



**Income Volatility, Algorithmic Management
Intensity and Employment Status Ambiguity:
Associations with Job Satisfaction among UK
Platform-Based Gig Workers**

Master's Dissertation

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Abstract

This research project examines whether **income volatility, algorithmic management intensity, employment status ambiguity**, and job satisfaction are related among gig economy workers in the UK. This analysis applies the two-factor theory of Herzberg and the job demands-resources model, using a cross-sectional survey design as part of an overall deductive approach grounded in a positivist philosophy. Data was collected through an online questionnaire. Recruitment closed once 50 complete, usable responses passed eligibility and data-quality checks; additional submissions were excluded during screening because they were incomplete or did not meet the required criteria. The sample included remote and local workers across eight occupations. Respondents' job satisfaction was assessed using the General Satisfaction score from the short form of the Minnesota Satisfaction Questionnaire. In addition, the author assessed all three predictor variables using Likert-type scales developed specifically for this study. Statistical analysis was conducted in SPSS. All four measures demonstrated adequate internal reliability. On average, respondents reported a job satisfaction of 2.35 out of five possible points, below the midpoint. The findings suggested that unpredictability of earnings and uncertainty about employment status were most strongly related to job satisfaction, as defined by the relationships in this dissertation. Larger representative samples should be studied to examine whether these relationships hold true and whether they will exhibit variability over time

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This work is the result of my own investigations, except where otherwise stated.

Other sources are acknowledged by footnotes giving explicit references. A bibliography is appended.

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List of Abbreviations

ACAS	Advisory, Conciliation and Arbitration Service
GDPR	General Data Protection Regulation
JD-R	Job Demands–Resources
MSQ	Minnesota Satisfaction Questionnaire
UK	United Kingdom
UWTSD	University of Wales Trinity Saint David
VIF	Variance Inflation Factor
AMI	Algorithmic Management Intensity
ESA	Employment Status Ambiguity

Chapter One: Introduction

1.1 Background to the Study

Digital technologies have significantly impacted how casual, task-based and short-term work is organised, distributed and supervised. Although casual, freelance, piece-rate arrangements existed before the emergence of the platform economy, the scale at which applications and web-based marketplaces facilitate the connection between workers and consumers has been greatly increased. Brinkley (2016) defines gig work as using digital platforms to engage in discrete tasks and arrangements for customers. Similarly, Montgomery and Baglioni (2021) emphasise that platforms enable short-term, tactical exchanges of labour.

Platform work is different from traditional employment practices because most people access tasks via an application or marketplace instead of through a fixed employee-employer relationship. Examples of location-based platforms include Uber, Deliveroo, Just Eat, Amazon Flex and TaskRabbit. In contrast to these are remote online platforms such as Upwork and Fiverr. Martindale et al. (2024) distinguish between two types of platform work. Local platform work consists of food delivery, ride-hailing and other forms of location-specific activity. Remote platform work includes activities such as data entry, graphic design and writing.

Workers engage in platform work for several reasons, including flexibility. Berger et al. (2019) studied Uber drivers in London and found that a large number of those drivers valued the flexibility they had regarding choosing when and for how long they work. While this type of flexibility provides workers with autonomy, it also generates insecurity. Hickson (2024) suggests that although gig-economy companies often advertise the rhetoric of "freedom", this ignores the vulnerabilities that exist for many workers who lack both legal and financial support structures.

The working conditions in platform work are also often insecure. Many workers do not receive a steady income; are subject to variable hours and days; require their own vehicles or equipment; and, consequently, often do not enjoy the same level of employment rights as traditionally employed individuals. Stewart and Stanford (2017) described the following as common characteristics of gig work: irregular schedules,

piece-rate payments and the provision of equipment by the workers themselves. Davies (2020) states that applying wage and working time protections to task-based work creates significant legal and operational challenges.

The UK offers an interesting context for researching these topics because platform work is present across many areas and occupations, though not equally. According to Johnes (2019), the highest concentration of gig economy jobs exists in London, whereas there has been less development in other locations. This spatial difference is important to note, since experience for employees can vary by type of occupation and location.

Platform workers in the United Kingdom cannot be categorised into one monolithic entity. While some engage in localised work, such as delivering goods or driving individuals, many are involved in remote professional and digital service platforms. In their research, Martindale, Wood and Burchell (2024) demonstrate that these various types of platforms provide workers with different types of work, compensation and levels of platform control. So, distinctions regarding local versus remote work will continue to exist within this project.

Job satisfaction is a good indicator for analysing the combination of flexibility and uncertainty which affects the lives of platform workers. Many platform workers find independent work to be desirable, and they appreciate flexible scheduling options and opportunities to generate extra income. However, the same workers often face problems including low wages, irregular earnings, risks associated with their employment status, limited organisational power and no guaranteed access to employment protections. As stated by Martindale, Wood and Burchell (2024), UK platform workers have expressed both insecurity about their current position as well as support for worker rights. This divide allows examination of how specific working-condition characteristics affect platform workers' job satisfaction.

This dissertation focuses on three working conditions: income volatility, algorithmic management intensity and employment status ambiguity. Income volatility means unstable or unpredictable earnings. Algorithmic management refers to the use of ratings, automated allocation, monitoring and platform rules to organise and evaluate

work. Employment status ambiguity refers to uncertainty about whether a worker is self-employed, a worker or an employee, and about the rights attached to that status.

All these issues have been addressed in the gig economy literature. Vallas and Schor (2020), for example, discuss how platforms operate to allow companies to maintain significant control over the workplace but shift both risk and liability from employers to employees. Tassinari and Maccarrone (2020) examine how mobile apps shape courier work through allocation and control. Davies (2020) discusses the legal problems that can arise from paying workers per task or by the hour. Finally, Hickson (2024) shows how this lack of secure legal and financial protection leaves workers vulnerable and creates employment insecurity.

Against this backdrop, this research investigates whether income instability, the degree to which algorithms manage platform workers, and ambiguity about workers' employment status are associated with job satisfaction among platform-based gig workers in the UK.

1.2 Research Problem

There has been increasing focus on the gig economy within both academia and policy, but little research on the association between various aspects of working for a platform (i.e., working conditions) and job satisfaction. Most existing literature presents an apparent trade-off between flexibility and insecurity. However, many gig workers face multiple working conditions simultaneously. Additionally, because of its unique nature, the gig economy is difficult to quantify or assess using traditional labour market measures. For example, local gig workers (e.g., delivery riders or drivers) have vastly different working conditions compared to remote freelance gig workers. This paper addresses this gap by quantitatively analysing income volatility, perceived algorithmic management, ambiguity around employment status, and job satisfaction among UK-based gig workers on platforms.

Another reason for examining these three working conditions together is that platform workers may experience them at the same time. A worker may have unpredictable earnings, receive work through an automated system, and also be unsure about their employment status. Treating these issues separately can therefore miss part of the working experience. Vallas and Schor (2020) describe platform work as an arrangement in which firms can retain significant control while shifting some risks to

workers. Martindale, Wood and Burchell (2024) also show that UK platform workers are not a single group and that experiences differ across local and remote forms of platform work.

These observations support examining several working conditions within the same model rather than assuming that one issue explains job satisfaction on its own. At the same time, the study does not attempt to capture every possible influence on satisfaction. The aim is narrower: to examine whether the three selected conditions are associated with job satisfaction in this sample and to compare the strength of those associations.

1.3 Research Aim and Objectives

The primary objective of this research project is to explore the interrelationships between income volatility (income instability), Algorithmic Management Intensity (AMI), Employment Status Ambiguity (ESA), and job satisfaction among platform-based gig workers in the United Kingdom.

To accomplish this primary objective, the research project has four secondary objectives:

1. To review relevant literature related to the gig economy, platform work, and gig worker experiences in a UK-based context.
2. To identify levels of job satisfaction for platform-based gig workers based in the United Kingdom.
3. To investigate whether there are relationships between income volatility and job satisfaction, AMI and job satisfaction, and ESA and job satisfaction.
4. To assess how strong an association each of these three working conditions has with job satisfaction.

1.4 Significance of the Study

The results of this study will help develop a deeper understanding of platform work in the UK by assessing three elements previously studied separately: income instability, the level of algorithmic control over the workplace, and ambiguity surrounding an individual's employment status. The findings may help platform providers identify aspects of workers' experiences that require attention, including pay transparency, communication, algorithmic decision-making and clarity about employment status. The study provides some evidence to support policy considerations regarding labour

protections, wage regulations and working time provisions. In addition, the findings could help worker advocacy groups by providing empirical evidence to support issues raised by respondents.

1.5 Scope and Delimitations

This study examines gig workers in the UK who use digital platforms (both online and offline) to find paid work. Online and offline platform work, which can be found through various local and remote digital platforms, may be considered part of this field. Examples of local digital platform work include: ride hailing, food delivery, courier services, house cleaning, and handyman services. Examples of remote platform work can include freelancing, data entry, writing, translation, graphic design and many other digital-based services.

As stated above, the aim of this study was not to look at all types of insecure work (casual work), nor to investigate all types of agency work or zero-hours contracts. As stated previously, there is a broader debate surrounding uncertainty in relation to insecure and precarious working practices. However, the primary interest of this study lies in examining platform-mediated gig work.

Additionally, the study examines three distinct independent variables: Income Volatility, Algorithmic Management Intensity, and Employment Status Ambiguity. There were potentially numerous additional variables that were relevant to the topic of study that were not included. For example: Customer behaviour, Health and Safety Risks, Social Isolation, Platform Fees charged by employers, Competition between Workers and Worker Identity. While each of the variables is relevant to the topic of study, they are not being explored in detail due to the scope limitations imposed by conducting a master's thesis.

A Quantitative Survey Design was utilised in this study. A survey provides researchers with the ability to measure relationships between different variables across a large population while providing less insight into how individuals relate their experiences to working conditions compared to what could have been provided via interview methodology. Hence, the study focused on quantifiable patterns rather than individual stories.

The author used a cross-sectional study design for this research, which means data were collected at a particular time. Though this type of study design allows researchers to determine whether there exists an association between working conditions and job satisfaction (and vice versa), it does not allow researchers to establish causal links between working conditions and job satisfaction.

1.6 Structure of the Dissertation

This dissertation is organised into five chapters.

Chapter One introduces the research topic, explains the background to the gig economy, identifies the research problem, and sets out the aim, objectives, significance and scope of the study.

Chapter Two reviews the literature on the gig economy, platform work, job satisfaction and the three main working conditions examined in the study: income volatility, algorithmic management intensity and employment status ambiguity. It also identifies the research gap and develops the study's conceptual framework.

Chapter Three explains the methodology. It discusses the research philosophy, research approach, research design, sampling strategy, data collection instrument, ethical considerations, reliability and validity, and data analysis strategy.

Chapter Four presents and discusses the research findings. It reports the sample profile, reliability results, descriptive statistics, correlation analysis and multiple regression used to evaluate the hypotheses.

Chapter Five concludes the dissertation by outlining its main limitations, identifying areas for further research and drawing together the overall conclusions of the study.

Chapter Two: Literature Review

2.1 Introduction

This chapter provides an overview of relevant literature in this research area. The purpose of the chapter is to establish a foundation for the research by exploring how researchers have defined platform work; how workers report experiencing platform work; what has been reported regarding the three variables of interest (income volatility, algorithmic management intensity, and employment status ambiguity). It also introduces the theoretical perspectives through which the collected data were interpreted (Herzberg's Two-Factor Theory and the JD-R Model).

Section 2.2 defines platform-based gig work and sets the study's inclusion criteria. Section 2.3 considers the scale, composition and legal context of UK platform work. Section 2.4 defines job satisfaction and distinguishes direct evidence from related measures such as well-being and strain. Sections 2.5 to 2.7 review the three predictors. Section 2.8 considers worker heterogeneity and the controls used in the final model. Section 2.9 develops the theoretical framework, and Section 2.10 presents the conceptual model and hypotheses.

2.2 Defining and scoping platform-based gig work

The term 'gig economy' is newer than the kind of work it describes. Short-term and task-based work has a much longer history; digital platforms have changed the way it is matched, monitored and paid. Brinkley (2016) describes the gig economy as people using digital platforms to negotiate discrete pieces of work with customers or clients. Montgomery and Baglioni (2021) emphasise the same platform-mediated, short-term exchange of labour, but place greater weight on the wider model of platform capitalism in which it occurs.

There is no single agreed definition in the literature. Singha and Saikia (2024) reviewed the range of definitions used across studies and found that most share three common features: work is broken into discrete tasks; workers are usually classified as self-employed or independent contractors; and the connection between worker and customer is mediated by a digital platform. Watson et al. (2021) identify five gig worker profiles: gig service providers (such as ride-share drivers and food couriers), gig goods providers (such as Etsy sellers), gig data providers (such as workers on Amazon Mechanical Turk), agency gig workers, and traditional gig workers (such as

substitute teachers and babysitters). Demands and rewards vary considerably across these profiles.

Davies (2020) argues that the payment mechanism is the clearest defining feature. Piece rates are not new, but technology now allows them to be combined with real-time monitoring, ratings, and automated allocation systems that would have been impractical without an app.

MacDonald and Giazitzoglu (2019) place contemporary gig work within the neoliberal restructuring of labour from the 1980s onwards. Whiteside (2021) reaches further back, showing that Britain had a substantial casual labour market before the First World War and that several policy questions now associated with the gig economy have older precedents. These accounts locate platform work within both recent labour-market change and a longer history of insecure work.

Here, platform-based gig work is defined as paid work in which (i) tasks are allocated through a digital platform, (ii) payment is made per task or short engagement rather than as a salary, and (iii) the platform classifies the worker as self-employed or as a 'worker' rather than as an employee. The study includes local platform work, such as ride-hailing, delivery, cleaning and handyman services, and remote platform work, such as freelance writing, translation, data entry and design. Agency temporary work, zero-hours employee contracts and self-employment that is not platform-mediated are excluded.

2.3 The scale, composition and legal context of UK platform work

Johnes (2019) shows that gig-economy activity in the UK is unevenly distributed, with London accounting for the largest share. He also notes that the scale of the sector is difficult to measure because the Labour Force Survey does not identify gig workers as a separate category. Brinkley (2016) makes a related measurement point and argues that direct surveys are needed to capture forms of platform work that conventional labour-market statistics can miss.

The UK platform workforce is heterogeneous. Martindale, Wood and Burchell (2024) distinguish local platform work (food delivery, ride-hailing, cleaning, handyman services) from remote platform work (writing, translation, data entry, graphic design). The two involve different labour processes, different levels of platform control, and

different rates of pay. The Gig Rights Survey they report also found that platform workers were slightly more likely to be male (72 % versus 62–69 % in national comparators) and considerably younger (median age 33 versus 47–51) than the general self-employed population.

The employment law framework in Great Britain distinguishes three main categories: employee, worker, and self-employed or independent contractor. Employees receive the strongest rights, including protection against unfair dismissal, statutory redundancy, and sick pay. Workers receive a narrower set of rights, including the National Minimum Wage and holiday pay. Self-employed people have very limited employment rights. A person's legal standing can be based upon their actual employment situation, as opposed to what a company states within a contract. In *Uber BV v. Aslam* (2021) UKSC 5, the Supreme Court supported a tribunal finding that the drivers who made claims against Uber BV were 'workers' under applicable employment laws and provided criteria regarding when they would be at work. While this ruling specifically relates to the parties involved in that case, it has generally been regarded as an important decision for the entire platform industry. Most of the research referred to in this review relates to Great Britain, where the majority of these authors are from. There is a different set of employment laws in place in Northern Ireland.

2.4 Defining and measuring job satisfaction

Job satisfaction here is defined as an individual's overall assessment of their work, seen as a composite attitude toward their job rather than separate emotional responses to specific aspects. The main dependent variable in this study is the overall evaluation, which is measured by the General Satisfaction score from the MSQ short-form, as detailed in Section 2.9.

Life satisfaction is a person's overall evaluation of their life as a whole, not their work in particular. Psychological well-being covers broader mental health, including anxiety and depression. Psychological strain and burnout capture the depleting effects of chronic job demands. Job quality is a set of features of the job itself (pay, hours, security, autonomy), often analysed feature by feature rather than aggregated into a single evaluation.

The evidence base for the association between platform-work conditions and job satisfaction is classified in this chapter into three categories. Direct evidence comes

from studies that measure job satisfaction with a validated instrument. Adjacent evidence comes from studies that measure life satisfaction, well-being or strain, and is informative but not equivalent to job-satisfaction evidence. Indirect evidence comes from qualitative accounts, behavioural evidence such as resistance, or single job-quality features.

The evidence does not point in a single direction. Duggan et al. (2026) describe an 'autonomy paradox' in which the ability to log on and off can coexist with limited control over the conditions set by the platform. Berger et al. (2019) found that Uber drivers in London reported higher life satisfaction than the average London worker, but also higher anxiety; their outcome was life satisfaction rather than job satisfaction. Martindale, Wood and Burchell (2024) found that workers could value flexibility while also supporting employment rights normally associated with employee status. These studies capture different parts of the same tension rather than measuring an identical outcome.

The distinction between job satisfaction and related outcomes is important for the dissertation. Some gig-economy research discusses well-being, anxiety, strain or general attitudes to platform work, but these outcomes are not identical. Berger et al. (2019), for example, reported higher life satisfaction among Uber drivers than among a comparison group of London workers, while also finding higher anxiety. This combination shows why a positive result on one outcome should not automatically be interpreted as evidence of positive job satisfaction. Similarly, Duggan et al. (2026) examine strain rather than job satisfaction. Their findings are useful for understanding possible pressures within gig work, but they answer a different question.

For this reason, the present dissertation uses the MSQ General Satisfaction score as the main outcome rather than combining several measures of well-being. The choice keeps the dependent variable clear and allows the three working conditions to be compared against the same measure. It also places a limit on interpretation. A worker with a low satisfaction score cannot automatically be described as having poor mental health, and a worker with a high satisfaction score may still experience insecurity or anxiety. Keeping these concepts separate reduces the risk of making a broader claim than the survey actually supports.

2.5 Income volatility

Income volatility refers here to the perceived unpredictability of the amount and timing of platform-derived earnings. It is different from absolute income level, perceived income adequacy and dependence on gig income. A worker can, for example, have relatively high earnings that still vary sharply from week to week. Income dependency was measured separately and included as a control in the final regression model; absolute income level and perceived adequacy were not modelled as separate controls.

Direct-satisfaction evidence on income volatility in gig work is limited; most of the literature uses adjacent measures. Davies (2020) describes volatility as a structural feature of gig work rather than an unfortunate side-effect, because piece-rate payment and platform control of task availability together mean weekly earnings cannot be predicted. Kaine and Josserand (2019) note that the uncertainty extends beyond weekly income to project frequency and available hours.

MacDonald and Giazitzoglu (2019) place income volatility in a longer list of ten features of UK precarious work, alongside disempowerment, low pay, and anxiety. Their argument is that these features travel together. Workers with unstable income typically also have limited choice about the work they take and higher day-to-day anxiety about paying the next bill.

Berger et al. (2019) and Hickson (2024) place different emphasis on variable earnings. Berger et al.'s Uber drivers often valued the ability to vary their hours and reported higher earnings than in previous jobs. Hickson interprets unstable earnings through republican political theory, arguing that income that can disappear quickly can increase workers' vulnerability to landlords, lenders and the platform itself. Almost a third of Berger et al.'s drivers did not report exact income, but that non-response cannot by itself be treated as evidence of volatility.

Duggan et al. (2026) provide adjacent evidence on compensation and psychological strain. Using more than six thousand Glassdoor reviews from transport, courier and food-delivery roles, they found that compensation-related content was associated with higher strain among gig workers relative to non-gig workers. The result is correlational and does not establish that compensation conditions caused strain. It nevertheless supports examining income instability as a possible job demand.

2.6 Algorithmic management intensity

Algorithmic management intensity, in this dissertation, refers to the degree to which the direction, monitoring, evaluation, and sanctioning of work is performed by automated platform systems rather than by human managers. Intensity is a matter of degree along several dimensions: frequency of monitoring, dependence on customer ratings, automation of task allocation, automation of sanctions such as deactivation, and the extent to which workers can challenge or appeal decisions.

Direct satisfaction evidence on algorithmic management intensity in gig work is limited. Most of the literature uses adjacent well-being or strain measures, or indirect behavioural evidence. Kaine and Josserand (2019) identify three main functions of algorithmic management in gig work. The first is discipline and control, which uses the app's ability to see everything the worker does to enforce compliance. The second is performance management, which uses customer ratings and automatic incentives to shape effort. The third is the legitimization of decisions to terminate workers, since the algorithm can be presented as an impersonal judge rather than a manager.

UK evidence on algorithmic management is largely indirect. Bates et al. (2021) describe food couriers in Manchester and York using informal WhatsApp networks to compare experiences and share ways of dealing with platform decisions. Cini, Maccarrone and Tassinari (2022) examine mobilisation among food-delivery workers in the UK and Italy. Neither study measures job satisfaction directly. Their value here is that they show how workers respond to platform control, while leaving open the question of how satisfied those workers are overall.

Christie and Ward's (2019) UK survey of 231 drivers and couriers provides further indirect evidence through health and safety outcomes. 42 % had been in a collision that damaged their vehicle, and 75 % had needed to take evasive action to avoid one. Many described being under constant pressure from the app to complete deliveries quickly, and a third worked more than fifty hours a week. Health and safety failures are a plausible mechanism for dissatisfaction but are not themselves a satisfaction measure.

Duggan et al. (2026) provide adjacent evidence on algorithmic management and strain. Their analysis suggests that, in gig work, resources such as compensation and work-life balance can relate to strain differently from the pattern expected in conventional

employment. Muhammed Ali and Chitra Sivasubramanian (2024) report a related result from 340 Uber drivers in India: techno-stressors were associated with lower psychological well-being, while job autonomy was not significantly associated with well-being. Neither study measures the same outcome as this dissertation, but both support treating algorithmic management as a condition that may shape workers' experience of their work.

2.7 Employment status ambiguity

Employment status ambiguity, in this dissertation, refers to the presence of uncertainty about a worker's legal employment classification and the rights that follow from it. The construct combines two distinguishable elements. Ambiguity arises when the boundary between employee, worker, and self-employed is disputed or unclear in a specific case. Subjective ambiguity is the worker's own uncertainty about which category they belong to and what rights they have. A participant may legally be a worker under British law while believing they are self-employed, or the reverse.

Davies (2020) argues that task-based pay conflicts with the assumptions underlying the National Minimum Wage Act and Working Time Regulations, both designed around an hourly work model. Stewart and Stanford (2017) explore five potential legal solutions: enforcing existing laws more strictly, clarifying or expanding the definitions of "work" and "employee," establishing a new category of 'independent contractor,' widening the scope of who is considered a worker beyond traditional criteria, and determining who qualifies as an employer.

Novitz (2020) shifts the frame to international regulation. She considers whether international labour standards under the International Labour Organization could be applied to gig work, given the cross-border nature of many platforms. Her key observation is that national litigation has produced inconsistent results across countries, which strengthens the case for coordinated international responses.

Martindale, Wood and Burchell (2024) provide direct empirical evidence on the subjective side. Most platform workers in their survey described their own status as self-employed, even though the same workers strongly supported basic labour rights such as minimum pay and protection against unfair dismissal. This included many Uber drivers, despite the *Uber BV v Aslam* judgment that supported worker status for the claimants in that case. The gap between how workers describe their status and what

the law recognises for at least some platform workers is one of the most notable observations in the recent UK evidence.

Whiteside's (2021) historical analysis applies here as well. The categories of 'employee' and 'self-employed' were built by early twentieth-century policymakers for a different labour market and were never intended to fit conditions where the boundaries between employment forms are constantly shifting. On this reading, subjective status ambiguity is the individual-level counterpart of a category system that no longer fits the labour market it is trying to describe.

2.8 Worker heterogeneity and control variables

Platform workers differ by occupation, work setting and reliance on platform income, so the analysis needed to account for at least some of that heterogeneity. With a final sample of 50, however, the regression could not include every background characteristic collected in the questionnaire without becoming over-specified. The final model then used a small set of controls chosen before interpretation of the outcomes.

Martindale, Wood and Burchell (2024) show that local and remote platform work involve different labour processes, levels of platform control and pay structures. Christie and Ward (2019) document health and safety risks among drivers and couriers that do not apply in the same way to remote workers. For that reason, the final regression distinguished local from remote platform work.

Dependence on platform income was also retained as a control. Vallas and Schor (2020) argue that workers who rely on gig income may experience platform conditions differently from those who use it only to supplement their income. Weekly hours worked on platforms and platform tenure were included as two additional indicators of exposure to platform work. Other variables were excluded from the regression because the sample size could not support a substantially larger model.

In addition to occupation, platform use, self-declared employment status on platforms, age, sex, education level, and nationality of origin, the questionnaire collected other information about respondents' backgrounds. Accordingly, the final regression model included four controls for platform work: whether the worker worked remotely or locally; whether platform work provided their primary income; the number of hours per week spent working on platforms; and how long they had been using platforms.

Worker heterogeneity also affects how the regression results should be interpreted. Local platform workers can face conditions that are less relevant to remote workers. Christie and Ward (2019), for example, identify road-safety pressures among drivers and couriers, whereas these risks do not apply in the same way to a remote translator or graphic designer. Martindale, Wood and Burchell (2024) also distinguish local and remote platform work because the labour process, pay arrangements and degree of platform control can differ between them. Including work setting as a control therefore helps reduce one obvious source of difference within the sample.

The same reasoning applies to dependence on platform income, weekly hours and platform tenure. A person who relies on platform work as a main income source may experience unstable earnings differently from someone using it only for supplementary income. Longer exposure to platform work may also shape how workers understand platform rules and employment status. These controls cannot remove all differences between respondents, especially with a sample of 50, but they allow the main predictors to be examined while accounting for several relevant features of platform work. The analysis therefore remains deliberately limited rather than adding a large number of demographic controls that the sample size could not support

2.9 Integrated theoretical framework

The two theories explained the relationships examined in the study, while the MSQ assessed job satisfaction levels. Herzberg's Two-Factor Theory classified work environment issues as either motivators or hygiene factors. The Job Demand-Resource (JD-R) Model helped understand how job demands could result in strain and dissatisfaction. Instead of serving as causal explanations based on cross-sectional data, these models were used as interpretive tools.

2.9.1 Herzberg's Two-Factor Theory

Herzberg's two-factor theory (developed in the latter half of the 1950s by Alshmemri et al., 2017) divides the components of job satisfaction into two categories. Motivators include achievement, recognition, responsibility, opportunities for growth, and meaningful work. If an employee experiences these at work, the employee will be satisfied. But if an employee doesn't experience them, they won't be unhappy because of it; instead, they'll lack motivation to perform their tasks. Hygiene factors, on the other hand, are outside the actual task itself. These include compensation (pay),

working conditions, quality of supervision, quality of company policies and procedures, job security, and relationships with co-workers. When employees perceive these factors negatively, they become dissatisfied. When employees perceive these factors positively, dissatisfaction decreases; however, motivation does not increase (Darthey-Baah and Amoako, 2011).

Criticism of Herzberg's theory has been ongoing. Three broad categories of criticism exist (Stello, 2011). Methodological critiques exist. This includes the fact that the Critical Incident Technique Herzberg used may allow self-serving biases (since people tend to attribute positive feelings to themselves and negative feelings to external sources). Empirical critiques also exist. Replication studies employing alternative methodologies have shown no support for Herzberg's clean separation of the two types of factors (e.g., some argue that one type of factor can result in both high and low levels of satisfaction depending upon who is experiencing those factors). Finally, a cultural critique exists. The original study consisted of U.S.-based engineers and accountants in the late 1950s. As such, there is little reason to believe that the observations would apply broadly across labour markets. An empirical test conducted in Ghana (Darthey-Baah and Amoako, 2011) showed that only some of the predicted outcomes were observed.

Despite the critiques outlined above, Herzberg's theory continues to be used to investigate issues related to platform-based work. For example, Mukhopadhyay and Chatwin (2020) examined issues related to platform work in China using Herzberg's theory, with a focus on weaknesses in the hygiene aspect of platform-based work. In this dissertation, Herzberg's theory is primarily used as a framework for categorising various elements associated with gig economy jobs. Income volatility, lack of job security and algorithmic supervisory mechanisms all fall under the category of hygiene factors, allowing the results to be discussed without accepting Herzberg's original two-factor distinctions as absolute.

2.9.2 The Job Demands–Resources model

The Job Demands–Resources (JD-R) model, as outlined by Bakker and Demerouti (2007), categorises all jobs into two categories of characteristics. The first category relates to job demands; these include what consumes the worker's energy. Some examples of job demands include: workload, time pressure, emotional strain, and

unpredictability. The second category includes job resources; these relate to the ways in which the worker is helped to deal with their workload. Examples of job resources include autonomy, feedback, social support, and fair pay. Demerouti and Bakker (2011) built upon this model when they formulated JD-R Theory. According to this theory, employee well-being will depend on the ongoing balance between the level of demands placed upon them and the amount of resources available to mitigate those demands. When there is an imbalance of such a nature, where the levels of demands remain at a high level and resources at a low level for extended periods of time, then burnout and job dissatisfaction are likely outcomes. On the other hand, when demands and resources are closely matched, then job engagement and motivation are likely to occur (Bakker and Demerouti, 2017).

There are several well-known limitations to the JD-R Model. Bakker and Demerouti (2017) identified three that are relevant to this dissertation. The first limitation is that determining whether a characteristic should be considered a demand or a resource is dependent upon individual differences. For example, one worker may experience exhaustion from a high workload while another worker experiences increased energy due to a similar workload. The second limitation is that the JD-R Model typically assesses individuals cross-sectionally. This limits our understanding of how depletion occurs over time as well as the processes of recovery. The third limitation is the most relevant to this research. The JD-R Model was originally based on employees within traditional employment settings. As such, the assumptions regarding how resources will protect against demands in algorithmically managed environments may not accurately reflect real-world conditions. Duggan et al. (2026) provided evidence supporting concerns related to this assumption. They found that resources delivered via algorithm-based systems were positively correlated with higher levels of strain.

In addition to being applied to gig workers in general, JD-R has also been used specifically to compare demands and resources across various subgroups of gig workers. Watson et al. (2021) employed JD-R as a theoretical framework to explore the differences between demands and resources experienced by gig workers who use different types of platforms (e.g. food delivery apps, ride-sharing services). Muhammed Ali and Chitra Sivasubramanian (2024) implemented JD-R to investigate techno-stress and job resources among Uber Drivers. Finally, Duggan et al. (2026) employed JD-R as a theoretical framework to analyse strain in gig work.

2.9.3 The Minnesota Satisfaction Questionnaire

The Minnesota Satisfaction Questionnaire (MSQ) is a survey tool or assessment instrument rather than a theoretical framework. This thesis utilised the short form to minimise participant burden while maintaining a well-established general job satisfaction measure.

The 20-item short-form can produce three types of satisfaction measures: Intrinsic, Extrinsic, and General Satisfaction. General Satisfaction was implemented for the results of this dissertation because it most closely aligns with the hypotheses in terms of measuring overall job satisfaction vs. the specific satisfaction areas. Although there may exist conceptual overlap between the intrinsic and extrinsic satisfaction areas of the MSQ and Herzberg's Motivators and Hygiene Categories, the MSQ was not specifically designed as a means to test Herzberg's Theory, and as a result, these two constructs are not considered equal.

There also exists evidence supporting the use of the MSQ as a reliable and valid measure; still, the literature does not support one common assertion. Hancer and George (2003) found Cronbach's Alpha = .9 using the US Restaurant Worker sample. Hirschfeld (2000) investigated the psychometric structure of the short-form and found that it supported the original version. Abugre (2014) utilised the MSQ within a Ghanaian Public Sector context, demonstrating that it could be used in other employment contexts. These studies provided support for the selection of the MSQ; however, they did not suggest that the MSQ possessed uniform properties across populations.

2.9.4 Integration

Table 2.1 summarises how the two theories were used to develop the hypotheses. Herzberg's framework classifies the type of working condition, while JD-R provides a

way to interpret the demand associated with it. Both frameworks are consistent with expecting negative associations between the three predictors and General Satisfaction.

Table 2.1: Integration of Herzberg's Two-Factor Theory and the Job Demands–Resources model 18

Predictor	Herzberg classification	JD-R mechanism	Predicted direction
Income volatility	Hygiene-side condition (pay unpredictability)	Job demand: cognitive load of planning and coping with uncertain earnings	Negative
Algorithmic management intensity	Hygiene-side (opaque supervision); reduced autonomy on the motivator side	Job demand (monitoring, opacity, deactivation risk) and a factor that may neutralise other resources	Negative
Employment status ambiguity	Hygiene-side (job security)	Job demand: cognitive load and vulnerability from uncertain rights and remedies	Negative

The two theories serve different purposes in the study. Herzberg distinguishes between types of job factors but gives less attention to the process through which a condition is experienced. JD-R focuses on demands and resources but does not make the same motivator and hygiene distinction. Used together, they provide two complementary ways of interpreting the expected negative associations. The analysis itself tests those associations, not the causal mechanisms proposed by either theory.

2.10 Conceptual model and hypotheses

The conceptual model treats income volatility, algorithmic management intensity and employment status ambiguity as separate predictors of job satisfaction. Each is expected to have a negative association with the MSQ short-form General Satisfaction score. The model is additive: it tests the predictors together but does not test interactions between them. Four work-related controls were included in the final regression to account for some of the heterogeneity in the sample.

The hypotheses are:

H1: Income volatility is negatively associated with job satisfaction among UK platform-based gig workers.

H2: Algorithmic management intensity is negatively associated with job satisfaction among UK platform-based gig workers.

H3: Employment status ambiguity is negatively associated with job satisfaction among UK platform-based gig workers.

The primary outcome was the MSQ short-form General Satisfaction score. Multiple regression was used to enter the three predictors together with four controls: local versus remote platform work, main-income status, weekly platform hours and platform tenure. Because the study was cross-sectional, the hypotheses concerned statistical associations rather than causal effects. *Figure 2.1 presents the conceptual model.*

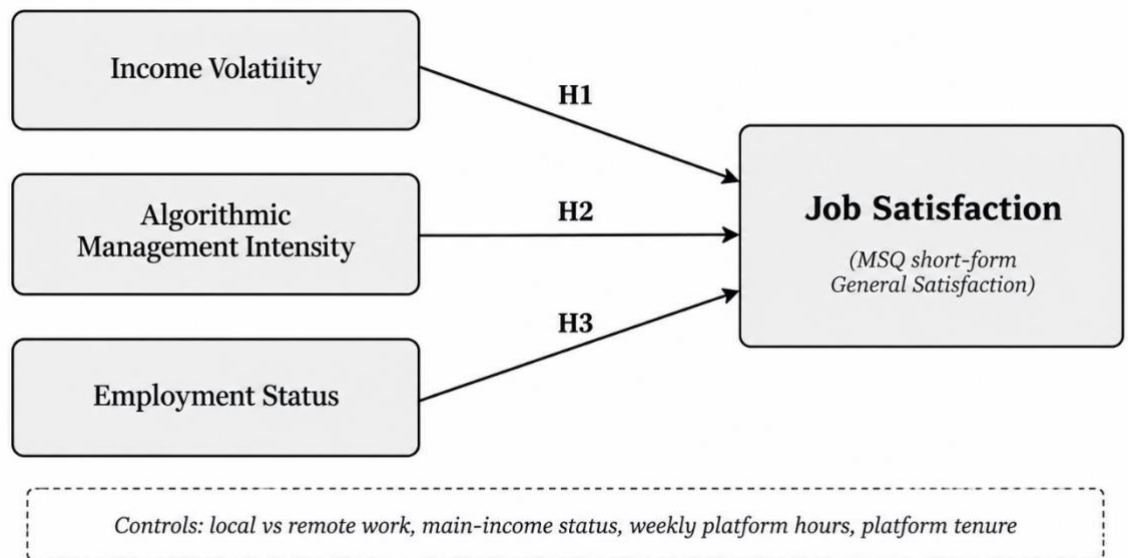


Figure 2.1: Conceptual model of the study. Income volatility, algorithmic management intensity and employment status ambiguity were each expected to show a negative association with MSQ short-form General Satisfaction (H1, H2, H3). The final regression controlled for local versus remote platform work, main-income status, weekly platform hours and platform tenure.

Chapter Three: Methodology

3.1 Introduction

This chapter explains how the study was designed, how the data were collected, and how the analysis was carried out. The study used a cross-sectional online survey of UK platform-based gig workers and multiple regression in SPSS to test the three hypotheses developed in Chapter Two. The chapter moves from the research philosophy and design choices to sampling, measurement, data collection, analysis, quality, and ethics.

Sections 3.2 to 3.5 set out the main design choices using Saunders' Research Onion as a guide. Sections 3.6 to 3.10 describe the population, sampling and recruitment, survey instrument, pilot work, data collection, and statistical analysis. Sections 3.11 and 3.12 address reliability, validity, and ethics, before Section 3.13 summarises the chapter.

3.2 Research philosophy: positivism

Research design rests on assumptions about what can be known and how that knowledge should be produced. Saunders, Lewis and Thornhill (2023) describe these assumptions as the research philosophy. Here, a positivist position was adopted.

Positivism treats social phenomena as capable of systematic observation and measurement. That position suited this dissertation because income volatility, algorithmic management intensity, employment status ambiguity, and job satisfaction were operationalised as measurable constructs. The purpose was to test specified relationships between those constructs using quantitative survey data rather than to develop an interpretive account of individual experience.

Interpretivism would have led to a different type of study, centred on how individual workers understood and described their experiences, most likely through interviews. That would have provided richer accounts but would not have matched the study's aim of testing relationships across a larger group. Critical realism was also considered because it allows observable patterns to be examined alongside underlying mechanisms. For the hypotheses developed in Chapter Two, alternatively, positivism provided the clearest fit with the planned quantitative analysis.

Saunders' Research Onion (Saunders, Lewis and Thornhill, 2023) was used to organise these design decisions. Figure 3.1 summarises the choices made at each layer.

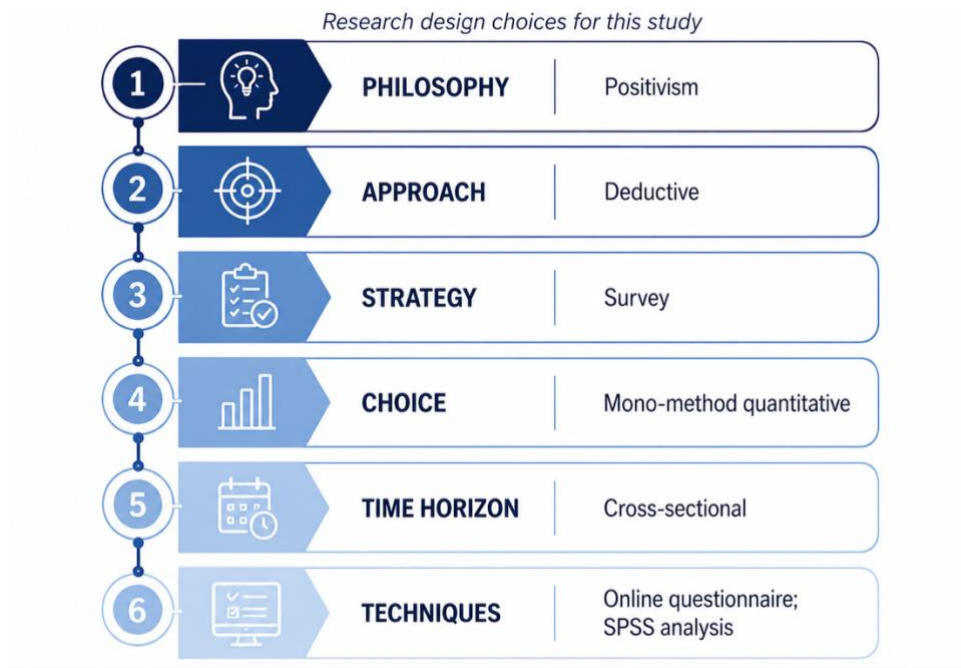


Figure 3.1: Saunders' Research Onion applied to the study. (adapted from Saunders et al. (2023))

3.3 Research approach: deductive

Deductive methods start with existing theories and then use data to test hypotheses generated from them. In contrast, inductive methods begin by developing a theory based on observed phenomena or patterns. Abduction is an intermediate method that oscillates back and forth between the development of theories based on data and testing these theories based on their fit with the available data. A deductive approach was applied here. Hypotheses (Chapter Two) were developed using Herzberg's Two-Factor Theory and the Job Demands – Resources model, and the survey instrument was designed to measure the study constructs and test the hypotheses.

3.4 Research strategy: survey

A survey approach was selected since this research needed standardised numerical data from an extensive range of dispersed workers. Bryman and Bell (2015) note that surveys are one type of quantitative methodology utilised to evaluate relationships between variables across a sample.

The questionnaire permitted the utilisation of the exact same measures on all participants and enabled researchers to gather data from platform workers throughout the UK, while still maintaining anonymity. The anonymous online format was also

beneficial given that many workers are hesitant to provide answers regarding their compensation, employment status, and satisfaction with platform work.

Other methodologies were evaluated, but none fit as well as the proposed survey methodology to address the specific research questions. For example, a single-platform case study would have provided greater contextual understanding of each participant's experience; at the same time, it limited the comparisons across occupations and platforms. Similarly, experimental methodology was not feasible due to ethical issues regarding manipulation of working conditions. Finally, interviews could have provided additional insight into participants' experiences; by contrast, they would not have generated the standardised numeric data necessary for conducting the proposed hypothesis testing.

3.5 Methodological choice and time horizon

This dissertation uses a mono-method approach, using a single online questionnaire for data collection and statistical analysis for examination. The initial plan was to conduct a mixed-methods study (both qualitative and quantitative), but the increased complexity of collecting two different types of data would have made the overall research project much larger than could reasonably be expected to be completed within the author's Master's time frame. As such, a quantitative methodology was chosen to provide a standardised method for constructing and administering the survey instrument, preparing the data for analysis, and analysing the data.

Additionally, the study used a cross-sectional methodology. A cross-sectional methodology involves obtaining a sample of participants at one point in time and then analysing those participants. While a longitudinal methodology would have allowed assessment of whether changes in the participant's work environment correlated with changes in job satisfaction, collecting repeated measures from the same participant across several time points is very difficult with a hard-to-reach population. Given the constraints of the current study, a cross-sectional methodology is most appropriate for meeting the study's goals.

3.6 Population, sampling and recruitment

To address sampling in this research, the author used a combination of methods, including convenience and snowball sampling. Convenience sampling is appropriate when no sampling frame is available for the population under study. In addition,

Brinkley (2016) identifies a problem with labour market measurement in the UK, and Johnes (2019) notes that current data make it difficult to estimate the number of gig workers, their demographic characteristics, and the size of the gig worker population. For this dissertation, both local gig workers (such as those undertaking food deliveries and providing clean-up services) and remote gig workers (i.e. writers, translators, designers, etc.) were included, so creating a comprehensive list of all eligible workers would have been impossible. Thus, a form of sampling that does not produce a random representation of the total population of interest (i.e., non-probability sampling) was selected. In terms of how the sample was collected (i.e., "recruited"), convenience and snowball sampling were both utilised. The vast majority of the first-round respondents were recruited personally and professionally through connections with individuals known to engage in gig work via online platforms. These potential recruits were then directly approached and invited to participate in the research study, provided they met all eligibility requirements. Additionally, respondents were asked to disseminate an invitation to take part in the research via their own networks to anyone else who may be eligible. This established the "snowball" aspect of the recruitment procedure and enabled the authors to expand the recruitment beyond relying solely on their direct social contacts.

Responses were continuously monitored throughout the recruitment phase. The recruitment phase continued until 50 responses were collected that were complete, eligible, and met the data quality screening criteria. Once this target was reached, the recruitment phase closed to allow adequate time for data cleansing, statistical analysis, and dissertation completion. Additional submissions were removed from consideration during screening due to being either partially completed or failing to satisfy one or more of the previously outlined data quality criteria.

As the sample size was 50, care was taken to limit the predictor variables in each model examined using multiple linear regression. The purpose of limiting predictor variables was to prevent overfitting in the models being developed. As such, the complexity of each statistical analysis was limited by the amount of data being analysed. Therefore, the conclusions are based on this sample, and the findings should be generalised cautiously when applying them to broader populations.

Because a non-probability sampling method was used, the resulting sample cannot be treated as representative of the broader UK Gig Economy. Thus, while the analysis

provides insight into the particular workers who responded to the survey, caution should be taken when drawing conclusions about the whole Gig Economy.



Figure 3.2: Sampling and recruitment process used in the study.

3.7 The survey instrument

Data collection involved completing an electronic version of a self-completion questionnaire that was built upon the operational definitions described in Chapter Two. The online questionnaire consisted of 9 different parts: a section for participant information and consent; an eligibility screening component; components to collect data regarding platform work; components that measure respondents' employment

status; three sections measuring the predictor variable; the MSQ (short-form); and components collecting demographic data.

Each predictor was assessed by developing scales based on the respondents' level of agreement or disagreement as indicated on a 5-point Likert-type scale. Income Volatility was assessed through 5 items related to variability in both the frequency and amount of income earned. Algorithmic Management Intensity was measured through 7 items assessing levels of monitoring, transparency, reliance on ratings, automation in the distribution of tasks, likelihood of being deactivated, and the opportunity to dispute decisions made regarding the respondent. ESA was calculated using five items concerning uncertainty about legal classification and employment rights.

Job satisfaction was measured using the MSQ short-form General Satisfaction score. The MSQ was developed by Weiss and colleagues at the University of Minnesota in 1967. Hirschfeld (2000) examined the short form as a measure of general job satisfaction. Hancer and George (2003) reported strong internal consistency for the instrument in a sample of US restaurant workers. Permission to use the MSQ was granted by Vocational Psychology Research at the University of Minnesota. Where original items referred to a boss, supervisor, or company, the wording was adapted to refer to the platform context.

The questionnaire also collected information that could be used to describe the sample and, where necessary, control for relevant differences between respondents. Platform-work variables included occupational category, tenure, weekly hours, income dependency, number of platforms used, and platform-claimed employment status. Demographic questions covered age, gender, education, country of birth, and UK region. Only a limited set of these variables was included in the regression to avoid fitting an overly complex model to a small sample.

3.8 Pilot testing and refinement

A pilot survey was conducted prior to conducting the major survey. It was designed to determine if the survey's questions were easy for platform workers to understand, to identify any survey items that may have been misunderstood, and to approximate how many minutes it would take each worker to complete the survey.

The pilot consisted of a very small sample of platform workers obtained from recruitment using the same methods as those intended for the larger study. Workers

provided comments about wording, response options, and overall length of the survey. Comments by workers caused minimal adjustments; some technical words were substituted with plain language, a few questions were reordered to allow better flow of the questionnaire, and the estimated completion time of approximately 8 to 10 minutes was validated.

No new survey items were created or deleted. Responses collected during the pilot survey are excluded from analysis within this research as the wording of the questionnaire had to be altered based on the pilot-observed patterns.

3.9 Data collection procedure

A total of 50 valid participant surveys were obtained via social media and a direct online link over approximately four to six weeks. Participant responses were assessed at regular intervals throughout this recruitment stage to evaluate both respondent eligibility and data quality. An additional method of recruiting participants was for the author to use their professional and personal connections to contact potential participants. Participants who met eligibility criteria were then asked to encourage colleagues, friends and acquaintances who worked on platforms to take part in the research by sharing the link to the survey. Recruitment continued until the target of 50 complete and usable responses was achieved. Screening was completed by assessing missing data percentages, response patterns and internal consistency across all study-related survey items. Any case(s) with greater than 10% missing data on any primary study variable were removed from further consideration. Likewise, any submission showing consistent "straight-line" responding (i.e., selected the exact same answer for more than 80% of survey items) was eliminated. Additionally, any responses providing obviously implausible or internally inconsistent answers were reviewed and subsequently removed if there was no reasonable explanation for these issues. A dataset consisting of 50 cases ultimately comprised the sample used for subsequent statistical analyses.

3.10 Data analysis strategy

All statistical analysis was carried out in IBM SPSS Statistics. The sequence of analysis is shown in Figure 3.3 and described below.

Data preparation came first. Reverse-coded items were recoded so that higher scores had a consistent direction within each scale. Composite scores were then calculated as

the mean of the relevant items for income volatility, algorithmic management intensity, employment status ambiguity, and MSQ General Satisfaction.

Descriptive statistics were used to summarise the sample before hypothesis testing. Frequencies were produced for categorical variables, including occupational category, employment status, and demographic characteristics. Means and standard deviations were calculated for the continuous study variables.

Internal consistency was assessed using Cronbach's alpha for each of the four multi-item scales. A value of 0.70 was used as the working threshold. Where a scale fell below this level, the item-level results were to be inspected before deciding whether any revision to the scale was justified.

Pearson correlation coefficients were calculated for the four continuous study variables to examine the direction and strength of the bivariate associations. The correlation matrix was also reviewed for unusually strong relationships between predictors before the regression model was fitted. Tabachnick and Fidell (2019) discuss this step as part of screening data for multivariate analysis.

Regression assumptions were checked before the model was interpreted. Linearity was examined visually using plots of the predictors against job satisfaction. Multicollinearity was assessed through variance inflation factors, with 10 used as the upper screening threshold. Residual normality was examined visually using a P-P plot and checked with the Shapiro–Wilk test. Homoscedasticity was assessed from the residual pattern and with the Breusch–Pagan test. These checks were completed before the regression coefficients were interpreted.

MSQ General Satisfaction was then regressed on the three main predictors together with a limited set of controls: local versus remote platform work, income dependency, weekly platform hours, and platform tenure. Demographic variables were reported descriptively but were not added to the model because the sample size did not support a large number of predictors. The regression produced standardised coefficients, significance levels, and an overall R-squared value. H1, H2, and H3 were evaluated using the direction, magnitude, and statistical significance of the coefficients for the three main predictors. Because the study was cross-sectional and non-experimental, the observations were interpreted as associations rather than causal effects.

Using both correlation and multiple regression served different purposes in the analysis. The Pearson correlations provided a simple view of how each predictor was related to job satisfaction on its own. The regression then examined the three predictors together while also accounting for the four selected controls. A coefficient in the regression therefore answers a different question from a bivariate correlation. It shows the association between one predictor and job satisfaction after the other variables in the model have been taken into account.

This distinction became important for algorithmic management intensity. Its simple correlation with job satisfaction was negative but not statistically significant, whereas its adjusted regression coefficient was statistically significant. The analysis did not assume in advance that these two results would be the same. Reporting both makes the change visible and avoids presenting only the result that supports the hypothesis. Because the sample is small, the adjusted coefficient is interpreted cautiously. The model can identify a statistical pattern in this dataset, but it cannot establish the process that produced the change or show that the same pattern would occur in a larger sample.

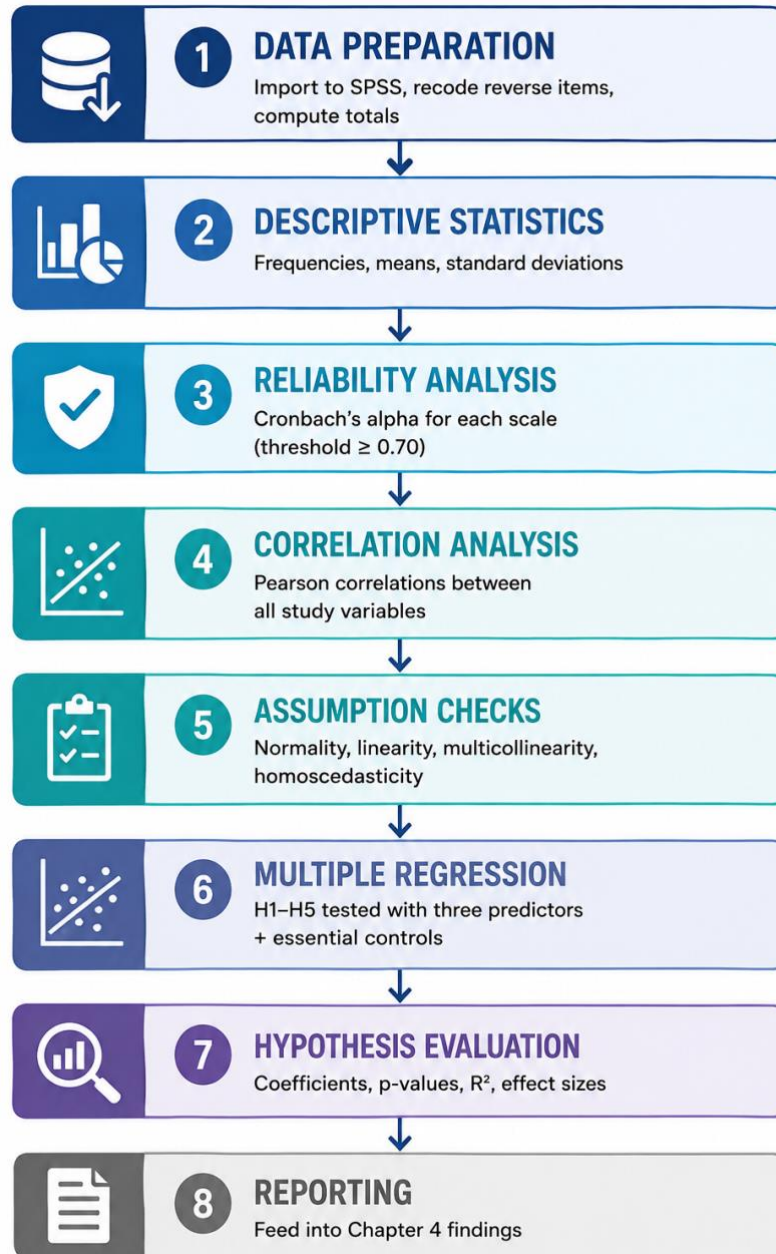


Figure 3.3: Data analysis workflow from data preparation to hypothesis evaluation and reporting.

3.11 Reliability and validity

Reliability concerns the consistency with which an instrument measures a construct. In this thesis, internal consistency was assessed for each multi-item scale using Cronbach's alpha. The MSQ short form has shown strong reliability in previous applications. Hancer and George (2003), for example, reported an alpha of 0.90 in a sample of US restaurant workers. The three predictor scales were developed for this

research, so their internal consistency was assessed separately using the same procedure.

Validity concerns whether the measures capture the constructs they are intended to measure. The predictor items were developed from the operational definitions established in Chapter Two and from the gig-economy literature reviewed there. The MSQ provided an established measure of job satisfaction. Face validity was also considered during the pilot, when participants were asked whether the questions were understandable and relevant to their experience of platform work.

The design still has limits. All main variables were self-reported by the same respondent in the same questionnaire, so common-method bias is a possible source of distortion. The questionnaire included both forward- and reverse-worded items and separated the predictor and outcome sections to reduce response-pattern effects. The cross-sectional design creates a second limitation: even where variables are associated, the study cannot establish the direction of causality.

3.12 Ethical considerations

The study was conducted in accordance with the ethical requirements of the University of Wales Trinity Saint David and UK GDPR. Ethical approval was granted by the UWTSD Research Ethics Committee before the main data collection began.

Informed consent was obtained through a participant information sheet and an explicit consent question at the start of the survey. The information explained the study's purpose, what participation involved, and how the data would be used. Respondents could leave the survey at any point. No names or contact details were collected, and the survey settings were configured not to record IP addresses. Open-text responses were checked for accidental identifying information and redacted where necessary. Data were stored on a password-protected computer accessible only to the author and will be destroyed once the dissertation and examination requirements have been completed. The debrief also signposted Samaritans, Citizens Advice, and ACAS in case participation raised concerns about work or wellbeing.

Permission to use the MSQ was granted by Vocational Psychology Research at the University of Minnesota before the instrument was used in the main study.

3.13 Chapter summary

This chapter has described the methodological decisions and procedures used in the study. The research followed a positivist, deductive design and used a cross-sectional online survey of UK platform-based gig workers. Participants were recruited through convenience and snowball sampling. Recruitment was closed when 50 complete and eligible responses had been obtained, and these 50 cases formed the final dataset. The questionnaire measured income volatility, algorithmic management intensity, employment status ambiguity, and job satisfaction, alongside a limited set of work and demographic variables. After pilot testing and data cleaning, the data were analysed in SPSS using descriptive statistics, reliability analysis, Pearson correlations, and multiple regression. The chapter has also set out the study's approach to reliability, validity, ethics, and the limits of a cross-sectional design. Chapter Four presents and discusses the analysis.

Chapter Four: Results and Discussion

4.1 Introduction

This chapter presents the survey observations and then discusses them in relation to the literature and theoretical framework developed in Chapter Two. Sections 4.2 to 4.7 report the sample profile, reliability results, descriptive statistics, correlations and multiple regression. Sections 4.8 to 4.10 interpret the outcomes, consider the contribution of the study and set out the practical implications.

4.2 Profile of the sample

The final sample consisted of 50 UK platform-based gig workers. Thirty-two respondents (64 %) carried out local platform work, including delivery, ride-hailing, and handyman services. The remaining 18 respondents (36 %) carried out remote platform work, including writing, translation, data entry, and design. Parcel delivery was the largest occupational group (22 %), followed by handyman or task services (20 %). Ride-hailing and translation each accounted for 12 % of the sample.

The gender distribution was almost even: 24 respondents were men (48 %), 25 were women (50 %), and one preferred not to say. The age profile was relatively young, with 42 % aged 25 to 34 and a further 22 % aged 18 to 24. Four respondents were aged 45 or over. In terms of education, 36 % held an undergraduate degree and 30 % held a postgraduate degree. Seventy-six % of respondents were born in the UK. Respondents came from all twelve UK regions, with no single region accounting for a dominant share of the sample.

Platform work formed a substantial part of respondents' working lives. On average, respondents had been engaged in platform work for about 27 months and worked approximately 27 hours per week. Platform work was the main source of income for 38 % of respondents, an important secondary source for 36 %, and a minor supplement for 26 %. Most respondents worked through one or two platforms, with a mean of 1.7 platforms. Platform-reported employment status varied across the sample: 32 % said they were classified as workers, 22 % as self-employed, 24 % as independent contractors, and 22 % were unsure of their classification. Figure 4.1 shows the distribution by occupational category.

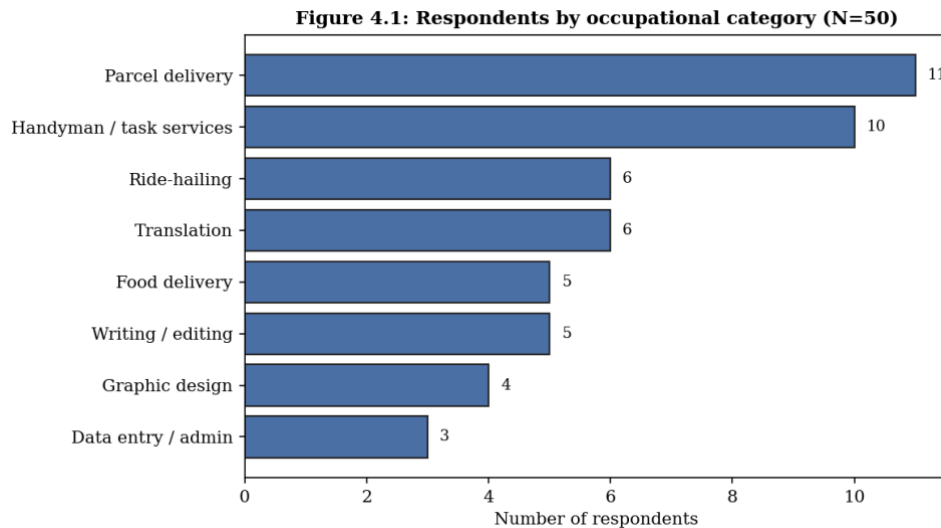


Figure 4.1: Respondents by occupational category (N = 50).

4.3 Reliability of the scales

Internal consistency was assessed for each of the four multi-item scales using Cronbach's alpha. The 0.70 threshold specified in Chapter Three was used as the criterion for acceptable reliability. As shown in Table 4.1, all four scales exceeded this threshold. All scale items were thus retained.

Table 4.1: Reliability of the four measurement scales 32

Scale	Number of items	Cronbach's alpha
Income volatility	5	0.88
Algorithmic management intensity	7	0.87
Employment status ambiguity	5	0.84
Job satisfaction (MSQ)	20	0.94

The MSQ job satisfaction scale had the highest Cronbach's alpha ($\alpha = 0.94$). Hancer and George (2003), for example, also reported high internal consistency for the MSQ in their study. The three predictor scales developed for this research had alpha values ranging from 0.84 to 0.88. These statistical findings indicate good internal consistency for all four scales within this sample.

4.4 Descriptive statistics for the study variables

All four study variables were scored on a scale from 1 to 5. Higher scores represented greater income volatility, more intensive algorithmic management, greater employment status ambiguity, and higher job satisfaction. Table 4.2 reports the mean, standard deviation, minimum, and maximum for each variable.

Table 4.2: Descriptive statistics for the four study variables (N = 50) 33

Variable	Mean	SD	Min	Max
Income volatility	3.06	0.79	1.20	4.80
Algorithmic management intensity	3.29	0.64	2.14	4.57
Employment status ambiguity	3.20	0.69	1.80	4.60
Job satisfaction	2.35	0.60	1.15	3.85

Job satisfaction had a mean score of 2.35, below the scale midpoint of 3. The three predictor variables were clustered around the midpoint: income volatility had a mean of 3.06, algorithmic management intensity 3.29, and employment status ambiguity 3.20. Figure 4.2 shows the distribution of the four study variables.

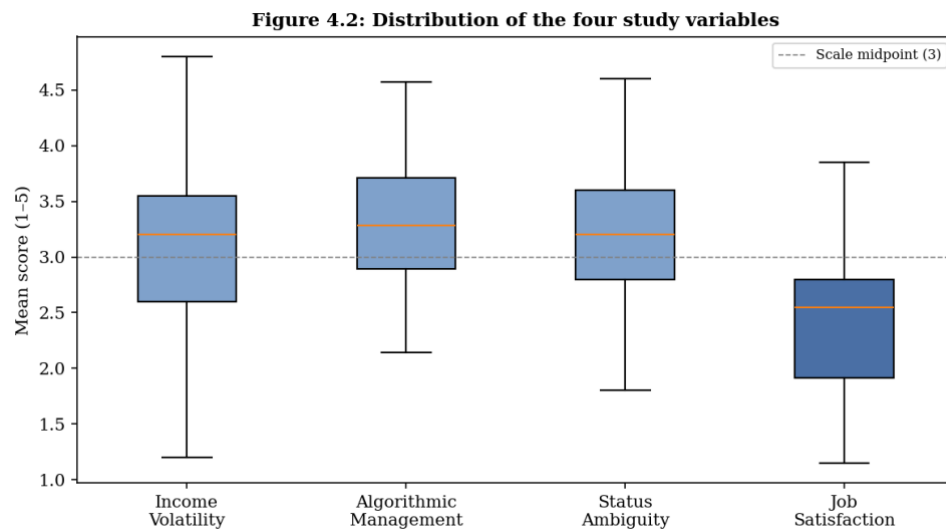


Figure 4.2: Distribution of the four study variables. The dashed line marks the scale midpoint of 3.

4.5 Correlations between the variables

Pearson correlations were used to examine the bivariate relationships between the four study variables. Table 4.3 presents the correlation matrix. The final row shows the relationship between each predictor and job satisfaction.

Table 4.3: Pearson correlations between the study variables (N = 50) 34

	Income vol.	Algo. mgmt	Status amb.	Job satis.
Income volatility	1.00			
Algorithmic management	0.08	1.00		
Employment status ambiguity	-0.16	-0.19	1.00	
Job satisfaction	-0.54**	-0.25	-0.40**	1.00

Note: ** $p < 0.01$.

Each predictor was negatively correlated with job satisfaction, which matched the direction specified in the hypotheses. Income volatility had the largest bivariate association with job satisfaction ($r = -0.54$, $p < 0.01$), followed by employment status ambiguity ($r = -0.40$, $p < 0.01$). Algorithmic management intensity also had a negative correlation, but it was not statistically significant at the 0.05 level ($r = -0.25$, $p = 0.08$). Correlations among the three predictors were small, ranging from -0.19 to 0.08 , which was consistent with the low multicollinearity reported in the regression diagnostics. Figure 4.3 plots each predictor against job satisfaction.

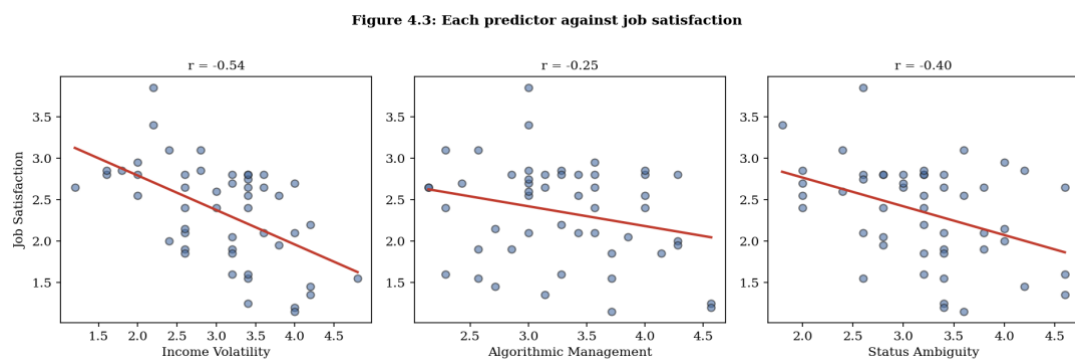


Figure 4.3: Scatterplots of each predictor against job satisfaction, with fitted lines.

4.6 Regression analysis and hypothesis testing

The three hypotheses were tested using multiple regression. Job satisfaction was entered as the outcome variable, with income volatility, algorithmic management intensity, and employment status ambiguity entered as the main predictors. Four control variables were also included: local versus remote platform work, whether platform work was the respondent's main source of income, weekly platform hours, and platform tenure. The regression assumptions were checked before interpreting the coefficients. Visual inspection indicated no material departure from linearity. Variance inflation factors were below 1.8, indicating no problematic multicollinearity under the criterion specified in Chapter Three. The residuals showed no evidence of a departure from normality (Shapiro–Wilk $W = 0.98$, $p = 0.42$), and the Breusch–Pagan test did not indicate heteroscedasticity ($p = 0.28$).

The regression model explained 67 % of the variance in job satisfaction ($R^2 = 0.67$; adjusted $R^2 = 0.62$). The overall model was statistically significant, $F(7, 42) = 12.18$, $p < 0.001$. Table 4.4 reports the regression coefficients.

After adjustment for the other predictors and the four control variables, all three main predictors had statistically significant negative coefficients. Income volatility had the largest standardised coefficient ($\beta = -0.61$, $p < 0.001$), followed by employment status ambiguity ($\beta = -0.56$, $p < 0.001$) and algorithmic management intensity ($\beta = -0.31$, $p = 0.007$). None of the four control variables reached statistical significance in this model.

Table 4.4: Multiple regression predicting job satisfaction (N = 50) 35

Predictor	B	Std. β	p
Income volatility	-0.47	-0.61	< 0.001
Algorithmic management	-0.29	-0.31	0.007
Employment status ambiguity	-0.49	-0.56	< 0.001
Local (vs remote) work	0.07	n/a	0.61
Main income (vs not)	0.15	n/a	0.19
Weekly hours	-0.004	n/a	0.45
Platform tenure	-0.004	n/a	0.25

Algorithmic management intensity showed a different pattern in the bivariate and multivariable analyses. Its correlation with job satisfaction was negative but not statistically significant ($r = -0.25$, $p = 0.08$), whereas its adjusted regression coefficient was statistically significant ($\beta = -0.31$, $p = 0.007$) once the other predictors and controls were included. Section 4.8 considers this pattern in relation to the literature.

Cohen's f^2 values were also calculated for the three main predictors. Income volatility had an f^2 of 1.03, employment status ambiguity 0.78, and algorithmic management intensity 0.19. Figure 4.4 presents the standardised regression coefficients.

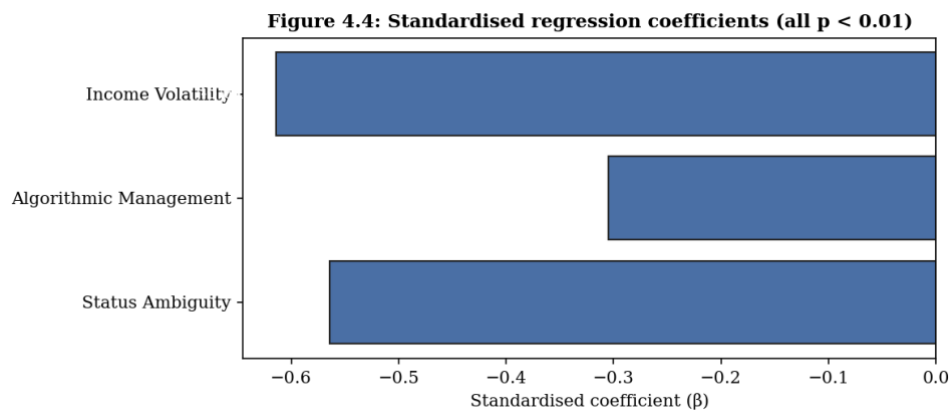


Figure 4.4: Standardised regression coefficients for the three predictors (all $p < 0.01$).

4.7 Summary of hypothesis testing

The regression results were used to evaluate the three hypotheses. Each hypothesis specified a negative association with job satisfaction, and each was supported by its corresponding regression coefficient.

Table 4.5: Summary of hypothesis testing 36

Hypothesis	Result
H1: Income volatility is negatively associated with job satisfaction	Supported ($\beta = -0.61$, $p < 0.001$)
H2: Algorithmic management intensity is negatively associated with job satisfaction	Supported ($\beta = -0.31$, $p = 0.007$)
H3: Employment status ambiguity is negatively associated with job satisfaction	Supported ($\beta = -0.56$, $p < 0.001$)

All three hypotheses were supported. Within this sample, higher income volatility, more intensive algorithmic management, and greater employment status ambiguity were each associated with lower job satisfaction after adjustment for the other variables in the model. Income volatility and employment status ambiguity had the largest standardised coefficients, while the coefficient for algorithmic management was smaller but remained statistically significant. The following sections discuss these observations in relation to the literature and theoretical framework developed in Chapter Two.

4.8 Discussion of the findings

The discussion below considers what outcomes mean in relation to the literature and theoretical framework developed in Chapter Two. It begins with the overall level of job satisfaction, then considers each predictor in turn before bringing the two theoretical perspectives together.

All three hypotheses were supported in the adjusted regression model. Higher income volatility, greater employment status ambiguity and more intensive algorithmic management were each associated with lower job satisfaction after the other predictors and controls were taken into account.

4.8.1 The overall picture: low satisfaction

The data indicate an overall job satisfaction score of 2.35 out of 5 among respondents, which is below the midpoint. This suggests that workers tend to be more dissatisfied

than satisfied. Berger et al. (2019) further noted that Uber drivers valued the ability to set their own hours as the most flexible aspect of their jobs. Similarly, Martindale, Wood, and Burchell (2024) found that while many UK platform workers have positive feelings about gig work, they also strongly support worker protections. This aligns with their findings that, although flexibility is valued, it does not necessarily eliminate dissatisfaction stemming from job insecurity. Duggan et al. (2026) identified the "autonomy paradox," where workers who enjoy autonomy over their schedule still often feel a lack of control over how their work is organised.

4.8.2 Income volatility

Income instability had the largest standardised regression coefficient for job satisfaction of the three predictor variables ($\beta = -0.61$; $p < 0.001$). Participants who reported less predictable income also reported lower job satisfaction. Hickson (2024) discusses how unstable income among gig workers creates vulnerability and stress, which supports this study's findings. The results can also be interpreted through the Job Demands-Resources Model. Bakker and Demerouti (2007) suggest that job demands require sustained effort and resources and are likely to incur psychological costs. Participants' uncertainty about how much and when they would be paid for their work appears to have created a similar demand.

In contrast to Berger et al. (2019), who found flexibility to be an important factor contributing to the value placed on platform work, the studies differed significantly in focus. Although these data do not indicate that flexibility was insignificant, income instability remained negatively associated with job satisfaction after adjustment. Income volatility remained negatively associated with job satisfaction after adjustments for the other variables in the model.

4.8.3 Employment status ambiguity

Employment status ambiguity had the second-largest adjusted association with job satisfaction ($\beta = -0.56$, $p < 0.001$), supporting H3. Respondents who were more uncertain about their legal status and employment rights tended to report lower satisfaction. Davies (2020) discusses the difficulty of applying established employment categories to non-standard work. The measure used here captured respondents' own uncertainty rather than an external legal assessment. Martindale,

Wood and Burchell (2024) found that UK platform workers may describe themselves as self-employed even when their legal position is more complicated. This suggests that uncertainty about status is relevant to how workers experience platform work.

The JD-R model offers a useful interpretation of this association. Uncertainty about rights and employment status may require workers to deal with an additional cognitive and emotional demand. The result does not show that status ambiguity causes dissatisfaction, but it does show that the two were closely associated in this sample. This matters because employment status is not only a legal or policy issue; it is also connected with workers' reported experience of their jobs.

4.8.4 Algorithmic management intensity

Algorithmic management intensity was also negatively associated with job satisfaction in the regression ($\beta = -0.31$, $p = 0.007$), supporting H2. Its bivariate correlation with job satisfaction was weaker and was not statistically significant ($r = -0.25$, $p = 0.08$). The association became statistically significant when income volatility, employment status ambiguity and the control variables were included in the regression. This difference between the bivariate and adjusted results should be interpreted cautiously and does not, by itself, establish why the coefficient changed.

Duggan et al. (2026) argue that algorithmic management shapes how platform workers experience control and autonomy. Tassinari and Maccarrone (2020) discuss algorithmic control in relation to the organisation of platform work. Bates et al. (2021) also examine how platform management is experienced through features such as work allocation and control. The outcomes are consistent with algorithmic management being related to job satisfaction, although its adjusted association was smaller than those for income volatility and employment status ambiguity.

One of the less straightforward findings was the change in the result for algorithmic management intensity. At the bivariate level, the relationship with job satisfaction was negative but did not reach the 0.05 significance level. After the other predictors and controls were included, the coefficient became statistically significant. This means that the evidence for H2 depends on the multivariable model rather than on a strong simple relationship between the two variables.

There are several reasons to avoid giving this result a stronger explanation than the data allow. First, the sample contained only 50 respondents, so individual observations can have more influence on an estimated coefficient than they would in a larger sample. Second, algorithmic management may be connected with other features of platform work even where the correlations among the three main predictors are small. Third, the study did not measure all possible factors that could affect satisfaction. The change in the coefficient should therefore be treated as a finding that needs further examination rather than evidence of a specific hidden mechanism.

This result is still useful. Tassinari and Maccarrone (2020) show that algorithmic control can shape the organisation of courier work. Bates et al. (2021) describe how platform workers respond to allocation and control through informal networks. These studies help show why algorithmic management deserves attention, but neither provides a direct explanation for the regression pattern observed here. The present result therefore adds a specific quantitative observation: algorithmic management was associated with lower job satisfaction after adjustment, but its unadjusted relationship was weaker. A larger study could test whether the same pattern is reproduced before stronger conclusions are drawn.

4.8.5 The two theories together

Herzberg's Two-Factor Theory and the JD-R model were used together to interpret the observations. Herzberg's framework places pay, working conditions and employment arrangements mainly on the hygiene side of job experience, where problems can be associated with dissatisfaction. JD-R approaches the same findings from a different direction by treating demanding working conditions as pressures that require sustained effort. The two frameworks offer complementary interpretations. The findings do not prove either theory or demonstrate the mechanisms they propose.

4.9 Contribution of the study

The study makes a limited but useful empirical contribution by examining income volatility, algorithmic management and employment status ambiguity together in a UK sample that included both local and remote platform workers. Berger et al. (2019) focused specifically on Uber drivers. Christie and Ward (2019) examined a particular segment of platform work rather than a broad cross-occupation sample. Bates et al. (2021) also concentrated on a defined platform-work context. In contrast, here

respondents are drawn from eight occupational categories. The sample is small and non-probability based, so this breadth should not be confused with representativeness, but it does allow the three working conditions to be considered across more than one type of platform work.

The study also applies Herzberg's Two-Factor Theory and the JD-R model to the same set of working conditions. Each framework offers a different way of reading the results. The regression result for algorithmic management is also worth further investigation because its coefficient was statistically significant in the adjusted model even though its bivariate correlation was not. A larger sample would be needed before drawing stronger conclusions about why that pattern occurred.

4.10 Implications

4.10.1 For platform companies

The observed patterns indicate that, for Platform firms, earnings predictability and clarity of employment conditions are clearly associated. Initiatives that make rates and fees more transparent, clarify how work is assigned on the platform, and explain how workers are classified (e.g., as employees or independent contractors) and what that classification entails may therefore be relevant to workers. As the research has not tested the effectiveness of a specific initiative(s), the implications for improving job satisfaction are viewed as opportunities for consideration rather than established solutions.

4.10.2 For policymakers

The finding on employment status ambiguity is also relevant to the regulatory debate discussed in Chapter Two. Stewart and Stanford (2017) examine questions around the employment status and protection of gig workers. Novitz (2020) also considers the legal and regulatory difficulties surrounding platform work. The association found here suggests that uncertainty itself may matter to workers, alongside the rights attached to any particular legal category. Clearer rules and clearer communication could therefore be relevant, although this study cannot establish their effect on job satisfaction.

4.10.3 For worker representatives

For unions and worker organisations, the evidence suggests that income security and clarity about employment status are issues worth particular attention. These were the two variables with the largest adjusted associations with job satisfaction in this sample. Martindale, Wood and Burchell (2024) also report strong support for basic labour rights among UK platform workers. The evidence here adds a job-satisfaction dimension to that discussion, while remaining limited to the respondents.

Chapter Five: Conclusion

This final chapter draws together the main limitations of the study, identifies priorities for further research and states the overall conclusion.

5.1 Limitations

When analysing and interpreting these findings, there are several limitations that must be taken into consideration.

Firstly, sample size and sample type. Data collection closed once 50 complete eligible responses were achieved due to limited time for data cleaning, analysis, and dissertation completion. Additional submissions were rejected by screening for being incomplete or not meeting the data quality checks mentioned in Chapter Three. The sample used in this research was collected using convenience and snowball sampling methods. Therefore, the sample cannot be regarded as representative of the UK gig economy. The sample was relatively youthful and highly educated. As such, the results provided from the survey analysis represent this specific sample and should not be generalised to the entire population of UK platform workers. In future research, a larger sample (probability-based) could provide a stronger foundation for making broader conclusions and allow researchers to determine if small effects exist.

Secondly, the cross-sectional nature of the study limits what can be determined. While the analysis provides associations between variables at one particular point in time, it does not indicate causality. For example, although high levels of income volatility were associated with low job satisfaction, it is impossible to infer which direction caused the other (e.g., income instability resulted in dissatisfaction; dissatisfied workers viewed their income as more volatile than others; some third variable has an effect on employee perceptions of wage instability). An alternative approach would be to collect data over a period of time, allowing researchers to understand temporal relationships between variables. Alternatively, a randomised experiment would only be possible in situations where manipulating the independent variable(s) is both feasible and ethically acceptable.

Lastly, this research relies solely on self-reported data with the predictors and the outcome measured in the same questionnaire. This creates a risk of common-method bias because part of the observed association may reflect the shared measurement

context. The questionnaire design attempted to reduce this risk through variation in item wording and separation of the predictor and outcome sections, but it cannot be ruled out. The three predictor scales were also developed for this study. Their internal consistency was good in this sample, but they require further validation before they can be treated as established measures.

5.2 Recommendations for further research

Further research should first test the findings with a larger and more diverse sample of platform workers. That would allow more reliable comparisons between occupational groups and between local and remote platform work. A longitudinal design would also help establish whether changes in income volatility, algorithmic management, or employment status ambiguity are followed by changes in job satisfaction. Finally, the difference between the bivariate and adjusted findings for algorithmic management warrants closer examination. Larger studies could test whether this pattern is replicated and investigate how algorithmic management relates to income volatility and employment status ambiguity rather than assuming a particular mechanism from the current data.

The findings also point to several specific priorities for future research. First, future studies should use larger samples so that local and remote workers can be analysed separately rather than treated mainly as a control variable. The current sample includes both groups, but it is too small to make reliable subgroup comparisons. Second, the three predictor scales developed for this study should be tested in another sample. Their Cronbach's alpha values were acceptable here, but internal consistency in one dataset is not enough to establish that the measures will perform in the same way elsewhere.

Third, future research could collect repeated observations from the same workers. This would help examine whether a rise in income volatility or a change in platform management is followed by a change in job satisfaction. It would still not remove every alternative explanation, but it would provide stronger evidence about timing than a single cross-sectional survey. Finally, qualitative work could be used as a separate follow-up study to explore why workers interpret automated decisions or employment status in particular ways. Interviews would not replace the statistical analysis, but they could help explain patterns that the current questionnaire cannot answer, especially the difference between the bivariate and adjusted results for algorithmic management.

5.3 Conclusion

This dissertation examined the associations between income volatility, algorithmic management intensity, employment status ambiguity and job satisfaction among UK platform-based gig workers. Using survey data from 50 respondents and multiple regression analysis, all three hypotheses were supported. Income volatility and employment status ambiguity had the largest adjusted associations with job satisfaction, while algorithmic management had a smaller but statistically significant association in the regression model. Average job satisfaction was below the midpoint of the scale.

These analyses need to be interpreted within the limits of a small, non-probability sample and a cross-sectional, self-report design. They do not show that the three working conditions cause changes in job satisfaction. What they do show is that, among the workers who took part, greater income volatility, more intense algorithmic management and greater uncertainty about employment status were each associated with lower job satisfaction. The results that came from the survey analysis provide a basis for further research into how the organisation of platform work relates to workers' experience of their jobs.

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Table of cases

Uber BV v Aslam [2021] UKSC 5.

Appendices

Appendix A: Survey questionnaire

A study of working conditions and job satisfaction among platform-based gig workers in the United Kingdom

Researcher: Shaeka Parveen Yusufmiya Kadri

Student Number: 2514895

Programme: MBA, University of Wales Trinity Saint David

Supervisor: Professor James Moore

Participant Information

You are invited to take part in a research study examining working conditions and job satisfaction among platform-based gig workers in the United Kingdom.

The study focuses on three aspects of platform work: income volatility, algorithmic management intensity and employment status ambiguity. It examines how these conditions are associated with workers' overall job satisfaction.

Participation is voluntary. Before deciding whether to take part, please read the information below.

What is the study about?'

The study examines whether unpredictability in earnings, the way digital platforms manage work, and uncertainty about employment status are associated with job satisfaction among UK platform-based gig workers.

The findings will be used as part of an MBA dissertation at the University of Wales Trinity Saint David.

Who can take part?

You may participate if you:

are aged 18 or over.

currently live and work in the United Kingdom; and

currently undertake paid work through a digital platform such as Uber, Deliveroo, Just Eat, Amazon Flex, TaskRabbit, Upwork, Fiverr or a similar platform.

What will participation involve?

You will be asked questions about:

your platform work.

your earnings.

how the platform manages your work.

`your employment status and rights.

your job satisfaction; and

]

basic demographic information.

The questionnaire should take approximately 8–10 minutes to complete.

Is participation voluntary?

Yes. Participation is entirely voluntary. You may leave the survey at any point before submitting your responses without giving a reason.

The questionnaire does not ask for your name. Responses will be treated confidentially and used only for academic purposes.

Data protection

Survey data will be stored securely in accordance with UK GDPR requirements. Only aggregated results will be reported in the dissertation.

Ethical approval for the study was granted by the University of Wales Trinity Saint David before the main data collection began.

Consent

C1. I confirm that I have read and understood the information above and voluntarily agree to participate in this research.

- ☐ Yes, I consent to participate
- ☐ No, I do not consent

Section A: Eligibility

A1. Are you 18 years of age or older?

- ☐ Yes
- ☐ No

A2. Do you currently live and work in the United Kingdom?

- ☐ Yes
- ☐ No

A3. Do you currently undertake paid work through a digital platform?

- ☐ Yes
- ☐ No

Participants selecting No to any eligibility question should exit the survey.

Section B: About Your Platform Work

B1. What type of platform work do you mainly undertake?

- ☐ Parcel or courier delivery
- ☐ Handyman or task services
- ☐ Ride-hailing
- ☐ Translation
- ☐ Food or grocery delivery
- ☐ Writing or editing
- ☐ Graphic design or other creative freelance work
- ☐ Data entry or administrative work
- ☐ Other: _____

B2. Which platform do you currently use most often?

Platform name: _____

B3. How many different platforms do you currently work through?

Number of platforms: _____

B4. How long have you been undertaking platform work?

Number of months: _____ months

B5. On average, approximately how many hours per week do you spend on platform work?

_____ hours per week

B6. How important is platform work as a source of your income?

- ☐ My main source of income
- ☐ An important secondary source of income
- ☐ A minor supplementary source of income

Section C: Employment Status

C1. How does the platform classify your employment status?

- ☐ Worker
- ☐ Self-employed
- ☐ Independent contractor
- ☐ Employee
- ☐ Not sure

C2. How would you personally describe your employment status when carrying out platform work?

- ☐ Worker
- ☐ Self-employed
- ☐ Independent contractor
- ☐ Employee

☐

Not sure

Section D: Income Volatility

Please indicate how much you agree or disagree with each statement.

Response scale:

1 = Strongly disagree

2 = Disagree

3 = Neither agree nor disagree

4 = Agree

5 = Strongly agree

IV1. My weekly earnings from platform work are unpredictable.

IV2. I can accurately predict how much I will earn from platform work next week.

IV3. The amount I earn from platform work varies significantly from week to week.

IV4. I usually know in advance when work will be available on the platform.

IV5. My monthly income from platform work is stable and consistent.

Section E: Algorithmic Management Intensity

Please indicate how much you agree or disagree with each statement.

Response scale:

1 = Strongly disagree

2 = Disagree

3 = Neither agree nor disagree

4 = Agree

5 = Strongly agree

AM1. The platform tracks or monitors my activity while I am working.

AM2. It is clear to me how the platform decides which tasks or jobs to send me.

AM3. Customer ratings have a significant effect on how much work the platform gives me.

AM4. The platform assigns tasks or jobs to me automatically, without any human being involved.

AM5. The platform can suspend or deactivate my account without a human reviewing the decision.

AM6. I can appeal or challenge decisions the platform makes about me.

AM7. I can easily find out why the platform makes the decisions it does about my work.

Section F: Employment Status Ambiguity

Please indicate how much you agree or disagree with each statement.

Response scale:

1 = Strongly disagree

2 = Disagree

3 = Neither agree nor disagree

4 = Agree

5 = Strongly agree

ES1. I am clear about my legal employment status when undertaking platform work.

ES2. I understand what employment rights I have as a platform worker.

ES3. I am uncertain whether I am legally self-employed, a worker or an employee.

ES4. I know what protections I would have if the platform ended my work.

ES5. I know who I could turn to if I felt my rights as a platform worker had been breached.

Section G: Job Satisfaction

Job satisfaction was measured using the 20-item Minnesota Satisfaction Questionnaire short form.

Permission to use the MSQ was granted by Vocational Psychology Research, University of Minnesota, before data collection.

Participants were asked to indicate how satisfied they were with different aspects of their platform work using the following scale:

1 = Very dissatisfied

2 = Dissatisfied

3 = Neither satisfied nor dissatisfied

4 = Satisfied

5 = Very satisfied

JS1. Being able to keep busy all the time.

JS2. The chance to work alone on the job.

JS3. The chance to do different things from time to time.

JS4. The chance to be "somebody" in the community.

JS5. The way the platform manages its workers.

JS6. The competence of the platform in making decisions.

JS7. Being able to do things that don't go against my conscience.

JS8. The way the platform provides for steady work.

JS9. The chance to do things for other people.

JS10. The chance to tell people what to do.

JS11. The chance to do something that makes use of my abilities.

JS12. The way platform policies are put into practice.

JS13. My pay and the amount of work I do.

- JS14. The chances for progression through platform work.
- JS15. The freedom to use my own judgment.
- JS16. The chance to try my own methods of doing the job.
- JS17. The working conditions.
- JS18. The way I get along with other platform workers.
- JS19. The recognition I get for doing a good job.
- JS20. The feeling of accomplishment I get from the job.

Section H: Demographic Information

H1. What is your age?

- ☐ 18–24
- ☐ 25–34
- ☐ 35–44
- ☐ 45–54
- ☐ 55–64
- ☐ 65 or over
- ☐ Prefer not to say

H2. How would you describe your gender?

- ☐ Man
- ☐ Woman
- ☐ non-binary
- ☐ Prefer to self-describe: _____
- ☐ Prefer not to say

H3. What is your highest completed educational qualification?

- ☐ No formal qualifications
- ☐ GCSEs or equivalent
- ☐ A-levels, BTEC or equivalent
- ☐ Undergraduate degree
- ☐ Postgraduate degree
- ☐ Other professional qualification
- ☐ Prefer not to say

H4. In which country were you born?

- ☐ United Kingdom
- ☐ Another European country
- ☐ A country outside Europe
- ☐ Prefer not to say

H5. In which UK region do you mainly undertake platform work?

- ☐ London
- ☐ Southeast England
- ☐ Southwest England
- ☐ East of England
- ☐ East Midlands
- ☐ West Midlands
- ☐ Yorkshire and the Humber
- ☐ Northwest England
- ☐ Northeast England
- ☐ Wales
- ☐ Scotland
- ☐ Northern Ireland

End of Survey

Thank you for taking the time to complete this questionnaire. Your responses will contribute to a better understanding of job satisfaction among platform-based gig workers in the United Kingdom.

If participation has raised concerns about employment, money or wellbeing, support is available from:

Samaritans: 116 123

Citizens Advice: employment and financial advice

ACAS: 0300 123 1100 for employment-rights guidance

For questions about the study, please contact:

2514895@student.uwtsd.ac.uk

Appendix B: Ethical approval form summary and allowance

SECTION A: About You (Principal Researcher)

1	Full Name:	Shaekaparvin Yusufmiya Kadri			
2	Tick all boxes that apply:	Member of staff:	☐	Honorary research fellow:	☐
	Undergraduate Student: ☐	Taught Postgraduate Student: ☒	Postgraduate Research Student: ☐	☐	☐
3	Institute/Academic Discipline/Centre:	Business and Management			
4	Campus:	Trinity Campus Saint Davids			
5	E-mail address:	2514895@student.uwtsd.ac.uk			
6	Contact Telephone Number:	07799515745			
For students:					
7	Student Number:	2514895			

April 2022

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PG2 Ethical Approval Form



PG2 / E1 FORM

8	Programme of Study:	Master's programme MBA
9	Director of Studies/Supervisor:	James Moore

SECTION K: Declaration

The information which I have provided is correct and complete to the best of my knowledge. I have attempted to identify any risks and issues related to the research activity and acknowledge my obligations and the rights of the participants. In submitting this application I hereby confirm that I undertake to ensure that the above named research activity will meet the University's Research Ethics and Integrity Code of Practice which is published on the website: https://www.uwtsd.ac.uk/research/research-ethics/			
1	Signature of applicant:	Shaekaparvin	Date: 28-05-26

For STUDENT Submissions:

2	Director of Studies/Supervisor:	James Moore	Date: 28-5-26
3	To be signed by supervisor		