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Enhancing Work Engagement in the Gig Economy: Evidence from Platform Workers

Yue Wen ^{1,*}, Benfu Lv ¹ and Jie Liu ²

¹ School of Economics and Management, University of Chinese Academy of Sciences, Beijing 101408, China; lubf@mailsucas.ac.cn

² School of political and economic management, Guizhou Minzu University, Guiyang 550004, China; 201301044@gzmu.edu.cn

* Correspondence: wenyue20@mailsucas.ac.cn

Abstract

Work engagement is pivotal for service quality and the long-term viability of platform businesses, yet its micro-level drivers remain insufficiently understood in algorithmically managed gig work. Drawing on self-regulation, social exchange, organizational justice, and algorithmic governance perspectives, this study develops an integrative framework linking workers' self-management, perceived organizational support, organizational justice, and perceived algorithmic control to work engagement. We surveyed 292 platform-based gig workers in China using an online questionnaire. Hierarchical regressions and robustness checks using structural equation models show that all four antecedents are positively associated with engagement; when considered jointly, perceived algorithmic control, organizational support, and organizational justice remain significant, whereas the incremental association of self-management becomes weaker. Facet-level analyses further indicate that self-improvement is the key self-management mechanism; supervisor, coworker, and climate support all contribute; distributive, procedural, and interactional justice are all positively associated; and the algorithmic process and outcome control matter more than perceived task discretion. The findings highlight actionable levers for social sustainability and decent work in the platform economy, including strengthening developmental opportunities, institutionalizing fair and contestable governance, and improving the transparency and predictability of algorithmic decisions.

Keywords: gig economy; platform work; employee engagement; algorithmic control



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1. Introduction

Over the past decade, the diffusion of digital platforms has reshaped labor markets and accelerated the expansion of the gig economy across the service and logistics industries [1]. Platform-mediated work—such as food delivery, ride-hailing, and on-demand household services—operates through online-to-offline (O2O) infrastructures that enable real-time information exchange, commercial intermediation, and algorithm-supported matching between consumers and service providers [2]. By lowering transaction costs and market-entry barriers, these platforms have enabled startups to scale rapidly and have introduced new forms of value creation in the digital economy [3]. At the same time, platform work is commonly categorized as non-standard employment: tasks are fragmented; compensation is often piece-rate, and work is organized through short-term, flexible arrangements that differ markedly from conventional employer–employee relations.

This transformation has been especially visible in China, where a large and heterogeneous gig workforce has emerged alongside the rapid expansion of platform-based services [4]. Blue-collar gig workers constitute a substantial share of the labor supply and frequently move across different platforms and application scenarios, reflecting both the inclusiveness of gig work and the fluidity of employment ties in the platform economy [5]. Workers' motivations are diverse—ranging from transitional employment and skill development to schedule flexibility and income supplementation—and vary across age and occupational groups. The gig economy spans a broad range of jobs, including traditional blue-collar sectors (e.g., services, manufacturing, and construction) and “new blue-collar” occupations enabled by platformization (e.g., delivery riders, couriers, and ride-hailing drivers). Industry reports further indicate that China's gig economy market and the digital gig platform market expanded rapidly between 2019 and 2023, while global forecasts suggest sustained growth and increasing economic significance of the gig sector.

Despite its contribution to labor market flexibility and service accessibility, the gig economy has raised pressing questions about social sustainability and worker welfare. Compared with standard employment, gig workers often face income volatility, irregular and extended working hours, occupational safety risks, limited access to benefits and insurance, and weaker social protection, which may heighten psychosocial strain and undermine long-term well-being [6]. Moreover, platform governance, particularly algorithmic management, can intensify perceived uncertainty by shaping task allocation, evaluation, pricing, and performance monitoring in ways that are not always transparent to workers. These challenges resonate with sustainability-oriented concerns such as “decent work”, inclusive labor markets, and the resilience of employment ecosystems, calling for evidence-based approaches that improve working conditions without compromising platform efficiency and service quality.

Within this context, work engagement is a pivotal yet under-examined factor for the sustainable development of gig platforms. Higher engagement is closely associated with service quality, reliability, customer satisfaction, and operational performance, whereas unstable engagement may amplify turnover intentions, reduce service consistency, and increase governance and training costs for platforms [7]. However, compared with traditional employees, gig workers' engagement is often more volatile due to task uncertainty, multi-platform participation, weaker organizational attachment, and perceived insecurity. Existing research has predominantly emphasized macro-level trends, legal classification, and regulatory debates, while comparatively less is known about the micro-level mechanisms shaping gig workers' engagement—particularly under algorithmic governance and welfare-constrained working conditions [8].

To address this gap, the present study makes three contributions. First, it shifts the analytical lens from “whether gig work is flexible” to “how engagement is sustained” and theorizes work engagement in platform-mediated labor as a social sustainability issue linked to decent work, worker well-being, and the resilience of employment ecosystems. Second, it integrates organizational behavior and platform governance perspectives by examining how workers' self-regulation in highly autonomous work, perceived organizational support and fairness, and perceived algorithmic control jointly shape engagement, thereby extending engagement research from conventional organizational settings to algorithmically managed labor relations. Third, using survey-based empirical analysis, we test an integrative explanatory model and translate the results into actionable recommendations, including enhancing transparency and contestability of algorithmic decisions, improving support systems and communication channels, strengthening procedural fairness in task allocation and performance evaluation, and exploring protection mechanisms that reduce income and safety risks. By connecting engagement outcomes with both platform per-

formance and worker welfare, this research offers a practical pathway for platforms and policymakers to improve service sustainability while promoting more inclusive and decent forms of work in the platform economy.

2. Literature Review and Hypothesis Development

2.1. Gig Economy and Platform-Based Gig Work

As an emerging labor market arrangement, the management of gig platform workers has attracted increasing scholarly attention. Researchers across countries have examined this form of employment from multiple perspectives, thereby establishing a robust theoretical foundation for understanding the gig economy and accumulating substantial practice-oriented evidence [9]. From a human resource perspective, flexible employment can be conceptualized in both broad and narrow terms. Friedman (2014) defines the gig economy broadly as an “online + offline” ecosystem grounded in two-sided matching, in which a large number of independent and flexible workers deliver services through digital intermediation [3]. Wang Jiabao and Cui Xiaoxuan (2018) analyze future trends in human resource management and argue that the gig economy will drive HRM toward greater flexibility and digitalization [10]. With respect to performance management, the study by Lehdonvirta (2018) offers a distinctive contribution by examining electronic work supervision mechanisms on online labor platforms and assessing their effects on individual workers’ engagement in long-term collaborative innovation, thereby providing new implications for performance management among gig workers [11]. This line of inquiry complements the research by Wei Wei and Feng Xiliang (2020) [12] on the psychological contract of platform-based ride-hailing workers in digital platform firms. Specifically, Yundian and Daolin (2022) not only investigate the content and measurement of the psychological contract, but also identify latent categories and group differences, offering a theoretical basis for individualized management of gig workers [13].

Mulcahy D (2017) argues that the apparent autonomy associated with gig work often conceals implicit control exerted through platform algorithms [14]. Similarly, Yan Yujun and Gong Xiaoying (2022) examine the impacts of algorithmic management on gig workers, noting that while such management may enhance efficiency, it can also increase workers’ alienation and psychological strain [15]. Consistent with these arguments, Tu Yongqian (2021) analyze the mechanism through which platform algorithmic control influences gig workers’ turnover intention, highlighting the far-reaching behavioral implications of technology-enabled management [16]. Using food delivery couriers as an empirical context, Bucher E L et al. (2021) further investigate the determinants and effects of gig workers’ algorithm perceptions, providing evidence for understanding worker–technology interactions in platform-mediated work [17]. Pei Jialiang et al. (2021) examine the effects of algorithmic management on gig platform workers and demonstrate how technology shapes work processes and employment relations [18]. From a more macro-level perspective, Chen Wanming et al. (2024) analyze the role of platforms in the gig economy and how they affect gig workers and the broader economy, offering important insights into the systemic functioning of the gig economy [19]. In a related vein, Lay-Raby et al. (2025) assess workers’ job autonomy in the gig economy—covering work status, job content, and working conditions—thereby deepening understanding of gig workers’ employment situations [20]. Yu Shengxian et al. (2024), drawing on an organizational behavior perspective, investigate how work identity is constructed in the gig economy, providing an additional lens for interpreting gig workers’ psychological states and behavioral motivations [21].

Overall, this body of research addresses multiple dimensions of gig platform worker management, including labor rights protection, the identification of employment relationships, and algorithmic management. Collectively, these studies are complementary and

contribute to a comprehensive research framework on managing gig platform workers. Nevertheless, despite broad thematic coverage, research remains relatively limited regarding the specific question of how to enhance work engagement among gig platform employees.

2.2. Research on Managing Gig Workers in Platforms

Employee engagement has long been regarded as a central topic in organizational behavior and human resource management, and it has attracted sustained scholarly attention in recent years. As employment arrangements have shifted from traditional employment relationships to emerging gig-economy models, the conceptualization of engagement, its antecedents, and its underlying mechanisms have continued to evolve. As early as 2006, Saks A M (2006) examined the relationship between job embeddedness and employee engagement, reporting a significant positive effect of job embeddedness on engagement [22]. This finding provides an important basis for explaining how engagement develops. Maslach C et al. (2001) highlighted the pivotal role of organizational climate, arguing that fair performance management and a supportive culture can strengthen employees' behavioral involvement and willingness to grow [23]. Basheer M F et al. (2019) further refined this line of research by showing that perceived organizational support is positively associated with engagement, and that demographic characteristics (e.g., age and marital status) are linked to significant differences in engagement [24]. Drawing on social exchange theory, Boon C and Kalshoven K. (2014) emphasized that long-term and stable employment relationships can enhance employee engagement through reciprocity-based mechanisms [25].

In addition, leadership style has been consistently identified as a key determinant of employee engagement. Lu, F and Yoon, S.J. (2025) indicate that ethically oriented management can significantly increase employees' work engagement through the mediating transmission of psychological commitment and organizational belonging [26]. He Jianhua et al. (2022) further clarify the importance of leaders' emotion regulation capabilities, showing that when leaders effectively manage their own emotional states and maintain positive interactions with team members, subordinates' trust, satisfaction, and sense of psychological safety are strengthened, which in turn promotes higher engagement [27]. He Jianhua et al. (2022) similarly confirms leadership as a critical factor influencing engagement, aligning with international findings while offering localized implications for leadership development in Chinese enterprises [28]. This evidence contributes to the understanding and management of younger cohorts and has practical relevance for contemporary talent management [29].

However, the rise of the gig economy introduces new challenges to conventional theories of employee engagement. In gig-economy settings, the relationship between platform workers and platforms is often short-term, flexible, and characterized by limited stability, which constrains the direct applicability of traditional engagement-enhancement strategies [30]. Prior research suggests that engagement among platform workers is shaped by multiple factors, including job autonomy, income stability, social support, and work meaningfulness [31]. Platform workers commonly experience substantial income volatility, limited social protection, and restricted career development opportunities, conditions that may undermine engagement [32]. Consistent with this view, Wei W and Liu B N (2023) argues that under gig-economy arrangements, workers frequently participate in work in non-fixed and short-cycle forms, which is associated with relatively weaker occupational investment and organizational identification [33]. Such contingent employment patterns may impede the development of sustained work enthusiasm and a stable sense of institutional belonging. These findings underscore how the gig economy disrupts traditional employee-organization relationships and raises new questions for human resource management on gig platforms.

Overall, existing research has examined employee engagement from diverse perspectives, including job embeddedness, organizational justice, leadership style, and belongingness. The literature has enriched the theoretical understanding of engagement and has provided useful directions for subsequent studies. Nevertheless, as the gig economy expands, established engagement theories face increasing challenges. How employee engagement can be enhanced under gig-economy conditions characterized by pronounced flexibility and short-term work arrangements remains an urgent issue. Systematically investigating the determinants of engagement among gig-economy platform workers and developing feasible and effective enhancement strategies are of substantial theoretical and practical importance for promoting the healthy and sustainable development of the gig economy.

2.3. Theoretical Framework and Hypotheses Development

Gig platforms operate within a triadic interaction structure involving the platform, workers, and customers. Rather than reflecting a closed employer–employee arrangement, platform work is embedded in an open, multi-actor ecosystem in which platforms, workers, and customers interact and co-create value [34]. Workers deliver services to customers, while customer ratings, complaints, and tips are subsequently incorporated into algorithmic task allocation and income distribution. Accordingly, managerial authority is exercised not only through platform rules but also through customer-mediated evaluations, generating a hybrid governance mechanism in which market feedback and managerial control are intertwined [35]. This triadic structure is critical for explaining work engagement in the gig economy because it reconfigures the sources of support and fairness signals and shapes how workers interpret algorithmic management [36]. As a result, traditional interpersonal management mechanisms may be attenuated, whereas technology-enabled governance and perceived legitimacy of platform rules are likely to become increasingly salient for workers' motivation and engagement.

Work engagement is a core outcome in this context because it is closely linked to service quality, reliability, and sustained participation, which are central to long-term platform viability and social sustainability [37]. Yet engagement in platform work is shaped by distinctive institutional conditions, including opaque algorithmic decisions, unstable income prospects, and ambiguous employment relationships [38]. To explain engagement under these conditions, we integrate four complementary theoretical lenses that are frequently used in research on motivation under non-standard employment. Self-regulation perspectives emphasize workers' capacity to manage goals and effort. Social exchange theory highlights perceived support and reciprocal motivation [39]. Organizational justice theory explains how fairness perceptions shape trust and willingness to invest energy. Algorithmic governance perspectives clarify how perceived predictability and controllability of platform rules shape motivation and compliance [40].

Self-management refers to individuals' active regulation of their goals, behaviors, and performance. In the workplace, self-management reflects how workers coordinate personal growth with task demands and organizational expectations [41]. Self-management capability has been identified as an important component of work engagement, with engagement partly manifesting as effective self-regulation [42]. Mechanistically, self-management influences engagement through goal commitment, behavioral choice, capability monitoring, and progress evaluation [42]. Empirical evidence further shows that daily self-management is positively associated with skill acquisition, feedback seeking, and development opportunities, thereby enhancing engagement [43]. In highly autonomous platform work, self-management becomes particularly salient because workers must plan time, allocate resources, and cope with uncertainty with limited direct supervision.

Based on the foregoing analysis, the following hypotheses are proposed regarding the self-management dimension.

H1: *Self-management is positively associated with work engagement among platform-based gig workers.*

H1a: *Self-awareness is positively associated with gig platform workers' work engagement.*

H1b: *Self-improvement (self-perfection) is positively associated with gig platform workers' work engagement.*

Perceived organizational support (POS) reflects workers' overall beliefs that the organization values their contributions and cares about their well-being [29]. When workers perceive support, they are more likely to develop trust and positive attitudes toward the organization, which strengthens commitment and motivates reciprocation through higher effort and engagement [29]. Empirical studies suggest that support systems and supportive climates enhance engagement by increasing emotional attachment and encouraging workers to invest energy and attention in their work. Related HRM evidence also indicates that high-commitment HRM practices are associated with engagement and commitment, with task proficiency shaping these effects [25]. Conversely, when workers perceive insufficient recognition and welfare concern, their obligation to contribute may weaken, resulting in reduced engagement and heightened turnover intentions.

In gig platforms, support can be particularly important because employment ties are weaker and workers rely more on social, informational, and developmental resources to sustain motivation [8]. Therefore, different forms of platform support (e.g., supervisor, peer, and climate support) are expected to contribute to gig workers' engagement through both socio-emotional and instrumental mechanisms.

Based on the foregoing analysis, the following hypotheses are proposed regarding the organisational support dimension:

H2: *Perceived organizational support is positively associated with work engagement among platform-based gig workers.*

H2a: *Supervisor support is positively associated with gig platform workers' work engagement.*

H2b: *Coworker/peer support is positively associated with gig platform workers' work engagement.*

H2c: *Climate support is positively associated with gig platform workers' work engagement.*

Organizational justice is widely recognized as a key determinant of positive work attitudes and behaviors. Work on burnout implies that fairness is linked to reduced exhaustion, and because burnout is often treated as the inverse of engagement, fairness is expected to support engagement [23]. Foundational engagement research distinguishes procedural and distributive justice and finds that procedural justice is positively related to engagement [22]. Subsequent studies also suggest that justice reduces turnover-related behaviors and encourages effort, with job embeddedness and justice sensitivity acting as relevant mechanisms [44]. In addition, interactional justice has been shown to influence well-being via psychological empowerment, with power distance shaping these relationships [45].

For gig workers, distributive justice concerns whether pay and rewards match effort and performance, thereby affecting trust and willingness to continue platform work [44]. Procedural justice concerns whether task allocation and evaluation rules are transparent, consistent, and contestable, shaping acceptance of platform governance [22,37]. Interac-

tional justice concerns respectful communication and humane treatment, fostering cooperation and a positive work climate [44]. These fairness perceptions are therefore expected to jointly contribute to higher work engagement in platform labor.

Based on the foregoing analysis, the following hypotheses are proposed regarding the organisational justice dimension:

H3: *Organizational justice is positively associated with work engagement among platform-based gig workers.*

H3a: *Distributive justice is positively associated with gig platform workers' work engagement.*

H3b: *Procedural justice is positively associated with gig platform workers' work engagement.*

H3c: *Interactional justice is positively associated with gig platform workers' work engagement.*

Algorithmic management is a defining feature of gig platforms, whereby algorithms influence task allocation, workflow guidance, performance evaluation, and reward outcomes [4,5]. Workers' perceptions of algorithmic control are consequential because perceived controllability and predictability shape motivation, resource allocation, and compliance behaviors [17]. Research has conceptualized and measured gig workers' perceived algorithmic control and verified its performance implications [18]. Subsequent evidence indicates a "double-edged sword" effect: moderate algorithmic control can reduce uncertainty by providing structured guidance and clearer allocation, while excessive control may intensify resource depletion, stress, and perceived unfairness, thereby undermining engagement and increasing turnover intentions [19]. Studies on delivery riders further show that perceived unfairness in algorithmic task assignment can reduce work positivity and service quality [20], and algorithmic control can shape turnover intentions through complex mechanisms [21]. Recent work also distinguishes "good algorithms" from "bad algorithms" in relation to overwork risks [31] and examines motivational pathways through which algorithmic control may stimulate proactive service behaviors [32]. Building on these findings, perceived algorithmic control is expected to influence gig workers' engagement through simultaneous guidance and constraint mechanisms.

Based on the foregoing analysis, the following hypotheses are proposed regarding the perceived algorithmic control dimension:

H4: *Perceived algorithmic control is positively associated with work engagement among platform-based gig workers.*

H4a: *Perceived algorithmic task control is positively associated with gig platform workers' work engagement.*

H4b: *Perceived algorithmic process control is positively associated with gig platform workers' work engagement.*

H4c: *Perceived algorithmic outcome control is positively associated with gig platform workers' work engagement.*

2.4. Summary of Literature

Overall, prior research has made substantial progress in describing the gig economy and platform-mediated labor, including debates on labor protection, employment relations, and algorithmic management. Studies on organizational behavior and HRM have also established robust antecedents of work engagement in conventional employment

settings, such as perceived organizational support, organizational justice, leadership, and embeddedness. Nevertheless, three gaps remain salient for platform-based gig work.

First, existing gig-economy research has been relatively macro-oriented (e.g., market trends, legal classification, and labor standards), while fewer studies systematically explain gig workers' work engagement as a micro-level psychological and behavioral outcome under platform governance. Second, engagement research is still dominated by standard organizational contexts, and thus its mechanisms may not fully capture platform work features such as weak employment ties, multi-platform participation, and algorithmic coordination. Third, although recent studies have examined algorithmic management, empirical work that integrates self-regulation resources (self-management), relational resources (organizational support), normative evaluations (organizational justice), and technology-mediated governance (perceived algorithmic control) into a unified framework to explain engagement remains limited.

To address these gaps, this study develops and tests a conceptual model in which work engagement is the key outcome (Figure 1). Self-management, perceived organizational support, organizational justice, and perceived algorithmic control are proposed as core antecedents, each further represented by multidimensional components. This integrative framework aims to explain how engagement is sustained in highly flexible yet governance-intensive platform work and provides evidence-based implications for platform management and socially sustainable labor practices.

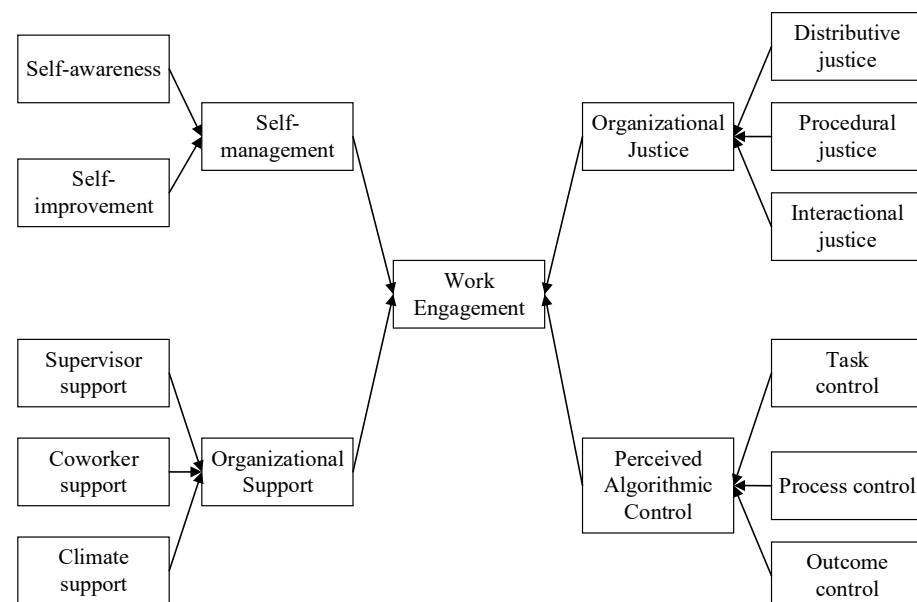


Figure 1. Proposed research model.

3. Methodology

3.1. Research Design and Data Collection

This study employed a quantitative questionnaire survey design to examine the determinants of work engagement among platform-based gig workers. With respect to scale selection, appropriate measurement instruments were identified through a systematic review of the relevant literature. In the questionnaire development process, the research team communicated with the target respondent group to solicit feedback and improve the clarity and contextual appropriateness of item wording. After the initial draft was completed, a small-scale pilot test was conducted to assess the accuracy and effectiveness of the items. Based on the pilot feedback, the questionnaire was revised and refined, resulting in the final version.

The questionnaire comprised two main sections: Part 1: Demographic variables, including basic characteristics such as gender and educational attainment, used to describe the sample. Part 2: Variable measurement, in which respondents were asked to rate, based on their experiences on gig-economy platforms, their levels of self-management, organisational support, organisational justice, perceived algorithmic control, and work engagement, thereby generating the measurement scores for each construct.

To mitigate potential self-selection bias, several procedural remedies were implemented during survey administration. Specifically, anonymity and academic-use-only purposes were emphasized; respondents were informed that there were no right or wrong answers to reduce evaluation apprehension; item wording was revised based on the pilot test to reduce ambiguity; the questionnaire was distributed through multiple online channels; and workers with diverse platform experience and work arrangements (full-time or part-time) were encouraged to participate. Low-quality responses were removed to enhance data validity. Data were collected via Wenjuanxing, and a total of 320 questionnaires were distributed. After excluding cases with missing values and low-quality responses, 292 valid questionnaires were retained for subsequent analyses. Participants were recruited through online communities and social-network channels commonly used by platform workers, including rider and driver groups and peer-sharing networks. Eligibility required respondents to have current platform-work experience and to complete the survey voluntarily with informed consent. Response quality screening excluded cases with substantial missingness, implausibly short completion times, and patterned responses lacking variance. Wenjuanxing (wjx.cn) is a large-scale online survey platform in China and provides functionality comparable to commonly used international survey tools such as Qualtrics.

3.2. Questionnaire Structure and Measures

The questionnaire consisted of two parts. Part 1 collected demographic information, e.g., gender, age, marital status, education, tenure, and job nature. Part 2 measured the core constructs: self-management, organizational support, organizational justice, perceived algorithmic control, and work engagement. Respondents rated items based on their experiences on gig platforms.

To make the measurement system transparent, Table 1 summarizes constructs, sub-dimensions, sources, and the number of items.

Table 1. Constructs and measurement overview.

Construct	Sub-Dimensions	Items	Scale Source/Basis
Self-management	Self-awareness; Self-improvement	8	Developed based on prior literature and conceptualization (e.g., Tseng & Wu,(2017) [39]; two-dimensional structure formed in this study
Organizational support	Supervisor support; Coworker support; Climate support	9	Multidimensional organizational support perspective (e.g., Hao et al., (2023)) [30]; adapted to platform context
Organizational justice	Distributive; Procedural; Interactional justice	9	Lu & Yoon(2025) [26]
Perceived algorithmic control	Task control; Process control; Outcome control	9	Pei et al. (2021) [18]
Work engagement	Organizational identification; Work involvement; Extra-role effort	9	Referenced the Hewitt engagement model; structure redefined to three dimensions; items adapted drawing on 3S/UWES/GWA-oriented measures

The final sample consisted of 292 platform-based gig workers in China (Table 2), primarily engaged in location-based on-demand services such as food delivery and ride-hailing, which are representative forms of algorithmically managed gig work. Overall, the sample was moderately diverse in both demographic and work-arrangement characteristics. Male respondents accounted for 55.48% of the sample and female respondents for 44.52%. Participants were distributed across age groups, with 23.63% aged 25 or younger, 31.51% aged 26–35, 34.59% aged 36–45, and 10.27% aged 46 or above. Marital status was balanced (50.34% unmarried; 49.66% married). In terms of education, 69.52% held a bachelor's degree, 23.29% had junior college education or below, and 7.19% held a master's degree. Regarding platform-work experience, 22.26% reported tenure of 3 years or less, 47.26% reported 3–5 years, and 30.48% reported 5–10 years. Finally, 58.90% identified their platform work as full-time and 41.10% as part-time, indicating variation in employment intensity.

Table 2. Sample characteristics (N = 292).

Variable	Category	Frequency	%
Gender	Male	162	55.48
	Female	130	44.52
Age	≤25	69	23.63
	26–35	92	31.51
	36–45	101	34.59
	≥46	30	10.27
Marital status	Unmarried	147	50.34
	Married	145	49.66
Education	Junior college or below	68	23.29
	Bachelor	203	69.52
	Master	21	7.19
Tenure	≤3 years	65	22.26
	3–5 years	138	47.26
	5–10 years	89	30.48
Job nature	Full-time	172	58.90
	Part-time	120	41.10

3.3. Confirmatory Factor Analysis

Confirmatory factor analysis (CFA) was conducted to assess the measurement model, including self-management (SM), organisational support (OS), organisational justice (OJ), perceived algorithmic control (AC), and work engagement (WE). The model fit was evaluated using multiple indices, including the chi-square statistic (χ^2) and degrees of freedom (dfs), the comparative fit index (CFI), the Tucker–Lewis index (TLI), the root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR). Convergent validity was assessed via standardized factor loadings, composite reliability (CR), and average variance extracted (AVE) (Table 3).

Table 3. Measurement model comparison and common method variance diagnostic using facet parcels.

Model	χ^2	df	CFI	TLI	RMSEA	SRMR
One-factor	233.431	77	0.941	0.931	0.083	0.040
Five-factor	124.361	67	0.978	0.971	0.054	0.030

To maintain a parsimonious measurement model that aligns with the theoretical structure of multifaceted constructs, we adopted a facet-as-indicators parceling strategy. Specifically, for each construct, we computed facet mean scores by averaging items within

each subdimension, after ensuring consistent coding direction. This yields 14 parcels in total (SA, SI; SS, CS, WCS; DJ, PJ, IJ; TC, PC, OC; ID, INV, ER), which serve as indicators of the five latent constructs (Table 4).

Table 4. Standardised factor loadings and convergent validity evidence for the parcel-based CFA.

Construct	Indicator	Std. Loading	<i>p</i>	CR	AVE
SM	SA	0.794	<0.001	0.802	0.669
	SI	0.841	<0.001		
OS	SS	0.726	<0.001	0.786	0.551
	CS	0.748	<0.001		
	WCS	0.753	<0.001		
OJ	DJ	0.750	<0.001	0.810	0.588
	PJ	0.756	<0.001		
	IJ	0.793	<0.001		
AC	TC	0.566	<0.001	0.773	0.539
	PC	0.742	<0.001		
	OC	0.863	<0.001		
WE	ID	0.868	<0.001	0.887	0.724
	INV	0.819	<0.001		
	ER	0.864	<0.001		

This approach is especially suitable here because each construct is explicitly theorised as multidimensional, and the facet structure is substantively meaningful in platform work. Using facet means as indicators preserves interpretability while reducing model complexity and estimation noise. It also follows the partial disaggregation tradition in SEM research for multifaceted constructs, where theoretically coherent parcels improve estimation stability and reduce the risk that local item-level idiosyncrasies dominate the global fit. Specifically, CFI increased from 0.941 to 0.978, and RMSEA decreased from 0.083 to 0.054, yielding a Δ CFI of 0.037 and a Δ RMSEA of 0.029, both exceeding commonly used thresholds for meaningful model differences, which reduces concern that a dominant common-method factor accounts for the covariance among indicators. Common method variance cannot be completely ruled out in cross-sectional self-report data, but the pattern of results suggests that it is unlikely to be the primary driver of the observed construct relationships. In addition, several procedural remedies were implemented during questionnaire design, including anonymous participation, clear item wording, and separation of construct blocks to reduce evaluation apprehension and consistency motives.

Together, these diagnostics suggest that common method variance is unlikely to be the primary driver of the observed construct relationships.

3.4. Multivariate Regression and SEM Testing

We used multiple regression as the primary hypothesis-testing approach rather than relying exclusively on a single full structural equation model. This choice was motivated by both substantive and statistical considerations. Substantively, the focal predictors represent closely related platform HRM signals and governance perceptions that are expected to co-occur in platform settings, so our goal is to estimate their incremental associations with engagement under transparent controls rather than to rank them by relative importance.

The core objective of this study is to test the independent associations and net effects of multiple antecedent variables on platform employees' work engagement. Within a regression framework, the marginal effects of each antecedent can be reported transparently, and the incremental explanatory power can be assessed through stepwise (hierarchical) model comparisons. Given the relatively high correlations among the study variables, multivariate regression also facilitates multicollinearity diagnostics (e.g., variance inflation factors, VIFs)

and a series of robustness checks, thereby enhancing the stability and interpretability of the estimates.

Therefore, to examine the quantitative relationships between the predictors and the outcome, the following multivariate regression model is specified:

$$Y = \beta_0 + \beta_1 H_1 + \beta_2 H_2 + \beta_3 H_3 + \beta_4 H_4 + \varepsilon \quad (1)$$

In Model (4-1), work engagement Y is the dependent variable. Self-management (H_1), organisational support (H_2), organisational justice (H_3), and perceived algorithmic control (H_4) serve as the independent variables. Model diagnostics included overall model significance (F-test), goodness-of-fit (R^2 and adjusted R^2), autocorrelation (Durbin–Watson), and multicollinearity (VIF). Additional regressions were then estimated for each construct's sub-dimensions to identify which components were most predictive of work engagement.

To validate the hypothesised directions under a latent-variable framework, we conduct parcel-based SEM as a robustness check. The SEM specification uses facet means as indicators and estimates single-path models that link each antecedent to engagement, allowing us to confirm that core associations are not an artefact of observed-score regression.

A practical motivation for this modelling choice is sample-size realism and estimation stability. The original instrument contains many items across multiple constructs; an item-level CFA/SEM would rapidly increase free parameters (factor loadings, error variances, indicator covariances, and structural paths), which for $N = 292$ may increase the likelihood of: (i) non-convergence or local solutions, (ii) fit being dominated by local item-level residuals rather than theory-relevant structure, and (iii) unstable standard errors. The partial disaggregation strategy compresses each construct into a small number of theoretically coherent indicators (facet means), substantially reducing free parameters and improving stability and interpretability. This modelling strategy follows the partial disaggregation tradition in SEM research for multifaceted constructs.

4. Results

4.1. Demographic Differences in Engagement

To examine whether gig workers' engagement and its three sub-dimensions (organizational identification, work involvement, and extra effort) vary across demographic characteristics, group difference tests were conducted for gender, age, marital status, education level, tenure, and job nature. The results are reported in in Sections 4.1.1–4.1.6.

4.1.1. Gender Differences

As shown in Table 5, male respondents ($N = 162$) reported a higher mean level of overall engagement than female respondents ($N = 130$) ($M = 3.413$ vs. 3.091). The overall engagement level differed significantly by gender (Sig. = 0.000). Regarding sub-dimensions, males scored higher than females on work involvement ($M = 3.192$ vs. 2.783), with a significant difference ($t = 2.182$, $p = 0.018$). Similarly, males scored higher than females on extra effort ($M = 3.251$ vs. 3.107), and the difference was significant ($t = -1.375$, $p = 0.015$). For organizational identification, although the male mean ($M = 3.331$) exceeded the female mean ($M = 2.946$), the difference did not reach statistical significance ($F = 11.462$, Sig. = 0.073).

Table 5. Analysis of differences based on sex.

Dimension	Gender	N	Mean	F	Sig.	t	Sig. (Two-Tailed)
Organizational identification	Male	162	3.331	11.462	0.073	2.293	0.006
	Female	130	2.946			1.814	0.015
Work involvement	Male	162	3.192	8.935	0.001	2.182	0.018
	Female	130	2.783			2.425	0.006
Extra effort	Male	162	3.251	9.573	0.000	−1.375	0.015
	Female	130	3.107			−2.164	0.004
Engagement (overall)	Male	162	3.413	9.403	0.000	1.382	0.319
	Female	130	3.091			1.478	0.231

4.1.2. Age Differences

Table 6 indicates that overall engagement differed significantly across age groups ($F = 6.932$, $\text{Sig.} = 0.001$). In terms of mean comparisons, the 26–35 group reported the highest engagement ($M = 3.542$), followed by the ≤ 25 group ($M = 3.119$), the 36–45 group ($M = 3.094$), and the ≥ 46 group ($M = 3.015$). For sub-dimensions, organizational identification differed significantly by age ($F = 7.635$, $\text{Sig.} = 0.017$), and extra effort also showed significant differences ($F = 9.446$, $\text{Sig.} = 0.000$). In contrast, work involvement did not differ significantly by age ($F = 10.451$, $\text{Sig.} = 0.221$).

Table 6. Analysis of differences based on age.

Dimension	Age	N	Mean	Std. Error	F	Sig.
Organizational identification	≤ 25	69	3.478	0.191	7.635	0.017
	26–35	92	3.219	0.084		
	36–45	101	3.151	0.062		
	≥ 46	30	2.936	0.141		
Work involvement	≤ 25	69	2.845	0.282	10.451	0.221
	26–35	92	2.725	0.193		
	36–45	101	3.173	0.167		
	≥ 46	30	3.169	0.082		
Extra effort	≤ 25	69	3.189	0.221	9.446	0.000
	26–35	92	3.221	0.152		
	36–45	101	3.104	0.089		
	≥ 46	30	2.995	0.074		
Engagement (overall)	≤ 25	69	3.119	0.241	6.932	0.001
	26–35	92	3.542	0.173		
	36–45	101	3.094	0.221		
	≥ 46	30	3.015	0.219		

4.1.3. Marital Status Differences

As reported in Table 7, marital status was significantly associated with overall engagement ($F = 8.477$, $\text{Sig.} = 0.002$), and significant differences were observed across all three sub-dimensions. Married respondents scored higher than unmarried respondents on organizational identification ($M = 3.246$ vs. 2.331), work involvement ($M = 3.456$ vs. 3.183), extra effort ($M = 3.632$ vs. 3.283), and overall engagement ($M = 3.724$ vs. 3.493).

Table 7. Analysis of differences based on marriage status.

Dimension	Marital Status	N	Mean	F	Sig.	t	Sig. (Two-Tailed)
Organizational identification	Unmarried	147	2.331	8.935	0.004	2.142	0.007
	Married	145	3.246			1.134	0.016
Work involvement	Unmarried	147	3.183	11.262	0.002	2.109	0.017
	Married	145	3.456			2.1562	0.005
Extra effort	Unmarried	147	3.283	9.592	0.000	1.946	0.019
	Married	145	3.632			2.361	0.005

Table 7. *Cont.*

Dimension	Marital Status	N	Mean	F	Sig.	t	Sig. (Two-Tailed)
Engagement (overall)	Unmarried	147	3.493	8.477	0.002	1.782	0.313
	Married	145	3.724			1.439	0.225

4.1.4. Education Level Differences

Table 8 shows that overall engagement differed significantly by education level ($F = 9.433$, $\text{Sig.} = 0.000$). Significant differences were also found for work involvement ($F = 6.932$, $\text{Sig.} = 0.006$) and extra effort ($F = 7.824$, $\text{Sig.} = 0.002$), whereas organizational identification did not show a significant difference ($F = 9.014$, $\text{Sig.} = 0.057$). In mean comparisons, the bachelor's group reported the highest engagement ($M = 3.622$), followed by the "junior college and below" group ($M = 3.148$), while the master's group reported the lowest engagement ($M = 3.003$).

Table 8. Difference analysis based on educational background.

Dimension	Education	N	Mean	Std. Error	F	Sig.
Organizational identification	Junior college & below	68	0.197	0.197	9.014	0.057
	Bachelor	203	0.061	0.061		
	Master	21	0.135	0.135		
Work involvement	Junior college & below	68	0.277	0.277	6.932	0.006
	Bachelor	203	0.021	0.021		
	Master	21	0.056	0.056		
Extra effort	Junior college & below	68	3.209	0.225	7.824	0.002
	Bachelor	203	3.523	0.172		
	Master	21	3.131	0.082		
Engagement (overall)	Junior college & below	68	3.148	0.225	9.433	0.000
	Bachelor	203	3.622	0.073		
	Master	21	3.003	0.019		

4.1.5. Tenure Differences

As shown in Table 9, tenure was significantly associated with overall engagement ($F = 9.462$, $\text{Sig.} = 0.002$). Significant tenure differences were also found for organizational identification ($F = 7.622$, $\text{Sig.} = 0.005$) and work involvement ($F = 8.478$, $\text{Sig.} = 0.006$), and extra effort also differed significantly ($F = 10.563$, $\text{Sig.} = 0.015$). Mean values indicated an upward pattern with longer tenure: ≤ 3 years ($M = 2.903$), 3–5 years ($M = 3.142$), and 5–10 years ($M = 3.361$).

Table 9. Difference analysis based on working years.

Dimension	Tenure	N	Mean	Std. Error	F	Sig.
Organizational identification	≤ 3 years	65	3.351	0.213	7.622	0.005
	3–5 years	38	3.109	0.346		
	5–10 years	89	3.516	0.215		
Work involvement	≤ 3 years	65	2.782	0.319	8.478	0.006
	3–5 years	138	3.049	0.334		
	5–10 years	89	3.315	0.283		
Extra effort	≤ 3 years	65	3.172	0.341	10.563	0.015
	3–5 years	138	3.315	0.283		
	5–10 years	89	3.415	0.267		
Engagement (overall)	≤ 3 years	65	2.903	0.270	9.462	0.002
	3–5 years	138	3.142	0.194		
	5–10 years	89	3.361	0.178		

4.1.6. Job Nature Differences (Full-Time vs. Part-Time)

Table 10 shows that job nature was significantly associated with overall engagement ($F = 8.493$, $\text{Sig.} = 0.000$). Full-time workers reported higher levels of organizational identification ($M = 3.152$), work involvement ($M = 3.526$), extra effort ($M = 3.442$), and overall engagement ($M = 3.425$) than part-time workers ($M = 3.003, 3.178, 3.108$, and 2.984 , respectively). Differences in all three sub-dimensions reached statistical significance.

Table 10. Difference analysis based on the nature of work.

Dimension	Job Nature	N	Mean	F	Sig.	t	Sig. (Two-Tailed)
Organizational identification	Full-time	172	3.152	9.462	0.002	2.178	0.009
	Part-time	120	3.003			1.115	0.015
Work involvement	Full-time	172	3.526	10.362	0.006	2.515	0.018
	Part-time	120	3.178			2.188	0.006
Extra effort	Full-time	172	3.442	9.361	0.021	1.146	0.025
	Part-time	120	3.108			2.054	0.027
Engagement (overall)	Full-time	172	3.425	8.493	0.000	1.312	0.215
	Part-time	120	2.984			1.468	

4.2. Correlation Analysis

Pearson correlation analysis was conducted to examine the linear relationships among self-management, organizational support, organizational justice, perceived algorithmic control, and engagement. The correlation matrix is presented in Table 11.

Table 11. Pearson Correlation Matrix among Study Variables.

	Self-Management	Organizational Support	Organizational Justice	Perceived Algorithmic Control	Engagement
Self-management	1				
Organizational support	0.409 **	1			
Organizational justice	0.427 **	0.412 *	1		
Perceived algorithmic control	0.391 **	0.462 *	0.428 **	1	
Engagement	0.502 **	0.526 *	0.487 **	0.552 **	1

Note: * $p < 0.05$, ** $p < 0.01$.

The results show that self-management was positively correlated with engagement. Organizational support was positively correlated with engagement. Organizational justice was positively correlated with engagement. Perceived algorithmic control was also positively correlated with engagement. Overall, correlations were within a reasonable range, suggesting no severe multicollinearity.

4.3. Regression and Hypothesis Testing

4.3.1. Overall Regression Model

Although correlation analyses show positive bivariate associations between self-management, perceived organisational support, organisational justice, perceived algorithmic control, and gig workers' work engagement, the correlations do not indicate the unique association of each predictor once the others are considered. We therefore estimated a multiple linear regression model with work engagement as the dependent variable, including control variables and the four focal predictors as independent variables.

As shown in Tables 12 and 13, the overall model explains substantial variance in work engagement, with an R squared of 0.773 and an adjusted R squared of 0.761. Multicollinearity diagnostics indicate moderate but acceptable collinearity, with variance inflation factors

ranging from 2.721 to 3.284, suggesting that coefficient estimates are interpretable as incremental associations.

Table 12. Regression model summary.

Model	R	R ²	Adjusted R ²	Std. Error of the Estimate	Durbin–Watson
1	0.879	0.773	0.761	0.371	1.712

Table 13. ANOVA (model significance test).

Model	Source	Sum of Squares	df	Mean Square	F	Sig.
1	Regression	129.770	14	9.269	67.216	0.000
	Residual	38.199	277	0.138		
	Total	167.969	291			

Table 14 reports the regression coefficients. Perceived algorithmic control shows the strongest positive association with work engagement. Perceived organisational support and organisational justice are also positively and significantly associated with engagement. The coefficient for self-management is positive and statistically significant at the 10% level.

Table 14. Regression coefficients (overall model).

Term	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
Constant	0.364	0.323		1.129	0.260		
H1 Self-management	0.132	0.073	0.100	1.814	0.071	0.368	2.721
H2 Organizational support	0.167	0.079	0.123	2.117	0.035	0.314	3.180
H3 Organizational justice	0.125	0.059	0.111	2.136	0.034	0.305	3.284
H4 Perceived algorithmic control	0.511	0.062	0.419	8.206	0.000	0.356	2.810

4.3.2. Subdimension Regression Analyses

To further identify which subdimensions significantly contributed to engagement, separate multiple regressions were conducted within each focal construct (H1–H4), using their respective subdimensions as predictors and engagement (Y) as the outcome.

(1) Self-management subdimensions (H1a–H1b)

Within self-management, the model was significant. Results indicated that self-improvement (H1b) was significantly and positively associated with engagement, whereas self-awareness (H1a) was not significant. Therefore, H1b was supported, but H1a was not (Table 15).

Table 15. Subdimension regression: Self-management → engagement.

Term	B	Std. Error	Beta	t	Sig.	Tolerance	VIF	R ²	F
Constant	2.172	0.342		6.354	0.000			0.662	45.503
H1a Self-awareness	0.066	0.074	0.056	0.891	0.373	0.440	2.271		
H1b Self-improvement	0.351	0.075	0.287	4.676	0.000	0.461	2.170		

(2) Organizational support subdimensions (H2a–H2c)

For organizational support, supervisor support (H2a), coworker support (H2b) and climate support (H2c) were significantly and positively associated with engagement (Table 16).

Table 16. Subdimension regression: Organizational support → engagement.

Term	B	Std. Error	Beta	t	Sig.	Tolerance	VIF	R ²	F
Constant	1.853	0.319		5.812	0.000			0.666	42.554
H2a Supervisor support	0.174	0.060	0.137	2.884	0.004	0.533	1.875		
H2b Coworker support	0.139	0.055	0.127	2.518	0.012	0.544	1.839		
H2c Climate support	0.178	0.055	0.168	3.232	0.001	0.487	2.054		

(3) Organizational justice subdimensions (H3a–H3c)

The justice subdimension model was significant. Distributive justice (H3a), procedural justice (H3b) and interactional justice (H3c) were significantly and positively associated with engagement (Table 17).

Table 17. Subdimension regression: Organizational justice → engagement.

Term	B	Std. Error	Beta	t	Sig.	Tolerance	VIF	R ²	F
Constant	1.945	0.266		7.305	0.000			0.689	47.430
H3a Distributive justice	0.198	0.055	0.192	3.604	0.000	0.524	1.908		
H3b Procedural justice	0.145	0.053	0.147	2.727	0.007	0.513	1.950		
H3c Interactional justice	0.121	0.050	0.138	2.429	0.016	0.470	2.127		

(4) Perceived algorithmic control subdimensions (H4a–H4c)

For perceived algorithmic control, the model was significant. Results showed that process control (H4b) and outcome control (H4c) positively predicted engagement, whereas task control (H4a) was not significant (Table 18).

Table 18. Subdimension regression: Perceived algorithmic control → engagement.

Term	B	Std. Error	Beta	t	Sig.	Tolerance	VIF	R ²	F
Constant	1.307	0.231		5.666	0.000			0.765	69.564
H4a Task control	0.063	0.039	0.055	1.614	0.108	0.711	1.407		
H4b Process control	0.269	0.051	0.253	5.247	0.000	0.544	1.839		
H4c Outcome control	0.306	0.041	0.354	7.449	0.000	0.394	2.535		

4.4. Robustness Checks

As a robustness check, we estimated parcel-based structural equation models using facet means as indicators. The parcel CFA reported in the Method section indicates good measurement model fit under the facet-as-indicators specification. We then estimated a set of single-predictor SEMs in which work engagement was modelled as a latent construct indicated by organisational identification, work involvement, and extra-role effort, and was regressed on one focal antecedent at a time. This design is used to verify the hypothesised directions under a latent-variable framework rather than to rank predictors by relative importance, given the high intercorrelations among platform HRM signals. As reported in Table 19, all four antecedents exhibited positive and statistically significant associations with engagement, and model fit was acceptable across models. The OJ-only model showed comparatively higher RMSEA, which is not uncommon in low-degree-of-freedom models; however, incremental fit indices and SRMR remained satisfactory, and the substantive conclusion is unchanged.

Table 19. Single-Predictor Parcel-Based Structural Equation Models as Robustness Checks.

Model	Path (Predictor → WE)	β (Std.)	p	χ^2	df	CFI	TLI	RMSEA	SRMR
SM-only	SM → WE	0.842	<0.001	9.521	4	0.994	0.984	0.069	0.016
OS-only	OS → WE	0.872	<0.001	11.859	8	0.996	0.992	0.041	0.017
OJ-only	OJ → WE	0.878	<0.001	28.781	8	0.980	0.962	0.094	0.027
AC-only	AC → WE	0.981	<0.001	11.084	8	0.997	0.995	0.036	0.017

A set of single-predictor structural equation models (SEMs) was estimated using the MLR estimator with latent variables standardized. In each model, Work Engagement (WE) was specified as a latent construct indicated by ID, INV, and ER and was regressed on a single focal predictor (SM, OS, OJ, or AC). Results indicated that each predictor exhibited a strong and statistically significant association with WE when modeled separately: SM ($\beta = 0.842$, $p < 0.001$), OS ($\beta = 0.872$, $p < 0.001$), OJ ($\beta = 0.878$, $p < 0.001$), and AC ($\beta = 0.981$, $p < 0.001$). Model fit was generally good across models (CFI = 0.980–0.997; TLI = 0.962–0.995; SRMR = 0.016–0.027), with RMSEA ranging from 0.036 to 0.094; the OJ-only model showed comparatively higher RMSEA (0.094) than the other models. Full fit indices and standardized path estimates are reported in Table 19.

5. Discussion

This study examined how platform HRM signals and individual resources are associated with work engagement among platform-based gig workers. Using regression as the main analysis and parcel SEM as a robustness check, we find convergent evidence that self-management, perceived organisational support, organisational justice, and perceived algorithmic control are positively related to engagement in platform work. Taken together, these findings highlight that engagement in the gig economy is not merely a matter of “flexibility” but is closely linked to how workers experience platform governance, fairness, and resource support.

5.1. Theoretical Implications

The results contribute to the engagement literature by showing that classic resource-based explanations remain relevant in non-standard, app-mediated work. Self-management emerges as a salient personal resource in fragmented work settings where workers must regulate routines, persist under uncertainty, and proactively improve capabilities. At the same time, platform-provided resources and governance signals—support, fairness, and algorithmic control—are linked to engagement, extending social exchange and organisational justice theories into platform contexts.

From a platform governance perspective, the positive association between perceived algorithmic control and engagement is theoretically meaningful. It suggests that algorithmic management may function as an enabling coordination device when workers perceive rules as understandable and predictable, rather than solely as a coercive constraint. This aligns with emerging arguments that the motivational meaning of algorithmic governance depends on transparency, contestability, and the extent to which control clarifies effort–reward linkages.

5.2. Subdimension Differences

A key contribution of this study is the explicit attention to facet-level heterogeneity. In platform work, classic HRM mechanisms are filtered through platform HRM and triadic platform–worker–customer interactions, which may change how workers experience support, justice, and control.

First, supervisor support is positively associated with engagement, suggesting that supervisory support can still be experienced in platform settings even when face-to-face contact is limited. Support may be conveyed through standardised guidance, responsive online coordination, and problem-solving interactions that workers interpret as supervisory resources.

Second, interactional justice is also positively associated with engagement. This indicates that respectful communication and dignified treatment remain relevant even when many decisions are mediated by algorithms. In platform work, interactional fairness may be experienced through appeals processes, customer-service interactions, and the tone and transparency of platform communications.

Third, within perceived algorithmic control, process control and outcome control show positive associations with engagement, whereas task control does not. This pattern suggests that engagement is more strongly linked to clear monitoring expectations and predictable consequences than to perceived discretion over task availability, which may be structurally constrained by demand fluctuations and platform allocation logic.

Overall, these subdimension patterns suggest that engagement in platform work is driven less by hierarchical interpersonal mechanisms and more by platform-level governance quality, peer resources, and rule-based transparency. This interpretation helps explain why some facets appear weaker or non-significant.

5.3. Implications for Social Sustainability

Because platform work is expanding rapidly, engagement is not only a performance-related construct but also a social sustainability issue. In sustainability terms, engagement matters insofar as it signals whether platform work supports workers' wellbeing, dignity, and longer-term livelihood prospects, rather than extracting short-term labour through precarious conditions. Our findings connect engagement to three pillars of decent work in platform settings: (i) capability development and future-oriented opportunities, (ii) fair and contestable governance, and (iii) accountable algorithmic management.

At the platform level, operators can strengthen social sustainability by investing in developmental pathways, supporting collective resources, and institutionalising fairness. Algorithmic management should be made explainable and predictable: workers need understandable dispatch logic, rating thresholds, and deactivation criteria, alongside opportunities to appeal or correct erroneous data. Given the triadic nature of platform work, platforms should also govern customer-mediated control by detecting abusive ratings, providing safeguards against customer incivility, and separating service feedback from punitive income shocks.

At the policy level, these implications translate into minimum standards for platform accountability, including transparency requirements for algorithmic decision-making, due process and data rights for workers, and baseline protections for income security, occupational safety, and social insurance portability. Such measures can advance decent-work goals while supporting long-term platform viability by reducing churn, reputational risk, and the hidden costs of disengagement.

6. Conclusions

This study advances our understanding of how to enhance work engagement in the gig economy by integrating organizational behavior and platform governance perspectives. Drawing on survey evidence from gig platform workers, the findings suggest that engagement in platform work is shaped by a multi-source resource exchange between workers and platforms, reflecting both individual resources and platform governance signals. At the overall construct level, the four focal predictors show positive associations with work

engagement. When considered jointly, perceived algorithmic control, perceived organisational support, and organisational justice exhibit statistically significant incremental associations with engagement, whereas the incremental association of self-management becomes weaker and does not reach the conventional 5 percent threshold.

More importantly, the subdimension results offer a sharper, practice-oriented interpretation of what truly drives engagement in gig contexts. Within self-management, self-improvement—rather than self-awareness—emerged as the key mechanism, suggesting that engagement increases when workers perceive concrete growth, capability upgrading, and progress. Within organizational support, supervisor support, coworker support, and climate support were all positively associated with engagement, indicating that both platform-side coordination and peer/climate resources matter in flexible, loosely coupled platform work. Similarly, distributive, procedural, and interactional justice were all positively associated with engagement, underscoring that workers respond not only to pay–effort alignment and transparent procedures but also to respectful and dignified communication. Finally, within perceived algorithmic control, process control and outcome control were positively associated with engagement, whereas task control was not, suggesting that workers engage more when platform rules clarify monitoring expectations and effort–reward linkages than when they perceive discretion over task availability.

Collectively, these results contribute to the literature in three ways. First, they extend engagement research into a non-standard employment setting by showing that classic levers remain relevant but operate through platform-specific forms. Second, the study highlights the dual role of algorithmic control: when perceived as clear and outcome-linked, algorithmic control can function as a coordinating and motivating infrastructure rather than purely a constraint. Third, the findings refine gig-economy HRM insights by revealing which management elements matter most for engagement, offering an empirically grounded basis for prioritizing interventions. For platform operators, the evidence suggests that improving engagement requires strengthening workers’ self-improvement opportunities, fostering peer support and a positive platform climate, ensuring distributive and procedural justice through transparent rules, and designing algorithmic mechanisms that make task allocation and performance outcomes understandable and predictable.

In sum, this research underscores that enhancing gig worker engagement hinges on aligning flexible work arrangements with credible systems of support, fairness, and algorithmic transparency. By clarifying both the overall drivers and the most influential subdimensions, this study provides a foundation for future research to examine boundary conditions (e.g., job-type differences and regulatory environments) and to explore long-term outcomes such as retention, well-being, and sustainable platform performance.

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