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Algorithmic Management and Turnover Intention in Platform Ride-Hailing: The Roles of Job Demands, Flexibility Constraints and Economic Dependence

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ALGORITHMIC MANAGEMENT AND TURNOVER INTENTION IN PLATFORM RIDE-HAILING: THE ROLES OF JOB DEMANDS, FLEXIBILITY CONSTRAINTS AND ECONOMIC DEPENDENCE

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Resumo

À medida que as plataformas de transporte por aplicação recorrem cada vez mais à gestão algorítmica para organizar e coordenar o trabalho, torna-se relevante compreender os seus efeitos nos trabalhadores. Apesar do crescente interesse na gestão algorítmica e no trabalho em plataformas, permanece limitada a compreensão dos mecanismos que ligam diferentes níveis de gestão algorítmica à intenção dos trabalhadores de abandonar a atividade e das condições em que esses efeitos podem variar. Este estudo analisa o efeito da exposição a níveis elevados versus reduzidos de Gestão Algorítmica na Intenção de Saída no setor TVDE, considerando as Exigências do Trabalho e as Restrições de Flexibilidade como potenciais mecanismos mediadores. Analisa ainda a Dependência Económica como moderador, procurando compreender de que forma os efeitos da Gestão Algorítmica variam consoante a dependência dos trabalhadores do rendimento proveniente da plataforma.

O modelo foi testado empiricamente através de um questionário online baseado em cenários, aplicado a 209 motoristas TVDE em Portugal, aleatoriamente distribuídos entre condições de elevada e reduzida gestão algorítmica. Os dados foram analisados com recurso ao IBM SPSS Statistics e à macro PROCESS (Hayes, 2022), através de modelos de mediação e moderação.

Os resultados mostram que a exposição a níveis elevados de gestão algorítmica está associada a uma maior intenção de saída. As exigências do trabalho mediam significativamente esta relação, enquanto as restrições de flexibilidade não apresentam um efeito mediador significativo. A dependência económica modera ainda os efeitos da gestão algorítmica nas exigências do trabalho e nas restrições de flexibilidade, indicando que estes variam consoante a dependência dos trabalhadores do rendimento da plataforma.

Ao integrar estas variáveis num único modelo, este estudo contribui para a literatura sobre trabalho em plataformas, proporcionando uma compreensão mais aprofundada de como e em que condições a gestão algorítmica influência a intenção dos trabalhadores de abandonar a atividade.

Palavras-Chave: Gestão Algorítmica, TVDE, Intenção de Saída, Exigências do Trabalho, Restrições de Flexibilidade, Dependência Económica

Abstract

As ride-hailing platforms increasingly rely on algorithmic management to organize and coordinate work, understanding how these practices shape workers' experiences has become particularly relevant. Despite growing research on algorithmic management and platform work, there is still limited understanding of the mechanisms linking different levels of algorithmic management to workers' intentions to leave and the conditions under which these effects may vary. This study therefore examines the effect of exposure to high versus low Algorithmic Management on Turnover Intention in the ride-hailing sector, exploring Job Demands and Flexibility Constraints as potential mediating mechanisms. It also investigates Economic Dependence as a core moderator to understand how the impacts of Algorithmic Management on workers' experiences vary according to their reliance on platform income.

The proposed model was empirically tested using data collected through a scenario-based online survey with 209 TVDE drivers in Portugal, who were randomly assigned to high or low algorithmic management conditions. The data were analysed using IBM SPSS Statistics and the PROCESS macro (Hayes, 2022), using mediation and moderation analyses.

The results show that exposure to high algorithmic management is associated with higher turnover intention. Job demands significantly mediates this relationship, indicating that algorithmic management increases job demands, which in turn is associated with greater turnover intention, whereas flexibility constraints does not emerge as a significant mediating mechanism. Furthermore, economic dependence is found to moderate the relationship between algorithmic management and both job demands and flexibility constraints, showing that the effects of algorithmic management vary according to workers' reliance on platform income.

By integrating these variables into a unified framework, this research contributes to the platform work literature by providing a nuanced understanding of how and under what conditions algorithmic management shapes workers' intentions to exit.

Keywords: Algorithmic Management, Ride-Hailing, Turnover Intention, Job Demands, Flexibility Constraints, Economic Dependence

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1. Introduction

Despite their growing importance in contemporary labour markets, ride-hailing platforms remain marked by a central contradiction: they are promoted as flexible and autonomous forms of work, yet they are also associated with unstable earnings, weak protection, algorithmic control and increasing worker insecurity (Muldoon & Raekstad, 2023; Ribbans et al., 2022). Recent research describes gig work as a significant and expanding part of the digital economy, where online platforms use algorithms to coordinate, allocate and evaluate labour (S. Li et al., 2025). Ride-hailing is particularly relevant in this debate because drivers are directly exposed to digital systems that perform core managerial functions, from the distribution of work to the calculation of pay, making a particular relevant context for examining how algorithmic management shapes workers' experiences (Ashkrof et al., 2020; Duggan et al., 2020; Mäntymäki et al., 2019).

Recent studies have linked algorithmic management to several labour-related consequences, including stress, burnout, dissatisfaction and turnover intention (Cheng et al., 2024; Liu et al., 2024; Samant & Malik, 2025). However, Adekoya et al. (2025) and Zheng et al. (2026) suggest that these effects are not only the result of algorithmic control itself, but of the way such control is translated into everyday working conditions. Turnover intention is therefore a particularly relevant outcome, as workers may consider leaving platform work when confronted with persistent work overload, burnout and limited long-term career prospects. (Adekoya et al., 2025; Liu et al., 2024; Zheng et al., 2026).

Although existing research has examined algorithmic management, worker well-being and platform precarity, future research recommendations argue that there is still room to better understand the mechanisms through which algorithmic management affects workers' experience and intention to leave the job (Duggan et al., 2020; Shi et al., 2025; Zhang et al., 2025). Job demands and flexibility constraints appear to play an important role. Studies show that platform workers often face work intensification, long and irregular hours, continuous responsiveness and emotional and cognitive pressure (Cheng et al., 2024; Koivusalo et al., 2024; Liu et al., 2024). At the same time, the flexibility promised by platforms is often limited in practice, as workers must adapt to peak demand, platform incentives and income needs (Fielbaum & Tirachini, 2021; Glavin & Schieman, 2022; Schor et al., 2020). These findings suggest that job demands and flexibility constraints may constitute distinct

mechanisms through which algorithmic management influences workers' turnover intention. Examining both mechanisms within the same framework may therefore provide a clearer understanding of how algorithmic management is associated with workers' intentions to leave.

Moreover, the literature highlights that platform workers are not equally affected by these dynamics (Glavin & Schieman, 2022; Kougiannou & Mendonça, 2025; Schor et al., 2020). Economic dependence has been identified by Schor et al. (2020) as a central factor explaining why some workers experience platform work as a flexible income opportunity, while others experience it as a precarious and constraining livelihood. Future research has also called for more nuanced approaches to dependence, moving beyond simple distinctions between primary and supplementary income and paying closer attention to how reliance on platform income shapes workers' behaviour, vulnerability and capacity to exit (Brawley Newlin, 2024; Saksida et al., 2026). Economic dependence may therefore operate as a boundary condition, strengthening or altering the effects of algorithmic management on workers' job demands and perceived flexibility constraints.

The aim of this study is, therefore, to examine how algorithmic management influences turnover intention in ride-hailing. More specifically, it investigates job demands and flexibility constraints constraints as potential mediating mechanisms and economic dependence as a moderating condition, to understand how and under what conditions algorithmic management shapes workers' intention to leave ride-hailing work.

The scientific relevance of this study lies in advancing research on platform work and algorithmic management by bringing together variables that are often examined separately, namely turnover intention, job demands, flexibility constraints and economic dependence (Duggan et al., 2020; Glavin & Schieman, 2022; Liu et al., 2024; Schor et al., 2020). Rather than focusing only on the direct effects of algorithmic management, this study integrates mediating and moderating mechanisms to better understand how different levels of algorithmic management may be associated with workers' intention to leave, through job demands and flexibility constraints and how these relationships vary according to workers' reliance on platform income. Its practical relevance lies in offering insights into the specific conditions that may increase vulnerability among ride-hailing drivers, particularly when platform work becomes an important source of income. Accordingly, the study is guided by the following research question:

Research Question: How does Algorithmic Management influence ride-hailing workers' Turnover Intention through Job Demands and Flexibility Constraints, and does Economic Dependence moderate the effect of Algorithmic Management on these two mediating mechanisms?

In order to answer the research question, a scenario-based online survey was conducted with 209 TVDE[1] drivers in Portugal, who were randomly assigned to high or low algorithmic management conditions. The responses were then used to empirically test the proposed model through mediation and moderation analyses using IBM SPSS Statistics and the PROCESS macro (Hayes, 2022).

The remainder of this work is organized as follows. The next section presents the literature review related to the research objective and develops the hypotheses that guide the study. The following section describes the research methodology, including the research design, data collection procedures, sample, measures and analysis strategy. This is followed by the presentation of the empirical results and their discussion in relation to the existing literature. The final section presents the theoretical and managerial implications, followed by the study limitations and directions for future research.

[1] Individual and remunerated passenger transport in unmarked vehicles via an electronic platform (Leonardi & Pirina, 2020).

2. Literature Review

In this section, the existing literature is reviewed to provide a comprehensive understanding of current knowledge on Ride-Hailing and its labour implications. More specifically, the review examines the context of gig work and ride-hailing, the relationship between Algorithmic Management, Turnover Intention and the roles of Job Demands, Flexibility Constraints and Economic Dependence in shaping these outcomes.

2.1. Gig Work and Ride-Hailing

Ride-hailing is one of the most visible and influential forms of platform work within the gig economy (Mäntymäki et al., 2019; Muldoon & Raekstad, 2023). Recent literature reviews indicate that gig work has become an important and expanding part of contemporary labour markets, typically characterized by short-term, digitally mediated engagements in which online platforms use algorithms to coordinate, allocate and evaluate work (S. Li et al., 2025). Although this category includes different forms of app-based labour, ride-hailing is especially relevant because it brings together many of the core features of platform work: real-time matching between supply and demand, heavy reliance on digital infrastructure, fragmented work arrangements and direct exposure to customer evaluation (Duggan et al., 2020; Mäntymäki et al., 2019).

The literature increasingly approaches ride-hailing not as an isolated activity, but as part of a broader transformation in work organization under digital capitalism (Muldoon & Raekstad, 2023). This shift is marked by the platformization of labour, the transfer of risks and costs to workers and the replacement of standard employment protections with more individualized and unstable forms of work (Duggan et al., 2020; Jeronimo et al., 2022; Ribbans et al., 2022; Schor et al., 2020). In this context, ride-hailing is often described as a form of "on-demand labour", in which work is allocated, managed and monitored entirely through an app (Glöss et al., 2016). Platform work represents more than a technological innovation in service provision; it entails a reconfiguration of labour relations in which digital intermediaries reshape the boundaries between employment, self-employment and market exchange (Duggan et al., 2020; Jeronimo et al., 2022; Mäntymäki et al., 2019; Maury, 2024; Meijerink et al., 2021; Zhao et al., 2026). Reflecting this development, the research agenda

has also widened considerably, moving beyond efficiency and participation to include issues such as worker safety, turnover, legal vulnerability and social inequality (S. Li et al., 2025).

At the same time, the literature suggests that workers do not experience ride-hailing in the same way (Glavin & Schieman, 2022; Mäntymäki et al., 2019; Schor et al., 2020). Some enter the sector because it offers quick access to income, others because it allows greater temporal adaptability and others because conventional labour market options are limited or inadequate (Maury, 2024; Mäntymäki et al., 2019; Schor et al., 2020). For this reason, ride-hailing can function as a practical source of paid work for individuals facing rigid schedules, caregiving responsibilities or unstable employment histories (Lin et al., 2026; Mäntymäki et al., 2019). Mäntymäki et al. (2019) show that the on and off nature of platform work can be especially valuable in such circumstances, while Fielbaum and Tirachini (2021) find that flexibility is the most highly valued job attribute among ride-hailing workers. Similar evidence suggests that drivers may also perceive this type of work as preferable to previous occupations because it offers greater dignity and more room to manage family needs (Khan et al., 2026). More broadly, this suggests that the expansion of ride-hailing is linked not only to platform growth strategies, but also to labour market conditions that make this type of work attractive, useful or necessary for different groups of workers (Mäntymäki et al., 2019; Fielbaum & Tirachini, 2021; Khan et al., 2026).

However, this appeal coexists with substantial insecurity (Khan et al., 2026; Reid-Musson et al., 2020; Saksida et al., 2026). A recurring finding across studies is that ride-hailing workers face unstable and often worsening earning conditions shaped by fare reductions, high commissions, vehicle-related expenses and market oversupply (Ashkrof et al., 2020; Fielbaum & Tirachini, 2021; Khan et al., 2026; Maffie, 2023; Mäntymäki et al., 2019; Sühr et al., 2019). Koivusalo et al. (2024) show that drivers often work substantially longer hours to compensate for low pay and high operating costs. Similar dynamics are reported by Ribbans et al. 2022, where drivers experienced lower earnings despite substantial increases in working time. The promise of autonomy is further undermined by debt burdens, declining fares and the need to pursue exhausting side hustles to remain financially viable (Khan et al., 2026). These patterns support the argument that platform work should be understood not only as flexible market participation, but also as a mechanism through which business risks are shifted onto workers (Glöss et al., 2016; Zhao et al., 2026).

Overall, the literature suggests that ride-hailing offers a useful lens through which to understand wider transformations in work under globalization and digitalization (Koivusalo

et al., 2024; Leonardi & Pirina, 2020; Mäntymäki et al., 2019). Platform work has been described as a social determinant of health, a generator of new inequalities and a setting in which labour protections are weakened even as digital coordination becomes more sophisticated (Koivusalo et al., 2024). It also raises broader questions about the future of labour markets, including the position of immigrants and other vulnerable workers who make up an important share of the gig workforce and whose challenges are intensified by economic disparities and algorithmic bias (S. Li et al., 2025). In this context, the increasing reliance on digital systems to organize, monitor and coordinate work makes algorithmic management a central feature of the ride-hailing model (Duggan et al., 2020; S. Li et al., 2025). Understanding how these systems shape workers' experiences is therefore essential to assessing the broader labour implications of platform work (Ashkrof et al., 2020; Mäntymäki et al., 2019). In this sense, ride-hailing and gig work provide the essential context for examining the more specific effects of algorithmic management on labour outcomes.

2.2. Algorithmic Management and Turnover Intention

Algorithmic management constitutes a key mechanism through which platform work is organized and controlled on digital labour platforms (Duggan et al., 2020; Samant & Malik, 2024). In the literature, algorithmic management is understood as the software-driven architecture that automates traditional managerial and administrative functions (Duggan et al., 2020). Within this broader concept, algorithmic control refers more specifically to the automated mechanisms through which management is exercised, including continuous monitoring, behavioral direction, performance evaluation and disciplinary enforcement (Kellogg et al., 2020; Wood et al., 2019). Rather than removing managerial authority, platforms reconfigure it: managerial functions are delivered largely through software, making algorithms the main infrastructure of labour coordination in gig work (Crayne & Brawley Newlin, 2024; Duggan et al., 2020; Meijerink et al., 2021). In practice, this means that workers encounter management through dispatch systems, dynamic pricing, behavioural nudges, ratings, performance metrics, deactivation rules and opaque decision-making processes rather than through direct human supervision (Chan, 2022; Duggan et al., 2020; Muldoon & Raekstad, 2023; Pignot, 2023; Samant & Malik, 2025; Zhao et al., 2026).

Research on ride-hailing shows that these systems shape both the material organization of work and workers' subjective experience of it (Cameron, 2024; Mäntymäki

et al., 2019; Muldoon & Raekstad, 2023; Zhao et al., 2026). Ashkrof et al. (2020) show that platform features such as request allocation, pricing, ride acceptance, relocation strategies and reputational pressures are central to drivers' day-to-day conduct. Their study also reveals strong mistrust toward the platform, driven by unreliable navigation, unfair reputation systems, high commissions and perceived informational asymmetries. Similar concerns appear in other studies. Mäntymäki et al. (2019) and Jeronimo et al. (2022) similarly show that, in ride-hailing, traditional hierarchies and informal, experience-based practices are increasingly replaced by algorithmic systems that regulate work through detailed yet opaque digital rules. These studies suggest that algorithmic management may contribute to a structurally asymmetric labour relation in which workers are required to comply with rules they often do not fully understand and cannot meaningfully contest (Chan, 2022; Duggan et al., 2020; Jeronimo et al., 2022; Muldoon & Raekstad, 2023; Samant & Malik, 2025; Zhao et al., 2026).

This control may also extend beyond the app itself. Li (2022) shows that in some platform settings organizational influence is reinforced by intermediaries and communication infrastructures, creating fluid workspaces in which control is exercised through both formal platform systems and informal managerial networks. This is important because it indicates that algorithmic management should not be understood only as an isolated technical feature of the app (Li, 2022; Muldoon & Raekstad, 2023). Instead, it operates within wider organizational arrangements that can intensify supervision, coordination and behavioural control (Li, 2022; Meijerink et al., 2021; Sun et al., 2023). For this reason, ride-hailing is better understood as a platform-mediated form of work in which algorithmic systems, intermediary structures and managerial networks jointly shape how work is organized and experienced (Duggan et al., 2020; Li, 2022; Zhao et al., 2026).

Algorithmic management has been increasingly linked to turnover intention, in the ride-hailing sector (Adekoya et al., 2025; Liu et al., 2024; Saksida et al., 2026). Conceptualized as an individual's subjective probability and conscious cognitive decision to voluntarily leave their organization or line of work within a specific time frame, turnover intention serves in platform work as a key indicator of psychological detachment and thoughts of withdrawal (Saksida et al., 2026; Yu & Abdul Hamid, 2024). Existing research shows that workers' decisions to remain on or leave platforms are shaped not only by income dissatisfaction, but by a broader evaluation of whether algorithmically governed work is sustainable over time (Duggan et al., 2020; Khan et al., 2026; Maffie, 2023; Saksida et al., 2026; Zheng et al., 2026).

In this context, monitoring, evaluation and customer feedback also play an important role in shaping workers' behaviour and intention to exit the job (Chan, 2022; Duggan et al., 2020; Pignot, 2023).

Empirical research illustrates several mechanisms through which algorithmic management may drive turnover intention. Specifically, Liu et al. (2024) illustrate indirect evidence of this relationship by showing that algorithmically driven work overload increases turnover intention through the mediating role of job burnout. Similarly, Yu and Abdul Hamid (2024) find that when algorithmic management fulfills both transactional and relational psychological expectations, it reduces turnover intention indirectly through higher job satisfaction and organizational identification. In contrast, Saksida et al. (2026) show that when unilateral platform decisions and algorithmic control violate psychological contracts, particularly in relation to safety and platform commitment, trust may weaken and cynicism may intensify, thereby increasing withdrawal intentions among workers who perceive limited alternatives. Crayne and Brawley Newlin (2024) add a further layer by showing that in the absence of human supervisors under algorithmic management, workers must rely on self-leadership, which can improve well-being while also encouraging workers under high financial stress to pursue more stable, non-gig employment.

At the same time, the literature also points to more conditional effects of algorithmic management, which complicates purely negative interpretations. Shi et al. (2025) find that perceived algorithmic control can, under certain conditions, support thriving at work, while Zhang et al. (2025) show that algorithmic transparency can improve both in-role and extra-role behaviour. These studies do not contradict the broader critical literature, but they do suggest that workers' reactions to algorithmic management depend on how these systems are experienced in practice (Cameron, 2024; Chan, 2022; Mäntymäki et al., 2019). Therefore, turnover intention may be shaped both by the intensity of algorithmic management and by how workers experience its mechanisms, particularly whether they perceive them as fair, transparent and manageable (Adekoya et al., 2025; Liu et al., 2024; Saksida et al., 2026; Samant & Malik, 2025).

Based on the literature reviewed, higher levels of algorithmic management are expected to increase workers' turnover intentions. Algorithmic monitoring, performance evaluation, behavioural control and limited transparency may increase perceived pressure and insecurity, making continued participation in ride-hailing work less attractive (Liu et al., 2024; Adekoya et al., 2025). Based on this reasoning, the following hypothesis is proposed:

H1: Ride-hailing workers exposed to high algorithmic management will report higher turnover intention than those exposed to low algorithmic management.

2.3. Mediators: Job Demands and Flexibility Constraints

2.3.1. Job Demands

Job demands are defined as those physical, psychological, social or organizational aspects of a job that require sustained physical, cognitive or emotional effort and are consequently associated with physiological and psychological costs (Bakker & Demerouti, 2007). In platform work, job demands extend far beyond the mere execution of immediate physical tasks (Glöss et al., 2016; Pignot, 2023). Instead, they encompass a broader set of algorithmically mediated pressures, including long and irregular working hours, workload pressure, continuous responsiveness, customer management and significant cognitive and emotional effort (Adekoya et al., 2025; Chan, 2022; Crayne & Brawley Newlin, 2024). In ride-hailing, these demands may be intensified by the fact that workers must constantly adapt to algorithmic management while also managing customer expectations and protecting their reputational standing (Adekoya et al., 2025; Chan, 2022; Duggan et al., 2020; Glöss et al., 2016; Zhao et al., 2026). As a result, the labour process becomes demanding not only in physical and temporal terms, but also in affective and psychological ones (Adekoya et al., 2025; Chan, 2022; Cheng et al., 2024; Samant & Malik, 2025).

A central mechanism through which these demands are produced is work intensification (Glöss et al., 2016; Liu et al., 2024; Maffie & Hurtado, 2025). Koivusalo et al. (2024) show that low fares and rising costs may lead drivers to compensate through longer working days, sometimes extending to sixteen hours. Ribbans et al. (2022) report a similar "work more, earn less" dynamic among UberGo drivers, while Zhao et al. (2026) connect high work intensity and surveillance to chronic fatigue, anxiety, depression and physical health problems. Pointing in the same direction, Maffie and Hurtado (2026) conceptualize platform decay as the gradual degradation of platform working conditions over time, arguing that platforms increasingly intensify work through changing algorithmic standards and deteriorating labour conditions. Similarly, Maury (2024) shows that platforms maximize unpaid labour by strategically shaping the balance between remunerated and unremunerated

activities such as waiting and transit. In all these cases, workers are required to expend greater effort, tolerate greater uncertainty and devote more unpaid time to maintain similar levels of income.

This intensification has measurable consequences for worker outcomes. Liu et al. (2024) provide clear empirical evidence that work overload increases burnout, which in turn raises turnover intention. Cheng et al. (2024) similarly show that labour control harms mental well-being through increased job demands. M. Li et al. (2025) add that perceived exploitation reduces workers' sense of work gain and security, with negative effects on subjective well-being. Together, these studies suggest that algorithmic managed working conditions may contribute to adverse worker outcomes by increasing the demands associated with platform work (Chan, 2022; Cheng et al., 2024; Muldoon & Raekstad, 2023; Samant & Malik, 2025; Zhao et al., 2026; Zheng et al., 2026). In this sense, its impact may operate through the lived conditions of the labour process rather than solely through workers' abstract attitudes toward technology (Cameron, 2024; Chan, 2022; Muldoon & Raekstad, 2023; Zhao et al., 2026).

The literature suggests that job demands may constitute an important mechanism linking algorithmic management to worker outcomes (Cheng et al., 2024). Algorithmic systems may shape the pace, uncertainty and emotional burden of work in ways that make the labour process more demanding (Cheng et al., 2024; Liu et al., 2024; Zhao et al., 2026). From this perspective, job demands can be understood as a mediating mechanism through which algorithmic management translates into labour consequences such as turnover intention. Building on this reasoning, the present study proposes the following hypothesis:

H2: Ride-hailing workers exposed to high algorithmic management will report higher job demands, which in turn will be associated with higher turnover intention, than those exposed to low algorithmic management.

2.3.2. Flexibility Constraints

Flexibility constraints refer to the extent to which algorithmic controls and platform mechanisms restrict or condition workers' perceived autonomy, independence and operational discretion regarding when, where and how to work (Duggan et al., 2020; Shi et al., 2025). In other words, while digital platforms formally promise temporal flexibility, workers' practical decision in scheduling work, accepting tasks and managing their

operational routines is shaped by platform algorithms, performance metrics and demand patterns (Duggan et al., 2020; Pignot, 2023; Shi et al., 2025).

The literature highlights a fundamental tension between the formal promise of schedule flexibility and the practical constraints imposed by platform dynamics (Duggan et al., 2020; Schor et al., 2020). Schor et al. (2020) similarly note that workers are often pushed toward rush hours, late nights and weekends, which reduces the leisure time that platform work is supposed to protect. Glavin and Schieman (2022) capture this contradiction particularly well: while platform workers may report high perceived schedule control, this flexibility fails to improve well-being because working hours remain effectively structured by customer demand rather than by personal choice. The result is a form of constrained flexibility in which workers appear autonomous while remaining tied to the rhythms of the platform (Duggan et al., 2020; Glavin & Schieman, 2022; Muldoon & Raekstad, 2023; Schor et al., 2020).

Several studies describe this contradiction in explicitly paradoxical terms. Kougiannou and Mendonça (2025) refer to an "illusion of autonomy", arguing that workers may rely on a sense of freedom as a coping mechanism even when algorithmic management increases insecurity and dependence. Li (2022) likewise shows that platform flexibility often operates as a psychological coping mechanism, where workers preserve a sense of personal control even as intermediaries and communication technologies encourage them to remain online for excessive periods. Cameron (2024) similarly shows that gig work can be perceived as a "good bad" job because the feeling of having choices helps conceal poor working conditions. Reid-Musson et al. (2020) add that some workers respond to the gap between promised and lived flexibility through misbehaviour aimed at reclaiming control. Flexibility constraints, then, are not only merely a matter of time management; rather they reflect a broader tension between the flexibility promoted by platforms and workers actual ability to organize their work on their own terms (Duggan et al., 2020; Muldoon & Raekstad, 2023; Pignot, 2023; Reid-Musson et al., 2020; Zheng et al., 2026).

The literature suggests that the effects of algorithmic management are also conveyed through restrictions on workers' effective flexibility. Although ride-hailing platforms present flexibility as a key benefit, workers' actual room for choice is often constrained by demand patterns, platform incentives and performance pressures that influence under what conditions they can work (Duggan et al., 2020; Fielbaum & Tirachini, 2021; Schor et al., 2020). Accordingly, flexibility constraints are treated here as an important mediating

mechanism through which algorithmic management may influence turnover intention. Based on that, the following hypothesis is proposed:

H3: Ride-hailing workers exposed to high algorithmic management will report higher flexibility constraints, which in turn will be associated with higher turnover intention, than those exposed to low algorithmic management.

2.4. Moderating Effect: Economic Dependence

Economic dependence helps explain why the effects of algorithmic management, job demands and flexibility constraints vary so markedly across workers (Chan, 2022; Glavin & Schieman, 2022; Schor et al., 2020; Sun et al., 2023). It refers to the extent to which workers rely on platform income for their basic living expenses rather than using it as a supplementary source of earnings (Brawley Newlin, 2024; Saksida et al., 2026; Schor et al., 2020). Across the literature, this has emerged as an important factor for understanding differences in satisfaction, autonomy, precarity, mental health and continuance decisions (Brawley Newlin, 2024; Glavin & Schieman, 2022; Maffie, 2023; Saksida et al., 2026; Schor et al., 2020).

This is closely related to the fact that platform workers are not positioned in the same way within the labour market (Khan et al., 2026; Lin et al., 2026; Schor et al., 2020). In ride-hailing, workers differ in whether they use the platform as a primary occupation or a supplementary income source and these differences shape both their behaviour and their experience of work (Adekoya et al., 2025; Fielbaum & Tirachini, 2021; Khan et al., 2026; Leonardi & Pirina, 2020; Schor et al., 2020). Ashkrof et al. (2020) show that full-time and part-time drivers display distinct behavioural patterns, while Hong et al. (2020) find that participation decisions depend partly on how ride-hailing compares with workers' main jobs in terms of flexibility and security. A similar hybrid logic appears in related platform sectors, where workers combine conventional employment with gig work to balance stable income with supplementary earnings (Lin et al., 2026). This broader variation in workers' labour market position helps explain why economic dependence has become such a central analytical variable (Khan et al., 2026; Saksida et al., 2026; Schor et al., 2020).

Schor et al. (2020) provide one of the clearest accounts of this issue, arguing that economic dependence is the main factor explaining why workers in similar platform environments report very different experiences. Supplemental earners are often more

selective, more satisfied and better able to avoid undesirable or unsafe jobs, whereas dependent earners are more likely to experience the platform as a site of precarity, rating anxiety and pressure to accept nearly all requests (Schor et al., 2020). Glavin and Schieman (2022) reinforce this interpretation by showing that dependent platform workers face significantly higher psychological distress than both secondary platform workers and workers in more conventional forms of employment, largely because of financial strain.

The potential moderating role of dependence becomes apparent when comparing workers who can use platform work opportunistically with those who cannot (Glavin & Schieman, 2022; Khan et al., 2026; Saksida et al., 2026; Schor et al., 2020). Kougiannou and Mendonça (2025) distinguish between casual giggers, who are protected by student benefits or other stable income sources and gig-dependent workers, who experience algorithm-driven flexibility as a direct form of insecurity. Fielbaum and Tirachini (2021) similarly find that satisfaction is highest among drivers who use ride-hailing as a complementary activity, while Khan et al. (2026) show that full-time drivers are more exposed to debt, vehicle costs and financial pressure. The literature further shows that earning a viable income often requires drivers to adapt to peak hours, high-demand areas and changing platform conditions (Ashkrof et al., 2020; Duggan et al., 2020; Maury, 2024; Muldoon & Raekstad, 2023; Schor et al., 2020; Zhao et al., 2025). Although drivers value flexibility, they may therefore follow relatively stable working routines to reach income targets (Fielbaum & Tirachini, 2021). Sun et al. (2023) add that this dependence can deepen over time, increasing workers' attachment to platform work.

Economic dependence also shapes how workers respond to unfairness, dissatisfaction and broken expectations (Maffie, 2023; Saksida et al., 2026; Schor et al., 2020). Saksida et al. (2026) show that cynicism and declining trust are especially harmful for workers with fewer external job alternatives, who may feel trapped rather than simply detached. Cameron (2024) similarly suggests that meaningful consent in platform work is partly limited by workers' financial need, while Maffie (2023) shows that greater acquired dependence increases the likelihood of developing off-app clientele rather than exiting altogether. Zheng et al. (2026) extends this argument by showing how dependence can contribute to career lock-in, as workers become so absorbed by immediate platform demands that they lose the capacity to plan a transition into more stable employment. Even questions of fairness take on greater importance under these conditions: Sühr et al. (2019) argue that fairness in algorithmic systems matters not only for technical efficiency but also for the broader social

consequences of on-demand platforms, especially as more workers become financially dependent on them. Finally, economic dependence matters because it is tied to wider inequalities. S. Li et al. (2025) highlight the vulnerability of immigrant gig workers, while Zhao et al. (2026) point to gender and age differences in how workers bear algorithmic demands and labour risks. This suggests that dependence is not only an economic condition, but also part of a broader social positioning within platform labour markets (Glavin & Schieman, 2022; Khan et al., 2026; Maury, 2024; Schor et al., 2020).

Treating economic dependence as a moderator is therefore analytically important because it helps explain how the exposure of high versus low algorithmic management on job demands and flexibility constraints may vary according to workers' reliance on platform income, rather than affecting all workers in the same way (Glavin & Schieman, 2022; Saksida et al., 2026; Schor et al., 2020). What appears as a flexible income opportunity for some may function as a highly precarious and constraining livelihood for others, making economic dependence central to understanding how platform work is experienced (Glavin & Schieman, 2022; Kougiannou & Mendonça, 2025; Schor et al., 2020). Based on that, the following hypotheses are proposed:

H4a: Ride-hailing workers exposed to high algorithmic management will report higher job demands than those exposed to low algorithmic management, and this difference will be stronger among workers with higher economic dependence.

H4b: Ride-hailing workers exposed to high algorithmic management will report higher flexibility constraints than those exposed to low algorithmic management, and this difference will be stronger among workers with higher economic dependence.

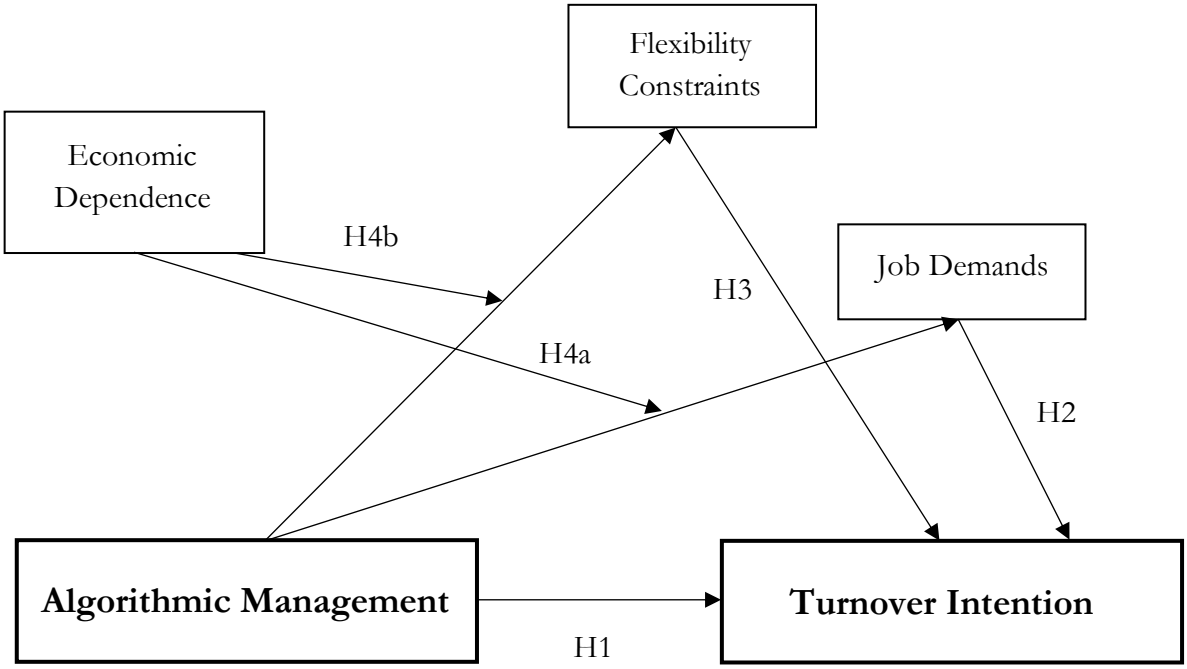


Figure 1 - Proposed Conceptual Model

2.5. Conclusion

In this section, the literature on Ride-Hailing and Gig Work, Algorithmic Management and Turnover Intention, Job Demands, Flexibility Constraints and Economic Dependence was reviewed. As shown in Figure 1, five hypotheses were proposed. The hypotheses proposed suggest a positive relationship between Algorithmic Management and Turnover Intention. This relationship is further expected to be mediated by Job Demands and Flexibility Constraints. To assess whether and how the effects of Algorithmic Management on Job Demands and Flexibility Constraints vary across workers, Economic Dependence is considered as a moderator of these relationships.

3. Methodology

This section presents the research methodology adopted in this study, including the methodological approach and research design, questionnaire and experimental procedure, measures and operationalization of variables, population, sample and data collection procedures, and data analysis strategy.

3.1 Methodological Approach and Research Design

This study adopts a quantitative, deductive and experimental methodological approach. The deductive approach is appropriate because the research is based on relationships identified in the existing literature, which are subsequently examined through empirical data (Yu & Abdul Hamid, 2024). A quantitative design is selected to allow the systematic comparison of participants' responses and the statistical testing of the proposed relationships (Saksida et al., 2026).

The research follows a scenario-based online experimental design, through a structured questionnaire and an experimental manipulation introduced through hypothetical work situations (Brawley Newlin, 2024; Hong et al., 2020). This approach is particularly suitable for the study because it allows specific working conditions to be varied in a controlled manner while keeping the broader context comparable across participants (Hong et al., 2020). More specifically, a between-subjects, post-test-only design was adopted (Brawley Newlin, 2024). Each participant is randomly assigned to one of two experimental conditions, representing high or low algorithmic management, and is exposed to only one scenario before completing the remaining questionnaire (Brawley Newlin, 2024; Hong et al., 2020). Random assignment is intended to increase the comparability of the groups and reduce the potential influence of pre-existing individual differences on the results (Brawley Newlin, 2024).

The questionnaire was developed and administered online through the Qualtrics platform, which enabled the implementation of the experimental conditions, the random allocation of participants and the structured collection of responses (Hong et al., 2020). The study is cross-sectional, as data are collected from each respondent at a single point in time and the individual TVDE worker constitutes the unit of analysis (Crayne & Brawley Newlin, 2024; Saksida et al., 2026). Overall, this design provides a consistent framework for

comparing responses across experimental conditions and evaluating how different platform-based working environments may influence drivers' perceptions and intended responses (Brawley Newlin, 2024; Hong et al., 2020).

3.2 Questionnaire Design and Experimental Procedure

The data collection instrument consisted of an online questionnaire developed and administered through the Qualtrics platform. The questionnaire began with a short introduction explaining the purpose of the study, the voluntary nature of participation, the anonymity of responses and the conditions of informed consent. Before proceeding to the main sections, respondents answered an eligibility question to ensure that they were currently working as TVDE drivers in Portugal or had worked in the activity within the previous six months.

Eligible participants were randomly assigned to one of two hypothetical scenarios: a high algorithmic management condition or a low algorithmic management condition. This randomisation was implemented through Qualtrics, allowing each participant to be exposed to only one scenario. Both scenarios described a work situation in which a TVDE driver provided services through a digital platform, differing mainly in the intensity of algorithmic management presented. The full version of both scenarios is presented in Table 1.

After reading the assigned scenario, respondents were instructed to answer the remaining questions according to how they would perceive and experience work under the conditions described. The questionnaire then included the main measurement scales for Turnover Intention, Job Demands, Flexibility Constraints and Economic Dependence, all operationalised through a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree), as presented in Table 1. A three-item manipulation check was also included to verify whether the two scenarios produced the intended difference in the perceived level of algorithmic management. These items were measured using the same seven-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree), and are presented in Table 1. The final section of the questionnaire collected information on respondents' demographic and work-related characteristics to describe the sample.

3.3 Measures and Operationalisation of Variables

The constructs included in this study – Turnover Intention, Job Demands, Flexibility Constraints and Economic Dependence – were measured using items adapted from existing literature, while Algorithmic Management was experimentally manipulated through high and low scenarios, as presented in Table 1.

Algorithmic Management was conceptualised based on the Perceived Algorithmic Control scale developed by Shi et al. (2025). However, rather than presenting the ten items as a conventional measurement scale, their content was adapted and translated into two hypothetical scenarios representing high and low levels of algorithmic management. The high algorithmic management scenario reflected a stronger presence of the practices described in the original items, whereas the low algorithmic management scenario reflected a weaker presence of those same practices. These scenarios incorporated the main dimensions identified by Shi et al. (2025), including task allocation, work instructions, information provision, monitoring, performance assessment, ranking, incentives and penalties. After reading the assigned scenario, respondents were asked to answer the remaining construct measures according to how they would perceive and experience work under the conditions described. Turnover Intention was measured through a three-item scale of Withdrawal Intentions, adapted from Saksida et al. (2026), assessing whether drivers intend to leave their current occupation, expect to change occupation soon or frequently think about leaving the activity. Although withdrawal intentions is not conceptually identical to turnover intention, the scale was considered appropriate for the context of platform work because its items capture workers' conscious thoughts and intentions to leave their current line of work (Saksida et al., 2026). This closely reflects the conceptual meaning of turnover intention as the intention to voluntarily exit an occupation or work activity (Saksida et al., 2026; Yu & Abdul Hamid, 2024). The scale is therefore particularly suitable for ride-hailing, where leaving is more appropriately understood as withdrawing from the activity or occupation rather than from a traditional organization (Maffie, 2023). Job Demands were measured using a five-item scale adapted from Cheng et al. (2024), covering perceptions of work intensity, physical effort, concentration requirements and hectic working conditions. Flexibility Constraints were assessed through items adapted from the Job Autonomy scale developed by Shi et al. (2025), capturing the extent to which drivers perceive autonomy when completing work through platform software. Since the items are positively framed in terms

of autonomy, they were reverse-coded (R) so that higher values indicate lower perceived autonomy and greater flexibility constraints. Finally, Economic Dependence was measured using four items adapted from Maffie (2023), capturing drivers' perceived dependence on ride-hailing work, difficulty exiting the activity and concerns related to expected earnings and vehicle maintenance costs.

Table 1

Experimental Scenarios, Measurement Items and Manipulation Check

Construct, Scenarios and Items	**Author(s)**
Algorithmic Management	
Scenario A – High Algorithmic Management Imagine that you are working as a TVDE driver through a digital platform. When you are online, the platform algorithm automatically assigns or prioritises trips and provides detailed instructions through the app, including suggested routes, expected response times, platform standards and performance targets. While you are working, the algorithm provides real-time information about your work and gives timely feedback on your performance. The platform continuously tracks your location, keeps records of your trips and monitors indicators such as acceptance rate, cancellation rate, customer ratings and trip completion times. Your work quality is automatically assessed by the algorithm. The platform ranks drivers based on their performance and drivers with better scores may receive priority access to trips, bonuses or cash incentives during specific periods. If a driver does not meet the platform's requirements, the algorithm may reduce access to work opportunities or apply penalties/fines	adapted from Shi et al. (2025)

through the app. Most work-related decisions are made automatically, with limited explanation or human intervention.	
Scenario B – Low Algorithmic Management Imagine that you are working as a TVDE driver through a digital platform. When you are online, the platform provides basic information about available trips, customer requests and possible routes, but you have considerable freedom to decide which trips to accept and how to organise your work. While you are working, the platform collects only the information needed to complete accepted trips. Your location and trip information are used mainly for operational purposes and the platform does not closely monitor your work behaviour or performance in real time. Your work quality may be assessed through basic service information and customer feedback, but this information is used mainly to provide transparent feedback rather than to automatically determine consequences. Ratings and indicators do not strongly determine your access to future trips, bonuses or work opportunities. If a problem occurs, decisions can be reviewed with human support and drivers can ask for clarification or appeal platform decisions before any penalties are applied.	adapted from Shi et al. (2025)
Turnover Intention	
Withdrawal Intentions 1. I intend to leave my current occupation. 2. I will probably change my occupation in the near future. 3. I frequently think about leaving my current occupation.	adapted from Saksida et al. (2026)

Job Demands	
Job Demands 1. My work requires me to work fast. 2. My work requires me to work hard. 3. My work requires a lot of physical effort. 4. My work requires me to concentrate on the job for a long time. 5. I am very hectic at work.	adapted from Cheng et al. (2024)
Flexibility Constraints	
Job Autonomy 1. I decide how to do the work by myself using platform software. (R) 2. When completing tasks with platform software, this job gives me the opportunity to use my personal creativity or judgment. (R) 3. My job provides me with considerable opportunities to independently and freely complete work tasks. (R)	adapted from Shi et al. (2025)
Economic Dependence	
Dependence on Ride-Hailing 1. I feel I cannot stop working rideshare. 2. I wish I would have never started working rideshare. 3. Rideshare vehicle maintenance is higher than I expected. 4. When I started rideshare, I thought I would earn more I actually do.	adapted from Maffie (2023)
Manipulation Check	
1. In the scenario, the platform relied heavily on algorithms to manage drivers' work. 2. In the scenario, the platform closely monitored drivers' work and performance. 3. In the scenario, important work-related decisions were made automatically by the platform.	

In addition to the main constructs included in the model, several individual and work-related characteristics were considered to describe differences among respondents. These included gender, age and highest level of education, as well as TVDE related characteristics such as length of experience as a TVDE driver, approximate monthly income from TVDE work, average weekly working hours, number of platforms regularly used and current professional situation as a driver. These variables were measured through categorical questions, allowing respondents to select the option that best described their personal and work profile. The questionnaire items and experimental scenarios adapted from the existing literature were originally available in English and were translated into European Portuguese for the purpose of this study. The translation aimed to preserve their original meaning while ensuring that the wording was clear and appropriate for the Portuguese TVDE context.

3.4 Population, Sample and Data Collection Procedures

Data collection regarding platform work can be particularly challenging, as platform companies treat worker data as proprietary assets, effectively restricting access to complete databases of the active workforce (Maffie, 2023). In the context of these barriers, the specific case of ride-hailing drivers remains significantly less explored than other platform mediated sectors such as tourism or Airbnb (Leonardi and Pirina, 2020). This difficulty in obtaining data is further intensified by the fact that ride-hailing drivers lack a shared physical workplace, making them a workforce that is hard to reach through traditional sampling frameworks (Maffie and Lakhani, 2025).

The target population of this study consists of individuals currently working as TVDE drivers in Portugal or who had worked in the activity within the previous six months, to ensure that the perceptions collected reflected current working conditions and platform practices. Because of the difficulty in identifying the total universe of active TVDE drivers in Portugal, the data collection process relied on a multi-channel recruitment strategy. This process was supported by ProTVDE, an association representing TVDE drivers in Portugal, which helped disseminate the questionnaire among workers and facilitated access to the target population. These efforts were complemented through informal communication channels such as WhatsApp and Facebook groups, where drivers commonly exchange information. In-person data collection was also conducted in Porto to contact TVDE drivers directly and increase the number of responses obtained.

The questionnaire was distributed online between June and August 2026 through ProTVDE, WhatsApp groups, social media and direct contacts. Since the survey was shared through intermediary channels and could be forwarded among drivers, the exact size of the contacted population is unknown. Therefore, the study uses a non-probabilistic convenience sample, with elements of snowball sampling, which is appropriate given the difficulty of accessing this specific group of workers through traditional sampling methods.

A total of 353 responses were collected. After data screening, responses were excluded when they were incomplete, when respondents did not meet the inclusion criteria of working as TVDE drivers in Portugal or having worked in the activity within the previous six months, or when they showed clear evidence of insufficient engagement with the questionnaire. This included clear failures in the manipulation check, namely responses that were directly inconsistent with the assigned experimental condition, such as perceiving the high scenario as very low or the low scenario as very high. These responses were considered inconsistent with the scenario presented and could compromise the validity of the experimental manipulation and subsequent analyses. Responses showing straight-lining patterns, in which the same response option was repeatedly selected across questionnaire items, or unrealistically short completion times were also excluded as indicators of insufficient response effort. The final sample included 209 valid responses, which were used for the empirical analysis.

3.5 Data Analysis Strategy

The data analysis was conducted using IBM SPSS Statistics. Before testing the proposed model, the dataset was screened to identify incomplete responses, eligibility failures, clear manipulation check inconsistencies and signs of insufficient response effort. Descriptive statistics were then used to characterise the sample in terms of demographic and work-related variables, such as gender, age, education, TVDE experience, monthly income, weekly working hours, number of platforms used and current professional situation as a driver.

The reliability of the multi-item scales was assessed using Cronbach's alpha to evaluate the internal consistency of the constructs included in the model. Where necessary, items with weak contribution to scale reliability were reviewed or removed, provided that such decisions are theoretically justified and do not compromise the meaning of the

construct. Composite scores were then created by averaging the items corresponding to each construct, after applying reverse coding where necessary. In addition, correlation analysis was conducted to examine the preliminary associations between the main variables.

A manipulation check was performed to verify whether participants exposed to the high algorithmic management scenario perceived a higher level of algorithmic management than those exposed to the low algorithmic management scenario. This step was necessary to confirm that the experimental manipulation worked as intended before testing the hypotheses.

To test the proposed relationships, regression-based analyses were conducted. The direct effect of algorithmic management on turnover intention was first examined, followed by mediation analyses to assess whether job demands and flexibility constraints helped explain this relationship. Moderation analyses were also used to test whether economic dependence changed the strength of the relationship between algorithmic management and the proposed outcomes. These analyses were conducted using the PROCESS macro (Hayes, 2022) for SPSS, with 5000 bootstrap samples used to estimate indirect effects and confidence intervals. All statistical tests were interpreted using a significance level of 5%. The results were reported through coefficients, significance levels, confidence intervals and explained variance, allowing the proposed hypotheses and conceptual model to be evaluated empirically.

4. Results

This section presents the results of the empirical analysis conducted to test the proposed relationships. It includes the preliminary analyses, mediation analyses and moderation analyses. The results are presented and interpreted in relation to the study hypotheses and conceptual model.

4.1 Preliminary Analyses

Following data screening and the application of the exclusion criteria, the final analytical sample consisted of 209 participants. Of these, 100 participants were randomly assigned to the low Algorithmic Management condition and 109 to the high Algorithmic Management condition.

To assess whether the experimental manipulation was successful, an independent-samples *t*-test compared the manipulation check scores between the two experimental conditions. As presented in Table 2, participants in the high algorithmic management condition reported substantially higher manipulation check scores than those in the low algorithmic management condition.

Table 2

Manipulation check scores by experimental condition

Algorithmic Management condition	*n*	*M*	*SD*
Low Algorithmic Management	100	3.51	1.44
High Algorithmic Management	109	5.72	1.11

Note. Higher scores indicate a stronger perception that work was managed algorithmically.

The difference between the two conditions was statistically significant, $t(207) = 12.44$, $p < .001$, Cohen's $d = 1.72$. These results indicate that participants perceived the high algorithmic management scenario as involving substantially more algorithmic control than the low algorithmic management scenario. Therefore, the experimental manipulation was considered successful.

4.1.1 Reliability and Descriptive Statistics

The internal consistency of the study scales was assessed using Cronbach's alpha. The Job Demands scale demonstrated good internal consistency, α = .837, while the Flexibility Constraints scale showed acceptable internal consistency, α = .762. The Turnover Intention scale demonstrated excellent internal consistency, α = .920.

The original four-item Economic Dependence scale yielded comparatively low reliability, α = .587. The item "I feel that I am unable to stop working in ride-hailing" presented a low corrected item total correlation of .140 and was therefore removed. The resulting three-item scale showed improved, although marginal, internal consistency, α = .679, and was retained for the subsequent analyses.

Table 3 presents the means, standard deviations, reliability coefficients and correlations among the variables included in the main analyses.

Table 3

Descriptive statistics, reliability and correlations

Variable	*M*	*SD*	α	1	2	3	4	5
1. Algorithmic Management	0.52	0.50	—	—				
2. Job Demands	4.95	1.31	.837	.315***	—			
3. Flexibility Constraints	3.70	1.53	.762	−.041	−.239***	—		
4. Economic Dependence	4.36	1.43	.679	.295***	.641***	−.038	—	
5. Turnover Intention	4.04	1.81	.920	.245***	.563***	−.044	.658***	—

Note. N = 209. Algorithmic management was coded as 0 = low algorithmic management and 1 = high algorithmic management. Its mean therefore represents the proportion of participants assigned to the high algorithmic management condition. Flexibility constraints items were reverse-coded so that higher scores represented stronger flexibility constraints. Correlations involving algorithmic management are point-biserial correlations, which are equivalent to Pearson correlations when a dichotomous variable is coded 0 and 1. *** $p < .001$.

Algorithmic management was positively correlated with job demands, $r = .315$, $p < .001$, economic dependence, $r = .295$, $p < .001$, and turnover intention, $r = .245$, $p < .001$. However, it was not significantly correlated with flexibility constraints, $r = -.041$, $p = .558$. Job demands was positively associated with economic dependence, $r = .641$, $p < .001$, and turnover intention, $r = .563$, $p < .001$. Job demands was also negatively correlated with flexibility constraints, $r = -.239$, $p < .001$.

Flexibility constraints was not significantly associated with economic dependence, $r = -.038$, $p = .581$, or turnover intention, $r = -.044$, $p = .531$. Finally, economic dependence was positively and strongly correlated with turnover intention, $r = .658$, $p < .001$.

4.2 Direct Effect of Algorithmic Management on Turnover Intention

To test H1, a simple linear regression analysis was conducted to examine the direct effect of Algorithmic Management on Turnover Intention.

Table 4

Direct Effect of Algorithmic Management on Turnover Intention

Predictor	*b*	*SE*	*t*	*p*	95% CI
Algorithmic Management	0.888	0.244	3.637	< .001	[0.407, 1.370]

Note. Unstandardized regression coefficients are reported. Algorithmic management was coded as 0 = low algorithmic management and 1 = high algorithmic management. CI = confidence interval.

Participants exposed to the high algorithmic management condition reported higher turnover intention ($M = 4.46$, $SD = 1.83$) than participants exposed to the low algorithmic management condition ($M = 3.58$, $SD = 1.69$). As shown in Table 4, Algorithmic management had a positive and statistically significant effect on turnover intention, $b = 0.888$, $SE = 0.244$, $t = 3.637$, $p < .001$, 95% CI [0.407, 1.370]. The model was statistically significant, $F(1, 207)=13.22$, $p < .001$, and explained approximately 6.0% of the variance in turnover intention ($R^2 = .060$).

These findings indicate that exposure to high algorithmic management was associated with significantly higher turnover intention compared with exposure to low algorithmic management. Therefore, H1 was supported.

4.3 Mediation Analyses

Simple mediation analyses were conducted using the the PROCESS macro Model 4 (Hayes, 2022) to examine whether Job Demands and Flexibility Constraints independently mediated the relationship between Algorithmic Management and Turnover Intention. Algorithmic Management was entered as the independent variable, Job Demands and Flexibility Constraints as mediators, and Turnover Intention as the dependent variable. The analysis included 209 participants and used 5000 bootstrap samples to estimate 95% percentile bootstrap confidence intervals for the indirect effect.

4.3.1 The Mediating Role of Job Demands

Table 5

Regression coefficients for the mediation model with Job Demands

Outcome	Predictor	*b*	*SE*	*t*	*p*	95% CI
Job Demands	**Algorithmic Management**	0.823	0.172	4.780	< .001	[0.484, 1.162]
Turnover Intention	**Algorithmic Management**	0.272	0.219	1.242	.216	[−0.160, 0.704]
Turnover Intention	**Job Demands**	0.748	0.084	8.914	< .001	[0.583, 0.914]

Note. Unstandardized regression coefficients are reported. Algorithmic management was coded as 0 = low algorithmic management and 1 = high algorithmic management. CI = confidence interval.

The model predicting job demands was statistically significant, $F(1,207)=22.85$, $p<.001$ and explained 9.9% of its variance, $R^2=.099$. Algorithmic management had a significant positive effect on job demands, $b=.823$, $SE=.172$, $t=4.78$, $p<.001$, 95% CI [.484, 1.162]. Given the coding of the experimental condition, participants exposed to high

algorithmic management reported job demands scores that were, on average, .823 points higher than those exposed to low algorithmic management.

The model predicting turnover intention was also statistically significant, $F(2,206)=48.84$, $p<.001$, explaining 32.2% of its variance, $R^2=.322$. When algorithmic management was controlled for, job demands had a significant positive effect on turnover intention, b=.748, SE=.084, t=8.91, p<.001, 95% CI [.583, .914]. Therefore, higher levels of job demands were associated with greater turnover intention. In contrast, the direct effect of algorithmic management on turnover intention, after accounting for job demands, was not statistically significant, b=.272, SE=.219, t=1.24, p=.216, 95% CI [−.160, .704].

Table 6

Total, direct and indirect effects of Algorithmic Management on Turnover Intention through Job Demands

Effect	Estimate	*SE*	*t*	*p*	95% CI
Total effect	0.888	0.244	3.637	< .001	[0.407, 1.370]
Direct effect	0.272	0.219	1.242	.216	[−0.160, 0.704]
Indirect effect through JD	0.616	0.148	—	—	[0.341, 0.930]

Note. Unstandardized effects are reported. Boot*SE* = bootstrap standard error. The confidence interval for the indirect effect was estimated using 5,000 bootstrap samples. Statistical significance of the indirect effect is determined by whether the bootstrap confidence interval includes zero. JD= Job Demands.

The total effect of algorithmic management on turnover intention was positive and statistically significant, b=.888, SE=.244, t=3.64, p<.001, 95% CI [.407, 1.370]. However, after job demands was included in the model, the remaining direct effect was no longer statistically significant.

Most importantly, the indirect effect of algorithmic management on turnover intention through job demands was positive and statistically significant, ab=.616, BootSE=.148, 95% bootstrap CI [.341, .930]. As the bootstrap confidence interval did not include zero, the results provide evidence that job demands mediated the relationship between algorithmic management and turnover intention. Thus, exposure to high algorithmic management was associated with greater job demands, which, in turn, were

associated with higher turnover intention. The proposed mediation effect through job demands was therefore supported.

4.3.2 The Mediating Role of Flexibility Constraints

Table 7

Regression coefficients for the mediation model with Flexibility Constraints

Outcome	Predictor	*b*	*SE*	*t*	*p*	95% CI
Flexibility Constraints	**Algorithmic Management**	−0.125	0.212	−0.587	.558	[−0.543, 0.294]
Turnover Intention	**Algorithmic Management**	0.883	0.245	3.607	< .001	[0.400, 1.366]
Turnover Intention	**Flexibility Constraints**	−0.040	0.080	−0.498	.619	[−0.198, 0.118]

Note. Unstandardized regression coefficients are reported. algorithmic management was coded as 0 = low algorithmic management and 1 = high algorithmic management. CI = confidence interval.

The model predicting flexibility constraints was not statistically significant, $F(1,207)=0.34$, $p=.558$, and explained only 0.2% of its variance, $R^2 =.002$. Algorithmic management did not have a significant effect on flexibility constraints, $b=-.125$, $SE=.212$, $t=-0.59$, $p=.558$, 95% CI [−.543, .294]. Thus, there was no evidence that participants in the high and low algorithmic management conditions differed in their reported levels of flexibility constraints.

The model predicting turnover intention was statistically significant, $F(2,206)=6.71$, $p=.002$, explaining 6.1% of its variance, $R^2=.061$. However, when algorithmic management was controlled for, flexibility constraints did not significantly predict turnover intention, $b=-.040$, $SE=.080$, $t=-0.50$, $p=.619$, 95% CI [−.198, .118]. In contrast, the direct effect of algorithmic management on turnover intention remained positive and statistically significant, $b=.883$, $SE=.245$, $t=3.61$, $p<.001$, 95% CI [.400, 1.366].

Table 8

Total, direct and indirect effects of Algorithmic Management on Turnover Intention through Flexibility Constraints

Effect	Estimate	*SE*	*t*	*p*	95% CI
Total effect	0.888	0.244	3.637	< .001	[0.407, 1.370]
Direct effect	0.883	0.245	3.607	< .001	[0.400, 1.366]
Indirect effect through FC	0.005	0.023	—	—	[−0.029, 0.071]

Note. Unstandardized effects are reported. Boot*SE* = bootstrap standard error. The confidence interval for the indirect effect was estimated using 5,000 bootstrap samples. Statistical significance of the indirect effect is determined by whether the bootstrap confidence interval includes zero.

The total effect of algorithmic management on turnover intention was positive and statistically significant, b=.888, SE=.244, t=3.64, p<.001, 95% CI [.407, 1.370]. After flexibility constraints was included in the model, the direct effect remained positive and statistically significant and was almost identical in magnitude, b=.883, SE=.245, t=3.61, p<.001, 95% CI [.400, 1.366].

The indirect effect of algorithmic management on turnover intention through flexibility constraints was very small and not statistically significant, ab=.005, BootSE=.023, 95% bootstrap CI [−.029, .071]. Because the bootstrap confidence interval included zero, the results did not provide evidence that flexibility constraints mediated the relationship between algorithmic management and turnover intention. Therefore, the proposed mediation effect through flexibility constraints was not supported.

4.4 Moderation Analyses

Moderation analyses were conducted using the PROCESS macro Model 1 (Hayes, 2022) to examine whether Economic Dependence moderated the relationship between Algorithmic Management and each mediator. Algorithmic Management was entered as the independent variable, Economic Dependence as the moderator, and Job Demands and Flexibility constraints as the dependent variables. Algorithmic Management was coded as 0 for the low Algorithmic Management condition and 1 for the high Algorithmic Management

condition. Economic Dependence was mean-centred before the interaction term was calculated. The analysis included 209 participants.

4.4.1 Economic Dependence as a Moderator of Job Demands

Table 9

Moderation analysis predicting Job Demands

Predictor	b	*SE*	*t*	*p*	95% CI
Algorithmic Management	0.346	0.140	2.469	.014	[0.070, 0.622]
Economic Dependence	0.732	0.072	10.218	< .001	[0.590, 0.873]
Algorithmic Management × Economic Dependence	−0.345	0.098	−3.506	< .001	[−0.538, −0.151]

Note. Unstandardized regression coefficients are reported. Algorithmic management was coded as 0 = low and 1 = high. Economic dependence was mean-centred. Accordingly, the coefficient for algorithmic management represents its effect at the mean level of economic dependence, whereas the coefficient for economic dependence represents its relationship with job demands in the low algorithmic management condition. CI = confidence interval.

The overall regression model was statistically significant, $F(3,205)=58.43$, $p<.001$, and explained 46.1% of the variance in job demands, $R^2 =.461$.

At the mean level of economic dependence, algorithmic management had a significant positive effect on job demands, $b=.346$, $SE=.140$, $t=2.47$, $p=.014$, 95% CI [.070, .622]. Thus, at the mean level of economic dependence, participants in the high algorithmic management condition reported higher job demands than those in the low algorithmic management condition.

Economic dependence also had a significant positive relationship with job demands in the low algorithmic management condition, $b=.732$, $SE=.072$, $t=10.22$, $p<.001$, 95% CI [.590, .873]. This indicates that, among participants exposed to low algorithmic management, higher economic dependence was associated with higher job demands.

Most importantly, the interaction between algorithmic management and economic dependence was statistically significant, $b=-.345$, $SE=.098$, $t=-3.51$, $p<.001$, 95% CI [−.538, −.151]. The interaction explained an additional 3.2% of the variance in job demands, $\Delta R^2 =.032$, $F(1,205)=12.29$, $p<.001$. The negative interaction coefficient indicates that the

positive effect of algorithmic management on job demands became weaker as economic dependence increased.

Table 10

Conditional effects of Algorithmic Management on Job Demands at different levels of Economic Dependence

Level of Economic Dependence	ED value	*Effect*	*SE*	*t*	*p*	95% CI
Low - 16th percentile	2.67	0.928	0.214	4.339	< .001	[0.506, 1.349]
Median - 50th percentile	4.67	0.239	0.144	1.655	.100	[−0.046, 0.523]
High - 84th percentile	5.80	−0.152	0.203	−0.748	.455	[−0.551, 0.248]

Note. Economic dependence was mean-centred for model estimation, but values are presented on the original scale for ease of interpretation. Conditional effects represent the difference in predicted job demands between the high and low algorithmic management conditions. CI = confidence interval.

The conditional effects analysis showed that, at a low level of economic dependence, algorithmic management had a significant positive effect on job demands, b=.928, SE=.214, t=4.34, p<.001, 95% CI [.506, 1.349]. Participants exposed to high algorithmic management therefore reported substantially higher job demands than those exposed to low algorithmic management when economic dependence was low.

At the median level of economic dependence, the effect of algorithmic management was smaller and not statistically significant, b=.239, SE=.144, t=1.65, p=.100, 95% CI [−.046, .523]. At a high level of economic dependence, the effect was negative but also not statistically significant, b=−.152, SE=.203, t=−0.75, p=.455, 95% CI [−.551, .248].

Table 11

Johnson-Neyman regions of significance for the conditional effect of Algorithmic Management on Job Demands

Economic Dependence range	Conditional effect	Statistical significance
Below approximately 4.55	Positive	Significant
At or above approximately 4.55	No statistically significant effect	Not significant

Note. Economic dependence values are presented on the original measurement scale. The Johnson-Neyman transition point was converted from the mean-centred value reported by PROCESS.

The Johnson-Neyman analysis identified an economic dependence score of approximately 4.55 as the transition point for statistical significance. Below this value, algorithmic management had a positive and statistically significant effect on job demands. At and above approximately 4.55, the effect of algorithmic management was no longer statistically significant. Therefore, the difference in job demands between the high and low algorithmic management conditions was only evident among participants with comparatively lower levels of economic dependence.

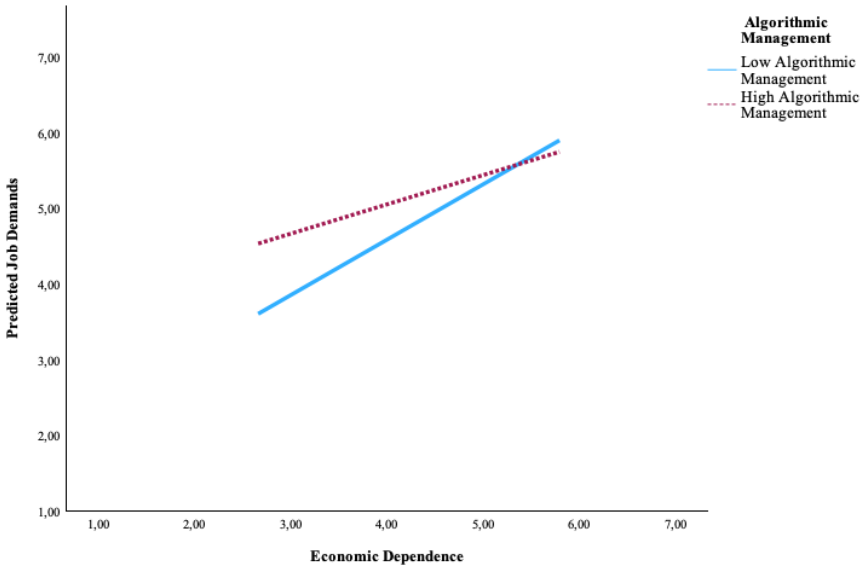


Figure 2 - The moderating effect of Economic Dependence on the relationship between Algorithmic Management and Job Demands

Overall, the results support the moderating role of economic dependence in the relationship between algorithmic management and job demands. Specifically, high algorithmic management was associated with higher job demands primarily among participants with relatively low economic dependence. As economic dependence increased, the difference in job demands between the high and low algorithmic management conditions became progressively weaker and was no longer statistically significant at moderate and high levels of economic dependence.

4.4.2 Economic Dependence as a Moderator of Flexibility Constraints

Table 12

Moderation analysis predicting Flexibility Constraints

Predictor	b	*SE*	*t*	*p*	95% CI
Algorithmic Management	−0.074	0.217	−0.343	.732	[−0.501, 0.353]
Economic Dependence	−0.320	0.111	−2.890	.004	[−0.538, −0.102]
Algorithmic Management × Economic Dependence	0.544	0.152	3.582	< .001	[0.244, 0.843]

Note. Unstandardized regression coefficients are reported. Algorithmic management was coded as 0 = low and 1 = high. Economic dependence was mean-centred. The coefficient for algorithmic management therefore represents its effect at the mean level of economic dependence. The coefficient for economic dependence represents its relationship with flexibility Constraints in the low algorithmic management condition. CI = confidence interval.

The overall regression model was statistically significant, $F(3,205)=4.45$, $p=.005$, and explained 6.1% of the variance in flexibility constraints, $R^2 =.061$.

At the mean level of economic dependence, algorithmic management did not have a statistically significant effect on flexibility constraints, $b=-.074$, $SE=.217$, $t=-0.34$, $p=.732$, 95% CI [−.501, .353]. Thus, when economic dependence was at its mean, participants in the high and low algorithmic management conditions did not significantly differ in their levels of flexibility constraints.

Economic dependence had a significant negative relationship with flexibility constraints in the low algorithmic management condition, $b=-.320$, $SE=.111$, $t=-2.89$, $p=.004$, 95% CI [−.538, −.102]. Therefore, within the low algorithmic management condition, higher economic dependence was associated with lower flexibility constraints.

Most importantly, the interaction between algorithmic management and economic dependence was positive and statistically significant, $b=.544$, $SE=.152$, $t=3.58$, $p<.001$, 95% CI [.244, .843]. The interaction explained an additional 5.9% of the variance in flexibility constraints, $\Delta R^2 =.059$, $F(1,205)=12.83$, $p<.001$. This indicates that the effect of algorithmic management on flexibility constraints changed significantly according to participants' level of economic dependence.

Table 13

Conditional effects of Algorithmic Management on Flexibility Constraints at different levels of Economic Dependence

Level of Economic Dependence	ED value	*Effect*	*SE*	*t*	*p*	95% CI
Low - 16th percentile	2.67	−0.993	0.330	−3.004	.003	[−1.644, −0.341]
Median - 50th percentile	4.67	0.095	0.223	0.425	.672	[−0.345, 0.535]
High - 84th percentile	5.80	0.711	0.313	2.272	.024	[0.094, 1.328]

Note. Economic dependence was mean-centred for model estimation, but values are presented on the original scale for ease of interpretation. Conditional effects represent the difference in predicted flexibility constraints between the high and low algorithmic management conditions. CI = confidence interval.

The conditional effects analysis showed that the effect of algorithmic management differed substantially across levels of economic dependence.

At a low level of economic dependence, algorithmic management had a significant negative effect on flexibility constraints, b=−.993, SE=.330, t=−3.00, p=.003, 95% CI [−1.644, −.341]. Participants in the high algorithmic management condition therefore reported flexibility constraints scores that were approximately .99 points lower than those in the low algorithmic management condition when economic dependence was low.

At the median level of economic dependence, the effect of algorithmic management was not statistically significant, b=.095, SE=.223, t=0.42, p=.672, 95% CI [−.345, .535]. At this level, there was no significant difference in flexibility constraints between the two algorithmic management conditions.

At a high level of economic dependence, algorithmic management had a significant positive effect on flexibility constraints, b=.711, SE=.313, t=2.27, p=.024, 95% CI [.094, 1.328]. Participants in the high algorithmic management condition therefore reported higher flexibility constraints than those in the low algorithmic management condition when economic dependence was high.

Table 14

Johnson-Neyman regions of significance for the conditional effect of Algorithmic Management on Flexibility Constraints

Economic Dependence range	Conditional effect	Statistical significance
Below approximately 3.62	Negative	Significant
Between approximately 3.62 and 5.52	No statistically significant effect	Not significant
Above approximately 5.52	Positive	Significant

Note. Economic dependence values are presented on the original measurement scale. The Johnson-Neyman transition points were converted from the mean-centred values produced by PROCESS.

The Johnson-Neyman analysis identified two transition points in the statistical significance of the conditional effect. The effect of algorithmic management on flexibility constraints was negative and statistically significant when economic dependence was below approximately 3.62. The effect was not statistically significant for economic dependence values between approximately 3.62 and 5.52. Above approximately 5.52, the effect became positive and statistically significant. This pattern indicates a crossover interaction, in which the direction of the effect of algorithmic management changed depending on the level of economic dependence.

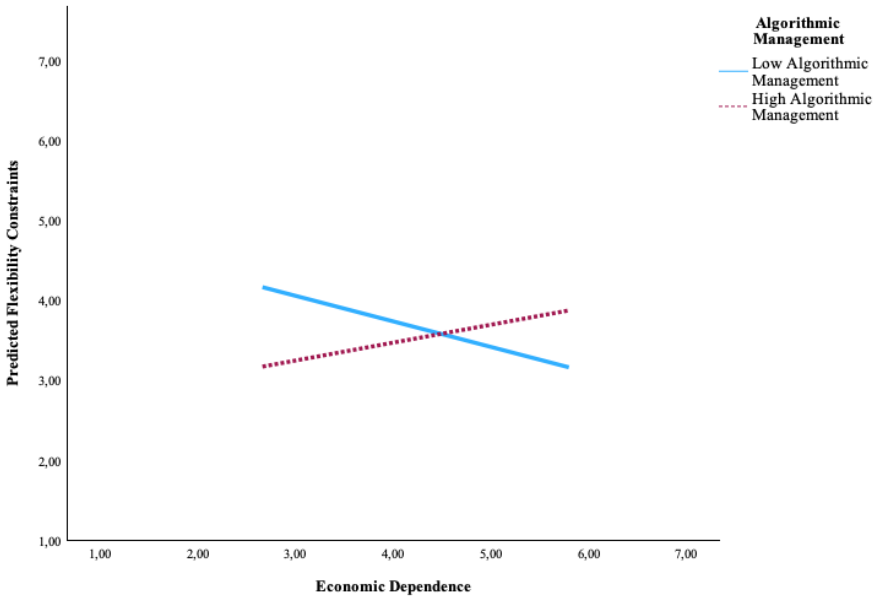


Figure 3 - The moderating effect of Economic Dependence on the relationship between Algorithmic Management and Flexibility Constraints

Overall, the results support the moderating role of economic dependence in the relationship between algorithmic management and flexibility constraints. The direction of the effect of algorithmic management depended on the level of economic dependence. High algorithmic management was associated with lower flexibility constraints among participants with low economic dependence, did not have a significant effect at intermediate levels, and was associated with higher flexibility constraints among participants with high economic dependence. Therefore, the proposed moderation effect was supported.

4.5 Results Analysis

As hypothesized, exposure to high algorithmic management was associated with higher turnover intention, supporting H1. Job demands also played a significant mediating role in this relationship, as high algorithmic management increased job demands, which in turn were associated with higher turnover intention. In contrast, flexibility constraints did not significantly mediate the relationship between algorithmic management and turnover intention.

Economic dependence significantly moderated the relationship between algorithmic management and both job demands and flexibility constraints. For job demands, the positive effect of algorithmic management was stronger at lower levels of economic dependence and weakened as economic dependence increased. For flexibility constraints, the direction of the effect changed across levels of economic dependence: high algorithmic Management was associated with lower flexibility constraints at low levels of economic dependence and with higher flexibility constraints at high levels of economic dependence.

Overall, the findings provide support for the direct effect of algorithmic management on turnover intention, the mediating role of job demands and the moderating role of economic dependence in these relationships. However, the proposed mediating role of flexibility constraints was not supported.

5. Discussion

As algorithmic systems become increasingly central to the organization of platform work, understanding how they shape workers' experiences is particularly relevant in ride-hailing, where management is largely performed through digital systems (Duggan et al., 2020; Mäntymäki et al., 2019). This study aimed to understand how the exposure to high versus low Algorithmic Management relates to Turnover Intention, whether this relationship operates through Job Demands and Flexibility Constraints and how Economic Dependence moderates the effects of Algorithmic Management on Job Demands and Flexibility Constraints.

From a theoretical perspective, the findings reinforce the idea that stronger algorithmic management can have adverse consequences for workers, particularly by increasing work-related pressures. Exposure to high algorithmic management was associated with greater turnover intention, which is consistent with previous research linking algorithmic control, monitoring and work pressure to withdrawal intentions and less sustainable work experiences (Adekoya et al., 2025; Liu et al., 2024; Saksida et al., 2026; Zheng et al., 2026). More importantly, job demands help explain how this relationship develops. Higher algorithmic management increased job demands, which were in turn associated with greater turnover intention. This supports research showing that algorithmic systems can intensify workload, responsiveness and psychological pressure (Cheng et al., 2024; Duggan et al., 2020; Liu et al., 2024; Pignot, 2023; Zhao et al., 2026), suggesting that the consequences of algorithmic management arise not only from the technology itself, but also from the demanding working conditions it creates. Flexibility constraints, by contrast, did not emerge as a significant mediating mechanism. This suggests that perceived constraints on flexibility may not operate uniformly across platform workers, as their relevance can depend on individual and work-related circumstances (Glavin & Schieman, 2022; Schor et al., 2020). Previous research also shows that algorithmic management can create different experiences of flexibility, since digital coordination may either support workers in organizing their schedules or restrict their discretion (Duggan et al., 2020; Kougiannou & Mendonça, 2025; Muldoon & Raekstad, 2023). Therefore, the role of flexibility constraints appears to be more conditional than direct, an interpretation that becomes particularly relevant when considering the moderating role of economic dependence (Brawley Newlin, 2024; Glavin & Schieman, 2022).

Building on this, economic dependence adds an important layer to this relationship by showing that the effects of algorithmic management are not experienced uniformly across workers. This is consistent with literature arguing that dependence on platform income is central to understanding differences in autonomy, precarity and working conditions (Brawley Newlin, 2024; Glavin & Schieman, 2022; Kougiannou & Mendonça, 2025; Maffie, 2023; Saksida et al., 2026; Schor et al., 2020). For job demands, however, the effect of algorithmic management was stronger among workers with lower economic dependence and became weaker as dependence increased. Although this pattern may initially appear counterintuitive, one possible explanation is that highly dependent workers already experience substantial work demands because of their financial reliance on ride-hailing. In such cases, stronger algorithmic management may add comparatively less to demands that are already elevated. This interpretation is consistent with research showing that dependent workers face greater financial pressure, reduced capacity to reject undesirable work and stronger exposure to platform precarity (Glavin & Schieman, 2022; Khan et al., 2026; Schor et al., 2020; Sun et al., 2023).

The results for flexibility constraints further illustrate this conditional nature of platform work. At lower levels of economic dependence, high algorithmic management was associated with fewer flexibility constraints, whereas at higher levels of dependence it was associated with greater constraints. This distinction reflects previous research showing that workers who use platform work as a supplementary source of income are generally better able to use its flexibility selectively, while economically dependent workers are more constrained by demand patterns, income needs and platform requirements (Fielbaum & Tirachini, 2021; Glavin & Schieman, 2022; Kougiannou & Mendonça, 2025; Saksida et al., 2026; Schor et al., 2020). It also suggests that algorithmic management is not necessarily experienced as restrictive in the same way by all workers. For those with lower economic dependence, algorithmic coordination may structure work without substantially limiting choice, whereas for workers who rely heavily on platform income, the same mechanisms may contribute to a more constrained form of flexibility. This is in line with research suggesting that the effects of algorithmic management depend on how workers experience and respond to algorithmic systems in practice (Cameron, 2024; Shi et al., 2025; Zhang et al., 2025).

Overall, this study makes key contributions to the platform work literature. By experimentally distinguishing between high and low levels of algorithmic management, it

shows that the intensity of algorithmic management matters for workers' turnover intention, rather than treating it only as a general feature of platform work. In addition, it identifies job demands as an important mechanism through which algorithmic management may influence turnover intention, while the non-significant mediating role of flexibility constraints suggests that flexibility may not operate uniformly across workers. Moreover, it highlights the role of economic dependence in explaining why the effects of algorithmic management on job demands and flexibility constraints vary according to workers' reliance on platform income. Ultimately, the study contributes to moving the discussion beyond whether algorithmic management affects platform workers towards understanding how its intensity matters and for whom its effects may differ.

6. Conclusion

6.1 Theoretical Contributions

This study extends previous research on the consequences of algorithmic management for platform workers. While previous studies have associated algorithmic practices with withdrawal intentions and less sustainable work experiences (Adekoya et al., 2025; Liu et al., 2024; Saksida et al., 2026; Zheng et al., 2026), the present study adds evidence that exposure to high, compared with low, algorithmic management is associated with greater turnover intention. It also shows a significant indirect effect through job demands: exposure to high algorithmic management was associated with higher job demands, which were in turn associated with greater turnover intention. This adds to the literature by identifying job demands as a relevant mechanism connecting different levels of algorithmic management to workers' intention to leave, supporting the idea that the consequences of this form of control arise partly through the demanding working conditions it creates (Cheng et al., 2024; Duggan et al., 2020; Liu et al., 2024; Zhao et al., 2026). Flexibility constraints, however, did not significantly mediate the relationship between algorithmic management and turnover intention. This finding is also theoretically relevant, as it suggests that constraints on flexibility may not represent a general mechanism explaining workers' intention to leave. Instead, their role appears to be more dependent on workers' circumstances, which becomes particularly relevant when considering economic dependence.

In this context, the study also highlights the importance of economic dependence in explaining why platform workers do not experience algorithmic management in the same way (Glavin & Schieman, 2022; Kougiannou & Mendonça, 2025; Schor et al., 2020). Its moderating effect on both job demands and flexibility constraints suggests that the effects of exposure to high versus low algorithmic management can produce different outcomes depending on workers' reliance on platform income. In particular, the findings support a more conditional view of platform flexibility, whereby workers with lower economic dependence may be better able to benefit from flexibility, while more dependent workers may experience the same arrangements as more constraining. Together, these findings show that the consequences of algorithmic management cannot be understood solely in terms of its intensity, but should also be considered in relation to workers' economic dependence.

6.2 Managerial Implications

The managerial implications of this study are particularly relevant for how ride-hailing platforms design and implement algorithmic management practices. The findings suggest that greater intensity of algorithmic management may be associated with higher job demands and stronger intentions to leave the activity. This means that platforms should consider not only the efficiency of algorithmic systems, but also how their management practices are experienced by drivers in their daily work. Practices related to work allocation, monitoring, performance evaluation and incentives should therefore be designed in ways that avoid creating unnecessary pressure and allow workers to maintain a reasonable level of control over how they organize their activity.

The findings also suggest that the same algorithmic management practices may not be experienced in the same way by all drivers. Economic dependence appears particularly relevant in this regard, as workers who rely more heavily on ride-hailing income may have less room to adapt their working patterns or respond to platform requirements. A standardized approach to algorithmic management may therefore overlook important differences within the workforce. Platforms should pay attention to whether their management practices preserve meaningful flexibility for workers with different levels of dependence on platform income, rather than assuming that the flexibility formally offered by ride-hailing is equally accessible to everyone.

From a practical perspective, these findings highlight the importance of balancing algorithmic efficiency with the sustainability of drivers' working conditions. Reducing unnecessary work pressure, providing clearer information about how algorithmic decisions affect work and preserving workers' ability to make meaningful choices may contribute to more sustainable participation in ride-hailing and potentially reduce intentions to leave the activity.

6.3 Limitations and Recommendations for Future Research

This study presents some methodological limitations that should be acknowledged. First, the use of a non-probabilistic convenience sample, with elements of snowball sampling, limits the representativeness of the results. The absence of a publicly available database of active TVDE drivers in Portugal, combined with the lack of a shared physical workplace

where these drivers could be easily reached, made the data collection process particularly challenging. As a result, additional efforts were required to disseminate the questionnaire through multiple channels and to contact drivers directly, although these constraints still limited the possibility of obtaining a larger sample. Since the questionnaire was shared through intermediary channels, it was also not possible to determine the exact size of the contacted population or calculate a precise response rate.

Second, the data were collected through self-reported measures, which may be affected by respondents' subjective perceptions, memory limitations or social desirability bias. Although the use of adapted scales from previous literature helps strengthen measurement validity, the responses still reflect how participants perceived or interpreted the situations and items presented in the questionnaire.

Third, the study follows a cross-sectional design, meaning that data were collected at a single point in time. As a result, the findings allow the identification of associations between variables but do not support strong causal conclusions over time. In addition, the use of hypothetical scenarios makes it possible to control the level of algorithmic management presented to participants, but it may not fully reproduce the complexity of drivers' real working experiences on digital platforms.

A further limitation is that the findings should be interpreted within the specific context of TVDE work in Portugal. Differences in platform regulation, labour market conditions and driver profiles across countries or platform sectors may limit the generalisation of the results to other contexts.

Future research could address these limitations by using longitudinal designs and more objective data collected directly from digital platforms, which could help provide a clearer understanding of how these relationships develop over time. It could also examine whether the findings of this study apply to other platform sectors and countries, particularly to understand whether the role of economic dependence remains similar across different labour markets and regulatory contexts. Beyond these methodological considerations, future studies could extend the model beyond turnover intention by examining alternative responses to algorithmic management, such as working across multiple platforms or developing strategies to adapt to algorithmic requirements.

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Annexes

A. Questionnaire - *Work Experiences of TVDE Drivers in Portugal*

A.1 Participation Information and Informed Consent

My name is Carolina Costa, and I am conducting a study on the work experiences of TVDE drivers in Portugal, as part of my Master dissertation in Economics of Business and Strategy at the Faculty of Economics of the University of Porto. This questionnaire aims to better understand how digital platforms and algorithmic management may influence drivers' perceptions of work demands, flexibility and work-related intentions. The questionnaire should take approximately 7 to 10 minutes to complete.
There are no right or wrong answers. Please answer as honestly as possible, based on your own perception and experience. Your participation is voluntary and all responses will be treated anonymously and confidentially. The data collected will be used exclusively for academic research purposes. Please read each question carefully before answering.

Do you agree to participate in this study?

- o Yes, I agree to participate.
- o No, I do not agree to participate.

A.2 Eligibility Question

This questionnaire is intended for individuals who currently work, or have recently worked, as TVDE drivers in Portugal. Do you currently work, or have you recently worked (within the previous six months), as a TVDE driver in Portugal?

- o Yes
- o No

A.3 Experimental Scenarios

Scenario A – Low Algorithmic Management

Imagine that you are working as a TVDE driver through a digital platform. When you are online, the platform provides basic information about available trips, customer requests and possible routes, but you have considerable freedom to decide which trips to accept and how to organise your work. While you are working, the platform collects only the information needed to complete accepted trips. Your location and trip information are used mainly for operational purposes and the platform does not closely monitor your work behaviour or performance in real time.

Your work quality may be assessed through basic service information and customer feedback, but this information is used mainly to provide transparent feedback rather than to automatically determine consequences. Ratings and indicators do not strongly determine your access to future trips, bonuses or work opportunities. If a problem occurs, decisions can be reviewed with human support and drivers can ask for clarification or appeal platform decisions before any penalties are applied.

Scenario B – High Algorithmic Management

Imagine that you are working as a TVDE driver through a digital platform. When you are online, the platform algorithm automatically assigns or prioritises trips and provides detailed instructions through the app, including suggested routes, expected response times, platform standards and performance targets.

While you are working, the algorithm provides real-time information about your work and gives timely feedback on your performance. The platform continuously tracks your location, keeps records of your trips and monitors indicators such as acceptance rate, cancellation rate, customer ratings and trip completion times.

Your work quality is automatically assessed by the algorithm. The platform ranks drivers based on their performance and drivers with better scores may receive priority access to trips, bonuses or cash incentives during specific periods. If a driver does not meet the platform's requirements, the algorithm may reduce access to work opportunities or apply

penalties/fines through the app. Most work-related decisions are made automatically, with limited explanation or human intervention.

A.4 Post Scenarios Measurement Scales

Please answer the following questions by imagining how you would experience work in the situation described earlier.

Please indicate your level of agreement with the following statements. 1 = Strongly disagree; 7 = Strongly agree

1. My work requires me to work fast.
2. My work requires me to work hard.
3. My work requires a lot of physical effort.
4. My work requires me to concentrate on the job for a long time.
5. I am very hectic at work.

1. I decide how to do the work by myself using platform software.
2. When completing tasks with platform software, this job gives me the opportunity to use my personal creativity or judgment.
3. My job provides me with considerable opportunities to independently and freely complete work tasks.

1. I intend to leave my current occupation.
2. I will probably change my occupation in the near future.
3. I frequently think about leaving my current occupation.

1. I feel I cannot stop working rideshare.
2. I wish I would have never started working rideshare.
3. Rideshare vehicle maintenance is higher than I expected.
4. When I started rideshare, I thought I would earn more I actually do.

A.5 Manipulation Check

Please answer the following questions based only on the scenario presented at the beginning of the questionnaire, even if your real experience as a TVDE driver is different.

Please indicate your level of agreement with the following statements. 1 = Strongly disagree; 7 = Strongly agree

In the scenario, the platform relied heavily on algorithms to manage drivers' work.
In the scenario, the platform closely monitored drivers' work and performance.
In the scenario, important work-related decisions were made automatically by the platform.

A.6 Demographic and Work-Related Characteristics

What is your gender?

- Male
- Female
- Other
- Prefer not to answer

What is your age?

- 18-24
- 25-34
- 35-44
- 45-54
- 55 or older

What is your highest level of education?

- Basic education
- Secondary education
- Bachelor's degree; Master's/Doctoral degree
- Other

How long have you been working as a TVDE driver?

- Less than 1 year
- 1-2 years
- 3-5 years
- More than 5 years

On average, what is your monthly income from TVDE work?

- Less than EUR 500
- EUR 500-999
- EUR 1000-1499
- EUR 1500-1999
- EUR 2000 or more

On average, how many hours per week do you work in TVDE?

- Less than 20 hours
- 20-34 hours
- 35-49 hours
- 50 hours or more

How many TVDE platforms do you regularly work with?

- 1
- 2
- 3 or more

Which best describes your current situation as a TVDE driver?

- I work through a TVDE operator/partner company
- I have my own TVDE operator/company
- Other (if you choose this option specify)

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