SD	α	1	2	3	4
1. Algorithmic management (T1)	3.71	0.68	.91	—			
2. Psychological capital (T1)	3.42	0.61	.90	-.09	—		
3. Perceived injustice (T2)	3.29	0.74	.89	.46**	-.33**	—	
4. Emotional exhaustion (T3)	3.18	0.79	.88	.33**	-.38**	.41**	—
5. Resistance behavior (T3)	2.96	0.83	.85	.29**	-.24**	.36**	.31**

Table 2. Descriptive Statistics, Reliabilities, and Zero-Order Correlations. Note: N = 438. T1 = Time 1, T2 = Time 2, T3 = Time 3. ** p < .01.

4.2 Measurement Model Assessment

Consistent with recommended criteria for reflective measurement models (Fornell & Larcker, 1981; Hair et al., 2019), all indicator outer loadings exceeded the .70 threshold (range = .71 to .90), composite reliability (CR) values ranged from .86 to .93, and average variance extracted (AVE) values ranged from .55 to .68, jointly supporting item reliability and convergent validity (Table 3).

Table 3. Measurement Model Summary

Construct	Items	Loading range	CR	AVE
Algorithmic management (2nd-order)	20	.71–.88	.93	.58
Perceived algorithmic injustice	8	.74–.87	.92	.62
Psychological capital	12	.72–.90	.93	.57
Emotional exhaustion	5	.76–.89	.91	.68
Resistance behavior	6	.71–.83	.86	.55

Table 3. Measurement Model Summary: Loadings, Composite Reliability, and Average Variance Extracted.

Discriminant validity was assessed using the full heterotrait–monotrait ratio of correlations (HTMT) matrix (Henseler et al., 2015) rather than relying on a single omnibus statistic. As shown in Table 4, all HTMT values fell below the conservative .85 threshold (range = .29 to .61), and the upper bound of each corresponding bootstrapped 95% confidence interval also excluded 1, jointly indicating that the five latent constructs were empirically distinct.

Table 4. Heterotrait–Monotrait Ratio

Construct	1	2	3	4
1. Algorithmic management	—			
2. Psychological capital	.12	—		
3. Perceived algorithmic injustice	.52	.37	—	
4. Emotional exhaustion	.38	.43	.47	—
5. Resistance behavior	.33	.29	.61	.35

Table 4. Heterotrait–Monotrait Ratio (HTMT) Matrix. Note: All values below the .85 threshold; 95% bootstrapped confidence intervals (5,000 resamples) for all values excluded 1.

Because algorithmic management was modeled as a second-order construct in which the five first-order dimensions (monitoring, goal setting, scheduling, performance rating, compensation) index a common higher-order factor, we additionally examined the outer weights and collinearity statistics of these dimensions using the repeated-indicators approach with a Type II (reflective-formative) specification, consistent with recommended higher-order construct validation procedures (Hair et al., 2019). As shown in Table 5, all five dimensions contributed significant, substantial weights to the higher-order AM construct, and outer VIF values for the five dimensions were well below the collinearity threshold of 3.3, indicating that the dimensions capture distinct facets of algorithmic management rather than redundant information.

Table 5. Outer Weights and Collinearity Statistics

First-order dimension	Outer weight	t-value	Outer VIF
Monitoring	.24***	6.85	1.78
Goal setting	.22***	6.11	1.85
Scheduling	.19***	5.34	1.71
Performance rating	.27***	7.42	2.02
Compensation	.18***	4.96	1.66

Table 5. Outer Weights and Collinearity Statistics for the Second-Order Algorithmic Management Construct. Note: *** $p < .001$. Estimated via the repeated-indicators, two-stage approach with 5,000 bootstrap resamples.

4.3 Structural Model Assessment and Predictive Validity

The structural model was assessed for explanatory power (R^2), predictive relevance (Q^2 , via blindfolding with omission distance = 7), and effect size (f^2). Algorithmic management explained 29% of the variance in perceived algorithmic injustice ($R^2 = .29$), which in turn, together with control variables, explained 34% of the variance in emotional exhaustion ($R^2 = .34$) and 27% of the variance in resistance behavior ($R^2 = .27$). Q^2 values for perceived algorithmic injustice (.19), emotional exhaustion (.22), and resistance behavior (.17) were all greater than zero, confirming the model's in-sample predictive relevance. As hypothesized, algorithmic management was positively related to perceived algorithmic injustice ($\beta = .42$, $t = 8.71$, $p < .001$, $f^2 = .24$), supporting H1. Perceived algorithmic injustice was positively related to emotional exhaustion ($\beta = .38$, $t = 7.02$, $p < .001$, $f^2 = .19$), supporting H2, and to resistance behavior ($\beta = .31$, $t = 5.66$, $p < .001$, $f^2 = .13$), supporting H3. The direct effect of algorithmic management on emotional exhaustion, controlling for perceived injustice, was small and non-significant ($\beta = .11$, $t = 1.84$, $p = .066$), consistent with full mediation, whereas the direct effect of algorithmic management on resistance behavior remained significant ($\beta = .14$, $t = 2.21$, $p = .027$), consistent with partial mediation. Figure 2 displays the fully estimated structural model, including the second-order measurement structure, standardized path coefficients, and R^2/Q^2 values for each endogenous construct.

Figure 2. Estimated Structural Model with Standardized Path Coefficients (PLS-SEM)

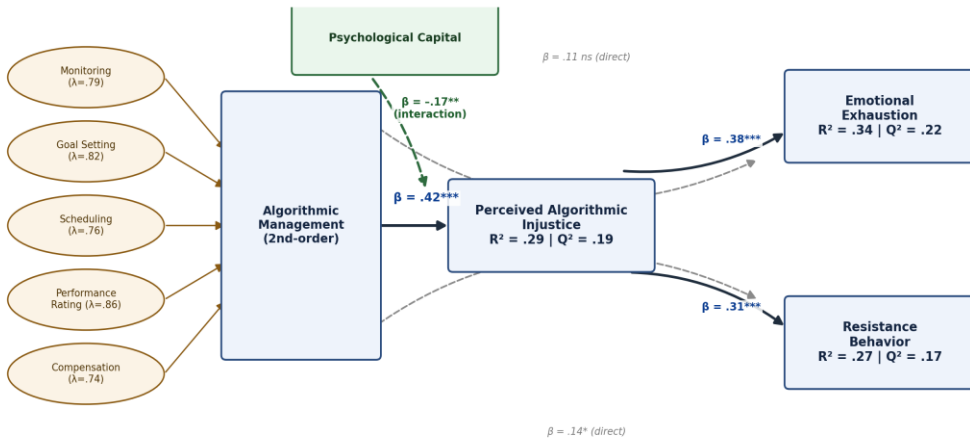


Figure 2. Estimated structural model with standardized path coefficients, R^2 , and Q^2 values (SmartPLS 4, bootstrapping with 5,000 subsamples). Dashed arrows represent non-hypothesized direct effects reported for transparency; *** p < .001, ** p < .01, * p < .05, ns = not significant.

Table 6. PLS-SEM Structural Path

Path	β	SE	t	p	f^2
AM $\rightarrow$ Perceived injustice (H1)	.42	.048	8.71	<.001	.24
Perceived injustice $\rightarrow$ Emotional exhaustion (H2)	.38	.054	7.02	<.001	.19
Perceived injustice $\rightarrow$ Resistance (H3)	.31	.055	5.66	<.001	.13
AM $\rightarrow$ Emotional exhaustion (direct)	.11	.060	1.84	.066	.02
AM $\rightarrow$ Resistance (direct)	.14	.063	2.21	.027	.03
AM $\times$ PsyCap $\rightarrow$ Perceived injustice (H5)	-.17	.056	3.02	.003	.05

Table 6. PLS-SEM Structural Path Results (Bootstrapping, 5,000 Subsamples). Note: AM = algorithmic management; PsyCap = psychological capital. Control variables (age, gender, tenure, platform type, income) included but omitted from table for brevity.

To move beyond in-sample fit and evaluate the model's out-of-sample predictive power, we conducted PLSpredict with 10 folds and 10 repetitions (Shmueli et al., 2019). As shown in Table 7, the PLS-SEM root mean squared error (RMSE) was lower than the naive linear-model (LM) benchmark for the majority of indicators of perceived algorithmic injustice, emotional exhaustion, and resistance behavior, and Q^2 predict values were positive for all indicators, jointly indicating that the model possesses medium-to-high predictive power in the sense defined by Shmueli et al. (2019) rather than merely describing in-sample covariation.

Table 7. PLSpredict Out-of-Sample Predictive Assessment

Construct	PLS (mean)	RMSE LM (mean)	RMSE Q ² predict (mean)
Perceived algorithmic injustice	0.663	0.681	.192
Emotional exhaustion	0.681	0.699	.217
Resistance behavior	0.732	0.741	.164

Table 7. PLSpredict Out-of-Sample Predictive Assessment (10-Fold Cross-Validation, 10 Repetitions). Note: Lower PLS RMSE than LM RMSE across the majority of manifest indicators, together with positive Q²predict values, indicates medium predictive power (Shmueli et al., 2019).

Finally, an importance-performance map analysis (IPMA) was conducted to identify which of the five AM dimensions most strongly drives perceived algorithmic injustice, information that standardized path coefficients alone do not convey (Ringle & Sarstedt, 2016). As shown in Table 8, performance rating exhibited both the highest total-effect importance (.31) and a comparatively high average performance score (68.4 on a 0–100 rescaled metric), identifying it as the AM dimension most in need of managerial attention, followed closely by monitoring. Compensation, although less important in relative terms, had the lowest performance score, suggesting it as a secondary priority for platform intervention.

Table 8. Importance-Performance Map Analysis

AM dimension	Importance (total effect)	Performance (0–100)
Monitoring	.29	71.2
Goal setting	.26	69.8
Scheduling	.22	66.5
Performance rating	.31	68.4
Compensation	.21	61.7

Table 8. Importance-Performance Map Analysis (IPMA) of Algorithmic Management Dimensions on Perceived Algorithmic Injustice.

4.4 Mediation Analysis

Bias-corrected and accelerated (BCa) bootstrapped confidence intervals (5,000 resamples) were used to test the indirect effects specified in H4. The indirect effect of algorithmic management on emotional exhaustion through perceived algorithmic injustice was significant (indirect effect = .160, SE = .028, 95% CI [.111, .222]), supporting H4a. The indirect effect of algorithmic management on resistance behavior through perceived algorithmic injustice was likewise significant (indirect effect = .130, SE = .027, 95% CI [.081, .189]), supporting H4b. Because the confidence intervals did not include zero, and because the direct effect of algorithmic management on emotional exhaustion was non-significant while the corresponding direct effect on resistance remained significant, the pattern of results is consistent with full mediation for emotional exhaustion and partial mediation for resistance behavior (Hair et al., 2019).

4.5 Moderation and Moderated Mediation

Consistent with H5, the interaction between algorithmic management and psychological capital significantly predicted perceived algorithmic injustice in the PLS-SEM model ($\beta = -.17$, $t = 3.02$,

$p = .003$). A simple slopes analysis (± 1 SD) indicated that the positive relationship between algorithmic management and perceived injustice was stronger among workers with low PsyCap (simple slope = .55, $t = 8.14$, $p < .001$) than among workers with high PsyCap (simple slope = .27, $t = 3.62$, $p < .001$), although the relationship remained significant at both levels, indicating that PsyCap attenuates rather than eliminates the effect of AM on perceived injustice. Figure 3 plots this interaction.

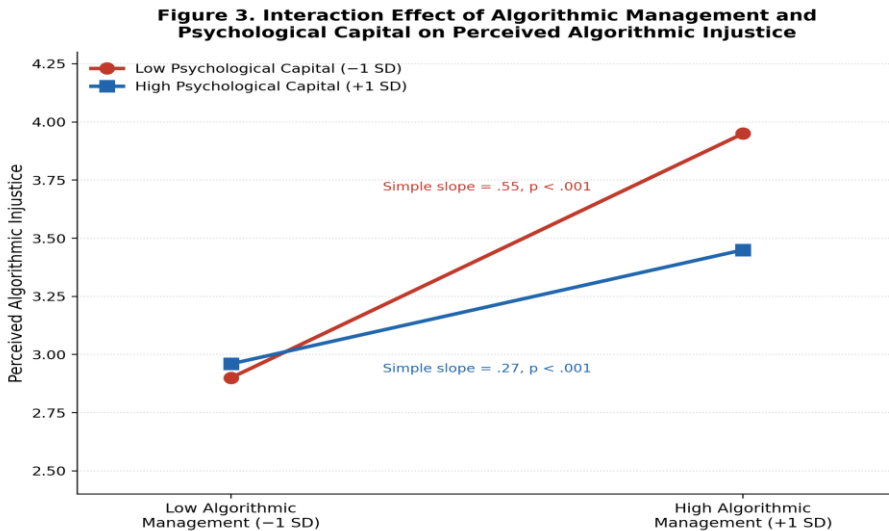


Figure 3. Interaction effect of algorithmic management and psychological capital on perceived algorithmic injustice. Simple slopes are plotted at ± 1 SD of psychological capital.

To formally test the moderated-mediation hypothesis (H6) and to triangulate the PLS-SEM findings with an independent analytic approach, the model was re-estimated in SPSS using Hayes's (2013) PROCESS macro (Model 7), specifying algorithmic management as predictor, psychological capital as first-stage moderator, perceived algorithmic injustice as mediator, and emotional exhaustion and resistance behavior as outcomes (estimated in separate runs), with 10,000 bootstrap resamples. The index of moderated mediation was negative and significant for both outcomes: emotional exhaustion (index = $-.061$, boot SE = $.019$, 95% CI $[-.102, -.026]$) and resistance behavior (index = $-.049$, boot SE = $.018$, 95% CI $[-.089, -.015]$). Conditional indirect effects, evaluated at low (-1 SD), mean, and high ($+1$ SD) levels of PsyCap, are reported in Table 9 and confirm that the indirect effect of algorithmic management on both outcomes, via perceived algorithmic injustice, weakened monotonically as PsyCap increased, providing convergent support for H6 across both analytic platforms.

Table 9. Conditional Indirect Effects

Outcome / PsyCap level	Indirect effect	Boot SE	95% CI (BCa)
Emotional exhaustion – Low PsyCap (-1 SD)	.223	.037	[.156, .301]
Emotional exhaustion – Mean PsyCap	.162	.029	[.109, .221]
Emotional exhaustion – High PsyCap ($+1$ SD)	.101	.027	[.052, .156]

Resistance behavior	–	Low	.186	.034	[.124, .258]
PsyCap (–1 SD)					
Resistance behavior	–	Mean	.137	.026	[.089, .191]
PsyCap					
Resistance behavior	–	High	.088	.025	[.043, .140]
PsyCap (+1 SD)					

Table 9. Conditional Indirect Effects of Algorithmic Management on Outcomes via Perceived Algorithmic Injustice at Values of Psychological Capital (PROCESS Model 7, 10,000 Bootstrap Resamples). Note: PsyCap = psychological capital; BCa = bias-corrected and accelerated. All confidence intervals exclude zero.

4.6 Summary of Hypothesis Testing

Table 10 summarizes the theoretical lens, statistical test, and decision for each of the six hypotheses. All hypotheses received empirical support, and the PLS-SEM and PROCESS results converged on a consistent substantive pattern.

Hypothesis	Theoretical lens	Path / test	Result	Decision
H1	Organizational Justice Theory	AM → Perceived injustice	$\beta=.42, p<.001$	Supported
H2	COR Theory	Perceived injustice → Exhaustion	$\beta=.38, p<.001$	Supported
H3	COR Theory	Perceived injustice → Resistance	$\beta=.31, p<.001$	Supported
H4a	Justice / (integrated) COR	AM → Injustice → Exhaustion	Indirect=.160, CI excl. 0	Supported
H4b	Justice / (integrated) COR	AM → Injustice → Resistance	Indirect=.130, CI excl. 0	Supported
H5	COR Theory (resource caravan)	AM × PsyCap → Injustice	$\beta=-.17, p=.003$	Supported
H6a	COR Theory (resource caravan)	Moderated mediation → Exhaustion	Index=-.061, CI excl. 0	Supported
H6b	COR Theory (resource caravan)	Moderated mediation → Resistance	Index=-.049, CI excl. 0	Supported

5. Discussion

5.1 Theoretical Implications

This study makes various contributions to the literature on algorithms for trading. First, it is a direct reaction to the recent call to go beyond fragmented and largely atheoretical description of AM to theory-driven, quantifiable testing of the mechanisms that connect AM to worker outcomes, which Kadolkar et al. (2025) refer to as the “black box of AM.” This study shows that the AM → outcome pathway is more than a single pathway of empirical associations; it is a potentially two-stage process: a justice-appraisal process of how AM translates into perceived injustice, and a resource-loss process of how perceived injustice translates into strain and resistance.

Second, our finding of psychological capital as a buffer but not as a barrier to the relation between AM and perceived injustice brings into the algorithmic-management realm the concept of psychological resource caravans, which has been explored in previous studies primarily from a structural or platform perspective, rather than the worker perspective, as in previous studies (e.g., Liang et al., 2023). This means that the effects of AM cannot be predicted, and are influenced by the algorithmic system and by the psychological resources that employees bring to their interactions with the system.

Third, this research focuses on the local context of Punjab, Pakistan, a region in which the majority of quantitative AM research has been conducted has been where AM has been studied. Third, the study is set in a setting quite different from the North American and European environments where most quantitative AM research has been carried out (Rani & Furrer, 2021). The relatively strong and consistent effect found here, even though the culture of Pakistan is characterized by high power distance, which is thought to make workers more prone to accepting hierarchical authority (Hofstede, 2001), indicates that the sense of illegitimacy towards impersonal, non-human authority of algorithms might be a more general cross-cultural phenomenon than one that is exclusively tied to individualist contexts in the West. This is broadly aligned with the perspective that algorithmic control is not just superior to traditional, bureaucratic control, but that it is of a different nature (Kellogg et al., 2020; Rahman, 2021).

Lastly, the time-lagged, three-wave design, along with the added rigor attained by HTMT-based discriminant validity assessment, formative-indicator validation of the second-order AM construct, PLSpredict out-of-sample testing, and IPMA diagnostics deal with the acknowledged methodological flaws in the AM literature, where cross-sectional, single-source survey designs and purely in-sample fit statistics dominate (Cropanzano et al., 2023). Because the results of PLS-SEM and PROCESS-based moderated-mediation corroborate each other, the directionality and robustness of the hypothesized pathways are strengthened, which is greater than what could be achieved by a single-wave, single-method design.

5.2 Practical Implications

From an operator perspective, the results from the AM dimensions of IPMA show that performance rating and monitoring are most strongly associated with perceived injustice, highlighting the need for interventions that make these two functions more transparent – an approach in line with the concept of “responsible AI” for designing platforms (Kadolkar et al., 2025; Liang et al., 2023). The results also indicate that the negative effects of AM travel primarily via workers' perceptions of fairness, not by the control itself; the availability of grievance and appeal systems would directly tackle the procedural and informational justice concerns found as central to workers' perceptions of injustice in this study.

The findings highlight the pressing need for policymakers in Pakistan and more specifically in Punjab to establish regulatory measures that tackle algorithmic opacity and informational and power imbalances in platform work, which are not yet well regulated in Pakistan, but have been in some other countries that have acted to provide greater transparency about algorithms and the rights of workers to access their data (Kadolkar et al., 2025; Ulbricht & Yeung, 2022). In the context of the un/under-employment among youth in urban areas that currently absorbs the gig work in Punjab, the youth of the province are significant beneficiaries of policy interventions addressing platform accountability.

Given the buffering effect of psychological capital, it is important to note that interventions to enhance hope, efficacy, resilience, and optimism via peer-support networks, financial education and goal setting training, or brief PsyCap-development sessions, such as those proven in other work contexts (Luthans & Youssef-Morgan, 2017), could help workers cope with the psychological strains of algorithmically-managed work, even when structural changes to the

platform are still to come.

5.3 Limitations and Future Research

These findings should be interpreted with a few caveats and suggest areas for further inquiry. First, while three wave design is an improvement on cross-sectional AM studies, it does not allow for strong causal inferences, whereas an experiment or quasi-experiment manipulating algorithmic transparency, as suggested by Kadolkar et al. (2025), would yield stronger causal evidence. Second, the sample was selected through convenient and snowball sampling methods suitable for a population which does not have a central sampling frame, which may restrict the generalizability of the findings to the larger population of gig workers in Pakistan; future studies could reach the platforms directly for data collection to get more representative samples. Third, this work was conducted on a fairly male-dominated sample, which is consistent with the current gender balance of Pakistan's gig market, suggesting that research should explore if the processes identified here apply to women as well, in light of evidence of algorithmic gender discrimination in other platform work settings (Greenwood et al., 2022). Fourth, this study focused on the two outcome variables, future research could build on this outcome domain to incorporate task performance, turnover intentions, and collective organizing as is proposed in the outcome agenda by Kadolkar et al. (2025). To conclude, it is recommended that further research consider other boundary conditions found in recent reviews, such as platform type, national culture, and the transparency of the platforms' monitoring, as well as the feedback mechanism that the resistance of workers triggers over time in the development of platforms' algorithms (Meijerink & Bondarouk, 2023).

5.4 Conclusion

The study examined a time-lagged, moderated-mediation model of algorithmic management for ride-hailing and delivery gig workers in the province of Punjab, Pakistan, which included all hypothesized relationships drawn from two theoretical frameworks: organisational justice theory and conservation of resources theory. The relationship between algorithmic management and perceived injustice in turn was predicted by increased emotional exhaustion and resistance behavior, and psychological capital, as a resource caravan in the COR framework, was a significant buffer of this relationship, buffering its downstream consequences. The results of this study, which included rigorous PLS-SEM analysis (HTMT discriminant validity, higher-order construct in formative mode analysis, PLSpredict out-of-sample testing, and importance-performance mapping) and PROCESS-based moderated-mediation analysis, were theory-grounded and quantitative to support the proposed process mechanisms in recent systematic reviews of the algorithmic management literature and to extend the research literature to an important, under-researched emerging gig economy. Understanding the psychological mechanisms and individual resources that influence the experience of algorithmic authority in platform-based and traditional organizations will continue to be a pivotal challenge for organizational behavior scholarship as algorithmic management continues to be a growing phenomenon.

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