
I work hard for the algorithm: job demands, resources and strain in (and beyond) the gig economy

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Abstract

Purpose – This study examines psychological strain in gig work by analyzing how algorithmic management (AM), framed through the Job Demands–Resources (JD-R) model and Self-Determination Theory (SDT), shapes strain outcomes. We compare gig and non-gig workers to isolate the influence of AM.

Design/methodology/approach – Using LIWC, we analyze 6,505 Glassdoor job reviews to compare psychological strain among drivers in gig versus non-gig roles.

Findings – Counterintuitively, compensation and work–life balance – typically strain-buffering resources – are associated with increased strain for gig workers, suggesting that algorithmic control alters how resources are experienced.

Research limitations/implications – The findings suggest that within the ‘digital cage’ of the gig economy, the traditional JD-R resource-to-strain pathway is reconfigured. This highlights the need for research that investigates how the delivery mechanism (AM) of a resource can neutralize its buffering potential.

Practical implications – Platform organizations must recognize that simply increasing pay or flexibility within need-thwarting structures may inadvertently worsen worker strain. Practitioners should prioritize autonomy-supportive algorithmic designs – moving away from gamified, opaque incentives toward transparent systems that restore operational control to the worker.

Originality/value – This research provides evidence that AM does not merely add demands but fundamentally reshapes the relationship between job resources and strain within the gig economy. It problematizes the “autonomy paradox” in gig work to explain why the JD-R resource pathway breaks down.

Keywords Gig work, Algorithmic management, JD-R model, Worker strain, Platform organizations, Organizational supports, Self-determination theory

Paper type Research article

Introduction

The widespread use of algorithms as managerial tools has generated significant debate about their implications for worker well-being. While algorithmic systems promise efficiency and cost reduction, research increasingly highlights concerns such as dehumanization, intensified control, and an overreliance on performance metrics (Duggan *et al.*, 2020; Oostrom *et al.*, 2023). A central question emerging from this literature is whether workers can meaningfully

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thrive in digitally managed work environments (Kellogg *et al.*, 2020; Wu *et al.*, 2019). Much of this debate has focused on the gig economy, where platform organizations use algorithmic management (AM) to coordinate freelance workers performing short, task-based work (Adams-Prassl, 2022). In sectors such as transportation and delivery, AM pervasively monitors, allocates, and evaluates work, exerting substantial control over the labor process (McDonnell *et al.*, 2021). Although the tasks themselves are not new, their digital mediation represents a qualitative shift in how work is governed.

Over the past decade, the intersection of gig work and AM has become a controversial subject, prompting researchers and policymakers to question the fairness and ethical treatment of gig workers by platform organizations (Adams-Prassl, 2022). While prior research has examined the technological features of AM, less is known about how these systems shape workers' psychological experiences. In this study, we address this gap by examining whether AM is associated with heightened psychological strain among gig workers, compared with workers in similar non-gig roles where algorithmic control is less pronounced. In doing so, we draw upon the Job Demands-Resources (JD-R) model (Bakker and Demerouti, 2007), which posits that worker well-being is influenced by the balance between job demands (e.g. heightened control, precarity) and job resources (e.g. compensation, work-life balance). We complement this with insights from self-determination theory (SDT) (Deci and Ryan, 2000) to better understand the underlying psychological mechanisms at play in this unique work context. Our central theoretical argument is that AM may function as a boundary condition that reconfigures the balancing logic of the JD-R model. This integrated JD-R/SDT framework helps to explain *why* resources may fail to buffer demands under algorithmic control, pointing to the frustration of workers' basic psychological needs (i.e. autonomy, competence, and relatedness). While autonomy is not directly measured in the present study, this framework provides a theoretically grounded explanation for the observed patterns.

Drawing on quantitative data, we compare gig workers' psychological strain (characterized by feelings of anxiety, tension, and being overwhelmed, which represents the emotional consequence of the stress process within the JD-R model's health impairment pathway; see Galanakis and Tsitouri, 2022; Schaufeli, 2017), with that of workers in similar roles outside the gig economy, where the same algorithmic tools are either less prominently used or absent. In addition, we investigate whether certain platform supports, namely work-life balance (WLB) and compensation, can help to moderate psychological strain. We do so drawing on inferred psychological strain via LIWC, a popular linguistic text analysis tool, on a sub-sample of 6,505 reviews posted on Glassdoor by workers in driver-based occupations, either in the transportation (e.g. Uber, Lyft), courier (e.g. FedEx, US Postal Services), or food-delivery sectors (e.g. DoorDash, Domino's Pizza).

This study presents several contributions. First, we provide a novel perspective on the experiences of gig workers operating under AM structures, whose working conditions continue to be subject to widespread scrutiny and debate (Sherman *et al.*, 2025; Bucher *et al.*, 2021). A recent review of studies on platform work highlighted the potential for negative attitudinal and mental health outcomes for workers arising from various features of gig work, including the use of algorithmic technologies to control workers' activities, which, from a JD-R perspective, can be conceptualized as specific job demands (Cropanzano *et al.*, 2023). We extend this discussion by providing empirical evidence of the psychological strain experienced by workers in this domain, particularly arising from their experiences with the control-based algorithmic technologies used by platforms.

Second, we advance theoretical understanding by demonstrating how AM fundamentally reconfigures the balancing logic of the JD-R model. Rather than merely acting as an additional job demand, we argue that the context of algorithmic management may create a boundary condition under which conventional resources (compensation, WLB) may cease to function as buffers. Integrating SDT allows us to explain this breakdown: because algorithmic control systematically thwarts the need for autonomy, the pursuit of resources (Galanakis and Tsitouri,

2022) transforms into a strain-inducing activity. This moves the literature beyond a simple catalogue of demands towards a contextualized understanding of how AM dismantles the protective mechanisms of work.

Finally, we employ a comparative design between gig and non-gig driving occupations as a methodological strategy to isolate this contextual reconfiguration. By comparing strain in gig versus non-gig work driving occupations, we can effectively control for the nature of the task (driving) and isolate the unique influence of AM on worker strain. This approach directly responds to calls for more empirical and quantitative examination of gig work (e.g. [Cropanzano et al., 2023](#); [Sherman et al., 2025](#)).

The rise of gig work and algorithmic management

Technological advancements have facilitated the rise of the gig economy, a labor market characterized by digital platforms that match service providers with customers for short-term tasks ([McDonnell et al., 2021](#); [Wood et al., 2019](#)). While gig work offers clear benefits for organizations and customers – such as reduced labor costs and convenient access to services – the implications for workers are more complex ([Kuhn and Galloway, 2019](#); [Waldkirch et al., 2021](#)). A growing body of research highlights that gig workers are subject to the intensified and often adverse capabilities of algorithmic technologies ([Parent-Rocheleau and Parker, 2022](#)).

In gig work, the promise of increased flexibility and autonomy, typically indicators of greater WLB ([Guest, 2002](#)), entices many individuals to this form of work. However, scholarship increasingly problematizes this autonomy as multidimensional, contingent, and often illusory ([Pichault and McKeown, 2019](#); [Wood et al., 2019](#)). It is crucial to distinguish between temporal flexibility (choosing when to log in) and operational autonomy (control over how work is done). While gig work may offer the former, recent literature emphasizes that autonomy erosion is an emergent outcome of specific configurations of algorithmic coordination and economic precarity ([Cruz et al., 2020](#); [Schafheitle et al., 2026](#)). As noted by [Esser and Olsen \(2012\)](#) and [Malhotra \(2021\)](#), this results in a “digital cage” where the freedom to log on is immediately countered by the algorithm’s opaque allocation of tasks and pricing. Crucially, this erosion of operational autonomy is exacerbated by a systemic lack of collective voice and bargaining power; without institutional mechanisms to contest or renegotiate algorithmic dictates, workers are often left with “nominal” flexibility that masks a rigid, non-negotiable labor process ([Pichault and McKeown, 2019](#); [Veen et al., 2020](#)). Consequently, we argue that autonomy-need frustration is central to the strain effects observed in this sector.

AM refers to systems that use self-learning algorithms to allocate tasks, evaluate performance, and distribute rewards with limited human oversight ([Duggan et al., 2020](#); [Wood et al., 2019](#)). While AM can, in some contexts, function as a job resource – such as enabling scheduling efficiency or decision support – in the low-autonomy gig roles examined here, its control-oriented features dominate the worker experience ([Meijerink and Bondarouk, 2023](#)). These processes empower platform organizations to manage and allocate work tasks efficiently, closely monitoring workers’ activities, generating individualized performance metrics, and issuing dynamic rewards based on worker compliance and performance ([Keegan and Meijerink, 2025](#)).

In particular, AM automates performance evaluation and reward distribution using customer ratings and real-time data, often without transparency or recourse ([Kellogg et al., 2020](#)). Dynamic pricing and piece-rate compensation models shift economic risk onto workers and obscure the link between effort and reward ([McDonnell et al., 2021](#); [Waldkirch et al., 2021](#)). Although these systems may enhance efficiency, they simultaneously create a context of pervasive yet opaque control, positioning AM primarily as a contextual job demand in gig work.

The JD-R model, SDT and gig worker strain

The Job Demands–Resources (JD-R) model provides a useful framework for understanding how AM influences psychological strain (Bakker and Demerouti, 2007, 2017). The model posits that employee well-being is shaped by the balance between job demands – energy-depleting aspects of work – and job resources, which support motivation and buffer strain. Importantly, the JD-R model conceptualizes strain as the emotional consequence of the health impairment process, whereby sustained demands exhaust workers’ adaptive capacity over time (Schaufeli, 2017). A key strength of the model is its contextual flexibility: whether a job characteristic functions as a demand or a resource depends on how it is experienced.

In gig work, AM introduces several salient job demands. The absence of human oversight, opaque decision-making, and automated performance evaluation reduce opportunities for interpersonal support and trust (Sherman *et al.*, 2025), while continuous monitoring and data-driven control intensify pressure to comply with algorithmic directives (Ostrom *et al.*, 2023; Veen *et al.*, 2020). Together, these features align with the JD-R health impairment pathway, in which sustained demands deplete psychological resources and elevate strain and burnout risk (Maslach *et al.*, 2001). Prior research has likened AM to a “boss from hell,” emphasizing its capacity to enforce labor through surveillance and the constant threat of discipline or deactivation (Duggan *et al.*, 2020; Wood *et al.*, 2019). Such control systems create pressurized work environments characterized by uncertainty, asymmetric power, and limited recourse, all of which are well-established antecedents of psychological strain (Shanahan and Smith, 2021).

While job resources typically buffer the effects of demands and support engagement, their functioning in gig work is more ambiguous. For instance, flexibility – often treated as a core resource – is frequently constrained by algorithmic coordination, income insecurity, and boundary erosion (Spieler *et al.*, 2017). This imbalance is exacerbated by the opacity and asymmetry inherent in AM systems, which can undermine workers’ sense of control over both their work process and economic outcomes (Wu *et al.*, 2019; Veen *et al.*, 2020). To explain why traditional resources may fail to buffer demands in this context, we integrate SDT (Deci and Ryan, 2000), which specifies autonomy, competence, and relatedness as universal psychological needs underpinning well-being. When these needs are frustrated rather than satisfied, individuals are more likely to experience ill-being, disengagement, and strain (Martins-Nunes and Proenca, 2024). SDT therefore provides a motivational and psychological mechanism that complements the structural logic of the JD-R model.

In traditional employment settings, algorithmic tools may function as resources by supporting competence through transparent feedback and assisting human managerial decision-making (Giermindl *et al.*, 2022). In contrast, in low-autonomy gig work, AM overwhelmingly operates as a hindrance demand. Pervasive surveillance frustrates autonomy (Bucher *et al.*, 2021), opaque evaluation undermines competence through unpredictability and deactivation risk (Norlander *et al.*, 2021), and the absence of sustained human interaction limits relatedness (Parent-Rocheleau and Parker, 2022). Under these conditions, extrinsic rewards such as compensation are more likely to be experienced as controlling pressures rather than supportive resources.

Integrating JD-R and SDT allows us to theorize AM as a boundary condition that reconfigures the resource–strain relationship. When job resources are delivered through opaque, autonomy-thwarting systems, their buffering capacity is neutralized or even reversed, intensifying the health impairment process. This framework also underpins our comparative design, which isolates the psychological consequences of demand-dominant algorithmic control by contrasting gig and non-gig work.

Organizational supports in gig work: a double-edged sword?

Organizational supports refer to the resources, systems, and structures designed to facilitate workers’ performance and well-being (Bakker and Demerouti, 2007). In the gig economy, the platform organization fulfills this role, and such supports are largely embedded within

algorithmic design. We therefore refer to these as *platform supports*: resources provided through compensation structures, incentive systems, and algorithmically enabled flexibility (Shanahan and Smith, 2021). This study examines whether these supports retain their buffering function when delivered within a high-demand context of algorithmic control. We focus on two central supports in gig work: compensation and work–life balance (WLB).

In traditional employment contexts, compensation is typically conceptualized as a job resource that alleviates financial strain and enhances security. However, consistent with the JD-R model’s emphasis on contextual dependence (Bakker and Demerouti, 2017), compensation in gig work is experienced differently. Platform-based pay is usually calculated through piece-rate systems characterized by volatility, opacity, and gamified incentives (Duggan *et al.*, 2020; Kellogg *et al.*, 2020). As a result, compensation operates as a dual-function construct, simultaneously providing financial resources while imposing cognitive and emotional demands.

While bonuses and surge pricing may temporarily increase earnings, they expose workers to unpredictable income fluctuations and compel constant monitoring of algorithmic signals (Adams-Prassl, 2022; Wood *et al.*, 2019). Managing this uncertainty requires sustained effort, as workers may feel pressured to accept undesirable tasks or work during unsocial hours to stabilize income (Dasgupta *et al.*, 2025). Unlike non-gig workers, gig workers typically lack access to human intermediaries or institutional mechanisms to contest pay decisions, further compounding insecurity and strain (Norlander *et al.*, 2021). Over time, this structural opacity could compound feelings of job insecurity and elevate strain levels (Cropanzano *et al.*, 2023).

Furthermore, from an SDT perspective, when compensation is delivered via controlling mechanisms that undermine autonomy - as is often the case in gig work with AM - its positive impact on well-being is diminished (Deci and Ryan, 2000). The platform uses opaque surge pricing and dynamic incentives to direct worker behavior, compelling them to work when the algorithm dictates, rather than when they autonomously choose (Kellogg *et al.*, 2020). This turns the pursuit of compensation into a coercive, extrinsic form of motivation.

From a contextualized JD-R perspective, the key issue is not just the compensation level, but how compensation is experienced when mediated by algorithmic control. Even if a worker rates their satisfaction with compensation highly, achieving that level of pay under AM often requires submission to constant performance monitoring and opaque surge pricing (Wood *et al.*, 2019). Therefore, in this context, high satisfaction with compensation is inextricably linked to high engagement with the algorithm’s autonomy-thwarting mechanisms.

H1. In the context of low-autonomy gig work, compensation is positively associated with psychological strain.

WLB is conventionally defined as satisfaction and perceived success in meeting work and non-work role demands (Guest, 2002). While typically theorized as a resource in the JD-R framework – helping employees maintain boundaries and mitigate spillover into personal life (Costa *et al.*, 2006) – AM fundamentally alters its relationship with strain. A core promise of gig work, regularly advertised by platform organizations, is flexibility (Waldkirch *et al.*, 2021). However, the distinction between gig workers’ temporal flexibility (i.e. choosing when to log in) and their limited autonomy over the labour process (i.e. minimal control over how work is designed and performed) is crucial. While platform organizations may offer high temporal flexibility, this freedom is often compromised by the coercive pressures of algorithmic control (see Wu *et al.*, 2019; Veen *et al.*, 2020)

This arrangement could paradoxically intensify strain if it necessitates perpetual connectivity to secure worthwhile tasks and earnings (Duggan *et al.*, 2023a, b; Shanahan and Smith, 2021). The need to constantly monitor demand and work during peak times to maximize earnings means that temporal flexibility does not necessarily translate into effective WLB; instead, it can lead to work intensification and boundary violations. Hence, an algorithmically enabled “flexibility” might enhance the sense of balance for non-gig workers

but could become a liability for gig workers who feel pressured to remain on standby, leading to workload unpredictability and weakened boundaries (Spieler *et al.*, 2017).

In short, although compensation and WLB measures are typically seen as strain buffers, we expect they can, under certain conditions, function as a double-edged sword. This seems particularly the case within the algorithmic ecosystem of gig work, where real-time demands and opaque decision-making can intensify the pressure to “make the most” of available job task opportunities. Accordingly, and counterintuitively, we expect the positive relationship between compensation and strain observed among gig workers to be stronger when WLB is high. We hypothesize the following:

- H2.* Work-life balance moderates the relationship between compensation and psychological strain in low-autonomy gig work, such that higher work-life balance amplifies the positive association between compensation and psychological strain.

Methodology

Sample and procedure

To infer worker strain, we used LIWC. This widely recognized text analysis software translates qualitative text data into quantitative indicators of various psychological constructs (Boyd *et al.*, 2022). The dataset used in our research comprises Glassdoor job reviews from workers in the United States between January 2015 and September 2020 and was shared by Glassdoor exclusively for academic research. The applicable sub-sample used for analysis comprised 6,505 job reviews from 6,505 workers across several gig and non-gig work companies. To determine this final sample, we ensured that all workers held similar roles, namely driver positions with different companies. The job category “driver” was provided by Glassdoor. We excluded any observations from workers who were at the same companies but in a different capacity (e.g. as a data analyst at Uber). The considered companies are provided in [Table 1](#).

Table 1. Overview of companies

	Company name	Number of job reviews	Percent
Non-gig work	Amazon.com, Inc	122	1.88
	Domino’s Pizza, Inc	351	5.40
	FedEx Corporation	153	2.35
	J.B. Hunt Transport Services, Inc	182	2.80
	Lowe’s Companies, Inc	168	2.58
	Papa John’s International, Inc	198	3.04
	PepsiCo, Inc	104	1.60
	Pizza Hut, Inc	142	2.18
	Schneider National, Inc	278	4.27
	Sysco Corporation	118	1.81
	US Foods, Inc	86	1.32
	United Parcel Service, Inc	412	6.33
	United States Postal Service	269	4.14
	Wal-Mart Stores, Inc	88	1.35
Gig work	DoorDash	610	9.38
	Grubhub, Inc	287	4.41
	Lyft, Inc	888	13.65
	Postmates Inc	12	0.18
	Uber	2,037	31.31
	Total	6,505	100.00

Measures

Psychological Strain. We inferred psychological strain using the LIWC stress dictionary (e.g. “anxious,” “tense,” “pressure”), which quantifies the percentage of words associated with psychological strain. This specialized dictionary captures the linguistic manifestation of psychological strain – the emotional outcomes of the stress process. The resultant measure, derived from the percentage of words in a text sample that appear in the strain dictionary, provides a quantifiable index of psychological strain expression ($M = 0.02$, $SD = 0.04$). Previous examples include the use of linguistic markers to study patients’ negative feedback (Ojo and Rizun, 2019) and monitor psychosocial health over time (Gruda and Ojo, 2022; Gruda et al., 2022).

Compensation and benefits. Our measure of compensation and benefits (hereafter referred to as compensation, to facilitate easier reading) was provided in the form of ratings (on a 5-point scale) by job reviewers when submitting their Glassdoor reviews. Importantly, Glassdoor asks reviewers to rate “Compensation and Benefits”. While traditional employees likely consider salary and benefits (e.g. health insurance), we acknowledge that the term “benefits” is vestigial mainly in the context of platform-based gig work, as traditional benefits are typically nonexistent. While the Glassdoor rating for compensation is a broad evaluative measure – hence referred to as “satisfaction with compensation” in our analysis – in the context of gig work, pay is inextricably linked to algorithmic mechanisms such as dynamic pricing, performance-contingent bonuses, and “gamified” incentives (Malhotra, 2021; Shanahan and Smith, 2021). Thus, a gig worker’s assessment of compensation is not merely a reflection of pay level, but an evaluation of their efficacy in navigating an opaque and volatile algorithmic reward system. We acknowledge that while this measure captures the outcome of this engagement, it serves as a proxy for the strain-inducing process of “chasing the algorithm” to achieve financial targets. This approach allows us to use an ecologically valid measure of perceived compensation value directly from the platform.

Work-life balance. Gig workers must balance a high degree of autonomy (i.e. when and how often they work) with a lack of a guaranteed income. Given that gig workers in our sample can work at any time, they likely also experience WLB quite differently compared to employees in similar, but traditional roles. Similarly to the compensation measure, WLB was assessed as a rating (on a 5-point scale) provided by job reviewers. Glassdoor’s WLB rating captures the worker’s *subjective satisfaction* with their boundary management, which is precisely the outcome that the pressure from temporal flexibility undermines.

Control variables. We controlled for Overall Company Rating (rated on a 5-point scale; $M = 3.01$, $SD = 1.44$) as a proxy for job satisfaction, length of employment ($M = 2.99$, $SD = 4.57$) to account for organizational tenure, time (review date) to capture time-specific effects, and gender (26.11% female; but missing observations, see robustness check).

Analytical strategy

Our dataset comprises worker reviews grouped by company, indicating that our observations are not independent, as noted by Rabe-Hesketh and Skrondal (2008). We employed a multilevel mixed-effects generalized linear model (GLM) with a logit function and robust standard errors. This approach accounts for the proportional nature of the dependent variable (worker strain) and the nested data structure (reviews within employers).

We acknowledge the potential for multicollinearity biasing our estimates, we calculated the Variance Inflation Factors (VIFs) for the variables in our main model. All VIFs were below the conventional threshold of 5, suggesting that multicollinearity is not severely impacting the regression results. All analyses were performed using Stata 18.0 software.

Results

Pairwise correlations are shown in Table 2. Two-way interaction results are shown in Table 3, and three-way interaction results are shown in Table 4.

Table 2. Pairwise correlations of main variables

Variables	M	SD	(1)	(2)	(3)	(4)	(5)
(1) Gig-Work	0.59	0.49					
(2) Worker Psychological Strain	0.02	0.04	-0.05***				
(3) Satisfaction with Compensation	2.70	1.45	-0.33***	-0.02			
(4) Work-Life Balance	3.24	1.54	0.26***	-0.04*	0.35***		
(5) Overall Company Rating	3.00	1.44	-0.09***	-0.02	0.67***	0.59***	
(8) Length of Employment	2.99	4.57	-0.38***	-0.03**	0.25***	-0.12***	0.06***

Note(s): Gig-Work coded as binary (0 = non-gig work; 1 = gig work); Satisfaction with Compensation = single score reflecting worker satisfaction with compensation and benefits; Length of employment coded as ordinal (0–1 year = 0, 1–2 years = 1, 2–4 years = 2, 4–5 years = 4, 5–6 years = 6, 7–9 years = 9, 10+ years = 20); *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $n = 6,505$

Table 3. Main two-way interaction regression results

DV: Psychological strain (LIWC)	b	SE	z	[95% CI]
Gig work	-0.33	0.17	-1.91	[-0.67; 0.01]
Satisfaction with compensation	0.03	0.05	0.61	[-0.06; 0.12]
Gig work × Satisfaction with compensation	0.11*	0.04	2.46	[0.02; 0.19]
Work-life balance	-0.02	0.02	-1.01	[-0.06; 0.02]
Overall company rating	-0.17***	0.03	-5.33	[-0.24; -0.11]
Length of employment	0.01	0.01	1.18	[-0.01; 0.02]
Word count	0.02***	0.00	12.68	[0.02; 0.02]
Date	-0.00*	0.00	-2.22	[-0.00; -0.00]
Constant	1.06	0.83	1.28	[-0.56; 2.68]
χ^2	1636.74***			

Note(s): *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $n = 6,505$

Table 4. Main three-way interaction regression results

DV: Psychological strain (LIWC)	b	SE	z	[95% CI]
Gig work	0.33	0.35	0.94	[-0.36; 1.03]
Work-life balance	0.17	0.12	1.44	[-0.06; 0.41]
Satisfaction with compensation	0.19*	0.08	2.46	[0.04; 0.33]
Gig work × Work-life balance	-0.24	0.13	-1.84	[-0.50; 0.02]
Gig work × Satisfaction with compensation	-0.22*	0.10	-2.08	[-0.42; -0.01]
Work-life balance × Satisfaction with compensation	-0.06*	0.03	-2.26	[-0.12; -0.01]
Gig work × Work-life balance × Satisfaction with compensation	0.10**	0.03	3.03	[0.03; 0.16]
Overall company rating	-0.17***	0.03	-5.40	[-0.24; -0.11]
Length of employment	0.01	0.01	1.19	[-0.01; 0.02]
Word count	0.02***	0.00	12.72	[0.02; 0.02]
Date	-0.00*	0.00	-2.22	[-0.00; -0.00]
Constant	0.56	0.87	0.65	[-1.13; 2.27]
χ^2	2539.14***			

Note(s): *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $n = 6,505$

The two-way interaction between gig work and compensation significantly predicted psychological strain ($b = 0.11$, $SE = 0.04$, $z = 2.46$, $p = 0.014$). To better understand this interaction, we graph it in Figure 1 (± 1 SD).

A simple-slope analysis revealed a significant, positive association between compensation and worker strain among gig workers (slope = 0.03, $SE = 0.01$, $z = 3.06$, $p = 0.002$). In the case of non-gig work, this was not the case (slope = 0.01, $SE = 0.01$, $z = 0.61$, $p > 0.10$).

We also found that the three-way interaction between gig work, compensation, and WLB significantly predicted psychological strain ($b = 0.10$, $SE = 0.03$, $z = 3.03$, $p = 0.002$). To better understand this interaction, we graph it in Figure 2 (± 1 SD).

Supporting Hypothesis 2, a simple-slope analysis revealed that for gig workers, as WLB increases, strain also increases when compensation is rated high (slope = 0.02, $SE = 0.006$, $z = 2.43$, $p = 0.015$). As hypothesized, this finding suggests that high WLB amplifies the positive association between compensation and psychological strain for gig workers. In contrast, strain remains stable when compensation is rated low (slope = -0.004 , $SE = 0.004$, $z = -1.04$, $p > 0.10$). In the case of non-gig work, as WLB ratings increased, strain decreased (slope = -0.02 , $SE = 0.006$, $z = -2.61$, $p = 0.009$). We interpret these results in the subsequent discussion section.

Robustness Checks. We purposefully did not include gender in the main regression model because of many missing observations (37.38% of participants did not indicate their gender). However, including this additional variable in the regression model did not change the main interaction result nor the direction of the main effect ($b = 0.11$, $SE = 0.05$, $z = 2.32$, $p = 0.02$).

Discussion

Our findings are consistent with the argument that AM functions as a boundary condition that reconfigures the JD-R resource pathway. The positive association between compensation and psychological strain among gig workers reinforces autonomy-centered critiques of gig work

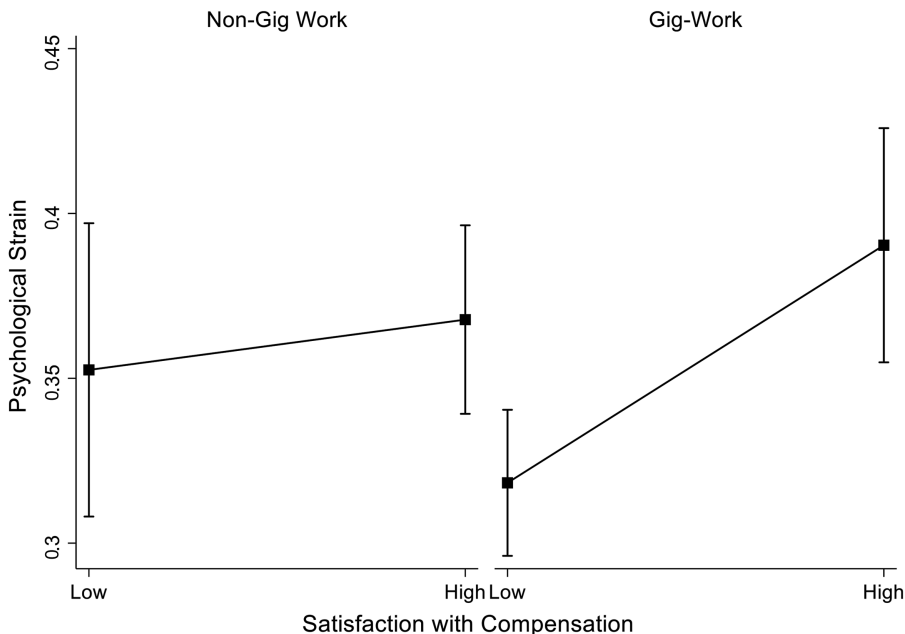


Figure 1. Interaction of gig-work and satisfaction with compensation predicting worker psychological strain

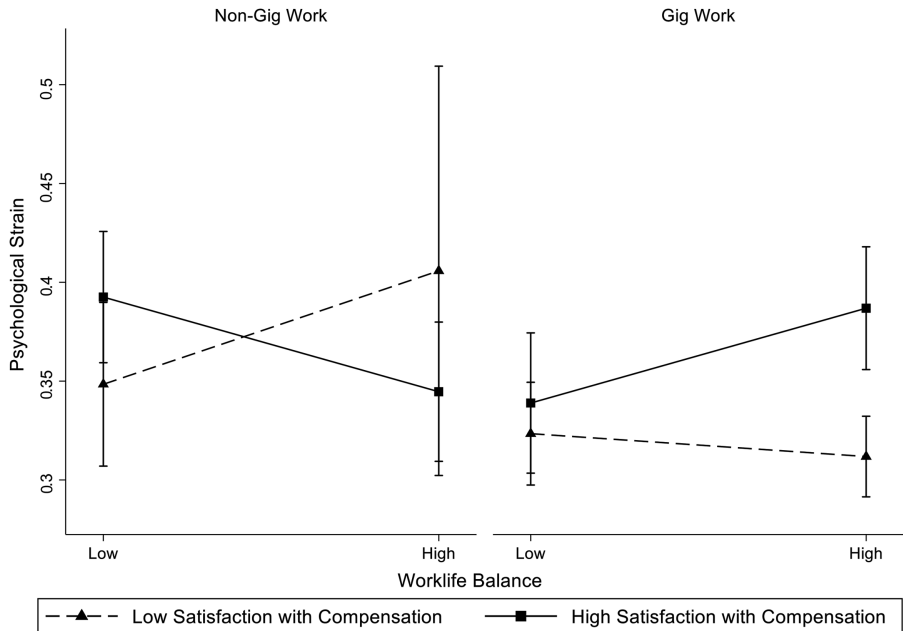


Figure 2. Interaction of gig-work, satisfaction with compensation and work-life balance predicting worker psychological strain

(Cruz *et al.*, 2020; Wood *et al.*, 2019) and suggests that compensation may operate more like a demand than a resource in this context. Rather than alleviating strain, financial rewards appear to be psychologically costly when earned through opaque and controlling algorithmic systems.

Notably, however, from an SDT perspective, these results may seem less counterintuitive and suggest a potent mechanism: basic psychological need thwarting (Olafsen *et al.*, 2017). From an SDT perspective, AM is theorized to undermine autonomy and competence, transforming extrinsic rewards into coercive pressures (Meijerink and Bondarouk, 2023; Schafheite *et al.*, 2020), thereby increasing overall psychological strain. This fundamentally alters the motivational process predicted by JD-R, showing how the health impairment pathway is powerfully mediated by the SDT need-thwarting mechanism (Schaufeli, 2017; Olafsen *et al.*, 2017; Deci *et al.*, 2017). While our results indicate that compensation is associated with higher strain in gig work, we must exercise caution in interpretation. Due to the aggregate nature of the Glassdoor compensation measure, we cannot isolate whether this effect is driven primarily by pay volatility, the opacity of the algorithm, or the effort required to meet algorithmic targets. Future research using more granular pay-process measures is needed to disentangle these effects.

Among gig workers, we found that WLB was positively associated with worker strain, but only when satisfaction with compensation was rated high. Rather than experiencing a decrease in strain as WLB improved (as evident in our non-gig work sample), our results suggest an inverse relationship. Conventionally, WLB is lauded for providing workers with a sense of freedom and time for personal rejuvenation (Guest, 2002). However, for gig workers bound by these “golden handcuffs”, time away from work may instead serve as a reminder of work-related pressures and responsibilities, exacerbating strain. Thus, when extrinsic rewards (compensation) and the resource of flexibility (WLB) are experienced within a context of algorithmic control that thwarts basic psychological needs for autonomy and competence, the positive effects of these resources may be neutralized or even reversed. This effect is amplified

when WLB is high, suggesting that perceived flexibility may intensify pressure to optimize earnings, creating self-imposed constant availability that represents a severe boundary violation and psychological crowding-out effect.

Accordingly, the AM system creates a high-demand environment where the pursuit of high compensation requires workers to relinquish control (Kellogg *et al.*, 2020; Duggan *et al.*, 2023a, b). Thus, perceived high WLB may not reflect genuine WLB but rather a stressful adaptation to unpredictable demands. For these workers, an improvement in WLB might paradoxically lead to an increase (rather than a decrease) in psychological strain. This adds another layer of complexity to our understanding of work in the gig economy, suggesting that the interplay between compensation, WLB, and strain is not as straightforward as it may initially seem.

In the case of low compensation ratings, gig worker strain remained essentially unchanged across WLB ratings, possibly because gig work often serves as a supplementary income source (Kuhn and Galloway, 2019). In this scenario, although compensation may be perceived as low, the opportunity to earn additional income at their convenience could help alleviate psychological strain and maintain stability. The promise of the gig economy may therefore hold most true for workers who engage sporadically rather than relying solely on gig work for income (Kuhn and Galloway, 2019; McDonnell *et al.*, 2021). Such workers likely possess greater autonomy over scheduling, resulting in stronger feelings of autonomy and empowerment (Veen *et al.*, 2020), without increasing strain.

Among non-gig workers, the interaction between compensation and WLB was negatively associated with strain only when compensation was rated highly, suggesting that the dynamics of traditional employment differ substantially. Employees in conventional jobs typically have more structured working hours, steady pay, and access to employment benefits, all of which may shape their perceptions of WLB and experiences of strain in ways that differ from gig workers. This aligns with prior research characterizing gig work as a catalyst for a novel cohort of “invisible workers” (Duggan *et al.*, 2020). These workers operate in a hyper-flexible manner and rely heavily on new technologies, rendering their labour susceptible to dehumanization, at least from the perspective of customers (Sherman *et al.*, 2025; Dasgupta *et al.*, 2025).

Our findings underscore that AM implementation is a critical, context-dependent moderator of well-being outcomes. The observed failure of resources to reduce strain in the gig economy stands in stark contrast to expectations for traditional employment and is consistent with the theorized boundary condition. The crucial difference lies in the mechanism of control: in gig work, AM’s implementation is designed to minimize human discretion and maximize platform control (Kellogg *et al.*, 2020), thereby thwarting basic psychological needs. This supports the notion that the presence or absence of human managerial mediation and employment protections fundamentally shifts the psychological experience of AM from a supportive resource to a coercive demand that neutralizes the benefits of other job resources.

Ultimately, while the potential of AM is attractive and innovative for organizations, workers may pay a high price as the recipients of these technologies. Although AM can heighten efficiency and grant flexibility around scheduling, workers are placed at the center of a control system where they have little choice but to comply with algorithmic directives to secure efficient service delivery, positive evaluations, and beneficial rewards (Norlander *et al.*, 2021; Wood *et al.*, 2019). These conceptualizations of algorithmic governance in gig work do not align with well-established views of worker well-being and based on our results, suggest that such conditions may be strain-inducing for workers who rely on gig work as a source of income.

Implications

This study offers several contributions to the literature on gig work, AM, and worker strain, with an overarching focus on extending and refining the application of the JD-R model and integrating it with SDT in this context.

First, we extend the JD-R model to the gig economy context, a setting characterized by pervasive AM influence. Our findings demonstrate how AM introduces unique job demands that fundamentally alter the functioning of job resources. Specifically, we show how compensation and WLB, typically considered crucial job resources that buffer strain and promote well-being (Bakker and Demerouti, 2007; Galanakis and Tsitouri, 2022), can take on demand-like characteristics and contribute to increased strain under algorithmic control. This highlights a key contribution: we move beyond simply classifying job characteristics as demands or resources by showing how AM reshapes the operation of traditional job resources, a nuance not fully explored in prior research (Cropanzano *et al.*, 2023; Meijerink and Bondarouk, 2023). Our findings therefore suggest a boundary condition for the JD-R model, challenging the universality of the resource-wellbeing pathway by demonstrating that, in the high-demand, need-thwarting context of AM, resources such as compensation and WLB are paradoxically associated with increased psychological strain. Thus, our study provides empirical evidence of AM's demand-like nature and its dominant effect (Sherman *et al.*, 2025; Parent-Rocheleau and Parker, 2022). In this context, AM is so powerful that it seemingly overrides the effects of resources, effectively "tainting" them and turning them into quasi-strainers.

Second, we contribute to the growing body of literature on AM and worker well-being (see Cropanzano *et al.*, 2023) by advancing a theoretical synthesis: while the JD-R model is essential for framing demands and resources, our integration with SDT provides a psychological mechanism that explains *why* resources fail to buffer demands under algorithmic control. Specifically, our findings suggest that algorithmic control's need-thwarting effects (SDT) fundamentally re-specify the resource process (JD-R), transforming compensation and WLB into strain-inducing pressures. This combined lens offers a more comprehensive framework for understanding worker well-being in technology-mediated work environments and addresses the *why* behind the health-impairment process in the gig context (Schafheitle *et al.*, 2020; Schaufeli, 2017).

Third, we provide initial empirical support for the validity of this theoretical reconfiguration through a rigorous comparative design. By examining strain in gig versus non-gig workers in similar roles, we utilize a methodological strategy that isolates the unique influence of AM, providing a clear baseline to identify how this specific job demand alters the standard demand-resource balance (Bakker and Demerouti, 2017). This approach addresses calls for more empirical and quantitative research on the gig economy and AM (McDonnell *et al.*, 2021; Sherman *et al.*, 2025) and provides a strong foundation for future JD-R research in technology-driven work contexts.

Finally, for practitioners, especially those in human resources and organizational leadership, our findings suggest that standard HR interventions – such as simply increasing piece-rates or touting flexibility – may backfire if the underlying mechanism remains unchanged. Because compensation and WLB currently function as strain-inducing "golden handcuffs" – where higher rewards are inextricably linked to higher submission to the algorithm – platform managers cannot solve the strain crisis through piece-rate increases alone. Because the algorithmic delivery of these "resources" currently induces strain, platform organizations must redesign the algorithms themselves. Platforms must transition from "coercive" algorithmic management, which thwarts basic psychological needs, toward "enabling" systems that provide transparency and restore worker agency over the labor process (Duggan *et al.*, 2023b).

Limitations and future research

This study acknowledges several important limitations. For example, on Glassdoor, self-reported ratings for WLB and compensation may introduce social desirability bias. Likewise, while our use of LIWC for strain inference offers objectivity and replicability, LIWC has limitations. It relies on predefined dictionaries, which may miss subtle linguistic nuances such

as irony or context-specific meanings, and does not directly measure subjective strain experience. Despite these, the combined approach offers a more robust assessment than surveys alone.

Furthermore, the lack of an experimental design precludes definitive causal inferences; we can only establish significant associations. Hence, we recognize the limitations of our cross-sectional design regarding internal validity. Additionally, there is a potential risk of conceptual collinearity, as gig work status, the prevalence of algorithmic control, and the nature of compensation (e.g. fluctuating pay) are tightly coupled in this context. These variables are mutually constitutive and reflect the contemporary structure of platform work itself. While our statistical checks (VIFs) suggest multicollinearity is not a severe issue, the cross-sectional design cannot fully disentangle these effects. Specifically, our reliance on a broad, aggregate rating for compensation limits our ability to distinguish between different facets of algorithmic pay – such as volatility, opacity, or the gamified effort required to meet targets – that may be the true drivers of strain. Future studies should employ more granular, multidimensional scales or longitudinal earnings data to disentangle how specific components of the platform reward system interact with worker autonomy to produce these effects. Our findings may also not be uniformly applicable across all gig work environments due to variations in AM across geographical locations and platforms.

Finally, our data do not capture the phenomenon of multi-homing (working for multiple platforms simultaneously), which is common in the gig economy. This limits our ability to observe the full complexity of the worker's experience. Multi-homing introduces institutional complexity where a worker might balance the demands of one platform with the resources of another (Cruz *et al.*, 2020). Furthermore, our focus on platform supports may rely on the naive assumption that platforms have an incentive to be supportive; however, in a multi-homing environment where labor is treated as a commodity, platforms may lack the economic incentive to provide genuine care or support unless compelled by external pressures. This suggests that the JD-R profile of gig work is not merely an organizational design choice but a regulatory one. Future research should examine how social actors (e.g. worker collectives) and labor regulations can intervene to mandate the “resources” that platforms currently have little incentive to provide (Duggan *et al.*, 2023b). Furthermore, because multihoming allows workers to balance the demands of one platform with the resources of another, our findings on single-platform strain may underrepresent the total cognitive load experienced by workers navigating multiple, potentially conflicting algorithmic systems simultaneously. Future research utilizing diary studies is required to fully disentangle how this institutional reality configures the overall JD-R profile of gig workers. Additionally, we did not directly measure autonomy or basic psychological need frustration; the SDT-based mechanism we propose is a theoretically grounded interpretation of the observed patterns. Future studies should incorporate validated measures of need frustration to directly test this mechanism.

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