Fairness Perceptions On Digital Labour Platforms: The Effect of Gender, Age, and Type of Platform Work

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Abstract

This study investigated the effect of demographic characteristics and type of platform work on digital platform workers' perceptions of fairness. Fairness perceptions have been demonstrated to have important effects on a number of individual outcomes, including work performance (Cohen-Charash & Spector, 2001; Colquitt et al., 2001), employee attitudes, such as job satisfaction and organisational commitment, and employee behaviours, such as turnover, absenteeism, and organisational citizenship behaviour (Colquitt et al., 2001). Organisational justice research has centred on fairness perceptions in traditional employment settings. Changes in the labour market and increased use of technology have produced new work arrangements (Mandl, 2020; Felfe et al., 2008), such as platform work which involves the matching and supply of paid contingent labour through a mobile app or online platform (Cappelli & Keller, 2013; De Stefano, 2016; Koutsimpogiorgos et al., 2020). There is a paucity of research concerning how workers providing labour services on digital labour platforms perceive the fairness of platform work. Understanding worker perceptions of fairness in platform work is important, not only because it can provide insights into the availability and conditions of work that individuals experience, but also for the design and implementation of policies and procedures by platform organisations to ensure sustainable business growth. In addition, insights into fairness perceptions can inform the development of regulatory and support frameworks in response to concerns associated with platform work.

Digital labour platforms, such as Uber, Deliveroo, TaskRabbit, and Amazon Mechanical Turk, utilise a system of digital control in which algorithms are configured to execute some, if not all, managerial activities traditionally executed by human agents (Kellogg et al., 2020). To attract workers, many platforms promise flexibility and autonomy (Griesbach et al., 2019). The promised flexibility and autonomy on digital labour platforms are however argued by many scholars to be illusory and synonymous with precarity and exploitation (Fiori, 2017; Glavin et al., 2021; Kalleberg & Vallas, 2017; Rosenblat & Stark, 2016; Vallas & Schor, 2020). Claims that platform work is precarious and exploitative are supported by evidence that low incomes are common among workers across different types of platforms (e.g., Berg, 2016; Mandl, 2020; Wood et al., 2019). However, an understanding of whether

platform workers perceive the features of their work as fair is still lacking, despite the increasing popularity of platform work. Although the importance of organisational justice has been established in many studies and there is some evidence suggesting platform work may be considered by workers as unfair, this question is underexamined. To explore the fairness perceptions of platform workers, this study drew upon organisational justice theory, focusing on two forms of justice – distributive and procedural.

Organisational justice refers to employees' judgment of how they are treated by the organisation (Colquitt et al., 2005; Cropanzano & Ambrose, 2015). Distributive justice reflects the perceived degree of fairness in the allocation of outcomes, such as pay and performance evaluations, that are received by an employee in relation to their contribution (Colquitt, 2001; Greenberg, 2011). Procedural justice is the extent to which decision-making procedures leading to the respective outcomes are perceived as fair (Colquitt et al., 2005; Folger & Konovsky, 1989; Tyler, 1987). Previous organisational justice studies have identified differences in the perceived fairness of outcomes and procedures, and according to demographic attributes such as gender and age (e.g., Greenberg & Cohen, 1982; Paul, 2006). Gender and age have also been identified as salient factors affecting participation in platform work (McDonald et al., 2019). The platform work literature highlights the heterogeneity of work and employment conditions, and varied worker experiences across different types of platform work (de Groen et al., 2018; Fieseler et al., 2019; Schor, 2017). These variations may produce a differential effect on worker perceptions of fairness. Nevertheless, the influence of gender, age, and type of platform work on fairness perceptions on digital labour platforms has not been investigated.

To address the identified research gap, this study utilised a sample of 888 current platform workers, with data being collected from the National Survey on Australians working in the gig economy (McDonald et al., 2019). The survey explored the nature and extent of digital platform work in Australia and provided insight into the experiences of workers engaged in platform work. The current study used the survey data on worker perceptions of features of platform work. These features encapsulate algorithmic monitoring, goal setting, performance management, scheduling, compensation, and job termination (Parent-Rocheleau & Parker, 2022), representing important components of distributive justice and procedural justice. In this study, the independent variables were gender and age of workers participating in platform work, as well as the type of platform work they offer. In-person platform work involves tasks performed on location or locally, whereas internet-based platform work entails tasks executed completely online. Some workers undertake both types of work. The dependent variable was overall fairness perceptions.

The findings demonstrated that autonomy and earnings represent major features of platform work that contribute to distributive and procedural justice on digital labour platforms. Autonomy and earnings in this form of work may be functionally similar (Cropanzano & Ambrose, 2001) or substitutable (Lind, 2001) in terms of organisational justice. That is, both of these factors might exemplify platform workers' perceived fairness of outcomes (i.e., distributive justice) and/or procedures that determine the outcomes (i.e., procedural justice). Autonomy and earnings might represent different justice-relevant information in platform work, thus substituting for each other through workers' overall perceptions of fairness. In contrast to earlier findings (e.g., Ghasi et al., 2020; Marchegiani et al., 2018; Paul, 2006; Tessema et al., 2014), there was no evidence of gender and age differences in platform workers' fairness perceptions. Thus, regardless of gender and age, workers engaged on digital labour platforms tended to perceive fairness similarly. However, significant differences in perceived fairness were found across the three types of platform workers (in-person, internet-based, and both). Doing both in-person and internet-based types of platform work, rather than one, matters as it impacts workers' perceived fairness associated with autonomy and earnings through platform work. The changes in fairness perceptions are significant when a worker concurrently provides labour services on both in-person and internet-based platforms, but fairness perceptions do not differ between those who are doing only one type of work. Workers engaged in both in-person and internet-based work, often on multiple platforms, indicated higher fairness perceptions. Those doing both types of platform work were found to have higher earnings-related fairness perceptions than their counterparts who engage in only one type of work. However, when doing both types of platform work, workers perceive less fairness in autonomy, indicating that they have to do more work and hours to earn an amount of income that they consider as fair.

This study made three significant contributions to the current literature. First, the study gave insight into how workers evaluate fairness in features of platform work in relation to autonomy and earnings, and generated new knowledge on the perceived fairness of platform features. Fairness perceptions in platform work, unlike in traditional employment contexts, are influenced by the type of work and not by demographic characteristics of the worker, such as gender or age. The study demonstrated that, regardless of gender and age, workers who participate concurrently in in-person and internet-based platform work are more likely to perceive their earnings as fair, but less likely to perceive fairness in relation to the autonomy of their work, compared to workers doing only one type of work. The study contributes to the conceptualisation and measurement of the current organisational justice paradigm by demonstrating that organisational justice theory needs to be expanded to encompass features of emerging forms of work. Further studies regarding the variables representing organisational justice dimensions in the platform work context are needed. Second, the study shed new light on the impact type of platform work may have on worker perceptions of fairness. Further research regarding the nature of the relationship between type of platform work and fairness perceptions would be worthwhile. Finally, the study contributed to our understanding of the role of earnings in influencing platform workers' fairness perceptions, providing a basis for more investigation into features of platform work that are salient to workers in terms of organisational justice.

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List of Abbreviations

ANOVA	Analysis of variance
CFA	Confirmatory factor analysis
CFI	Comparative Fit Index
DDA	Descriptive discriminant analysis
EFA	Exploratory factor analysis
GPS	Global Positioning System
ILO	International Labour Organisation
KMO	Kaiser-Meyer-Olkin
MANOVA	Multivariate analysis of variance
MAP	Minimum Average Partial
MAR	Missing at random
MCAR	Missing Completely at Random
MSA	Measures of sampling adequacy
NA	Not applicable
QUT	Queensland University of Technology
RMSEA	Root Mean Square Error of Approximation
RQ	Research question
SD	Standard deviation
SPSS	Statistical Package for Social Science
SRMR	Standardised Root Mean Square Residual
TLI	Tucker-Lewis Index

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Chapter 1: Introduction

The growth of platform work has provoked scholarly and public discussion on the benefits and risks for platform workers. Digital labour platforms provide access to income-generating opportunities (Choudary, 2018; Industrial Relations Victoria, 2020). Often used as a supplementary source of income by individuals who are already in employment, platform work may also constitute the main source of income for those with limited alternative sources of work (Florisson & Mandl, 2018; Huws et al., 2017), such as long-term unemployed, people with disability (Pesole et al., 2018), and workers in developing countries or those with migrant backgrounds (Graham et al., 2017). Digital labour platforms often claim to provide workers with flexibility, which is seen as a major attraction of platform-based work (de Groen et al., 2018; Rani & Furrer, 2021). Unlike workers in more traditional work settings, platform workers can supposedly exercise flexibility and autonomy over their work processes, having a say or making decisions about tasks they wish to do, and when and where to work (Healy et al., 2017). These decisions may in turn influence their working conditions, and outcomes, such as pay and access to work opportunities (Eurofound, 2017). However, there is an ongoing debate about the realities of autonomy afforded by digital labour platforms, including the amount of control workers have in practice (Jarrahi et al., 2020; Laursen et al., 2021; Lehdonvirta, 2018), and the potential impact on access to fair and decent work (Duggan et al., 2020; Shapiro, 2018; Wood et al., 2019).

Platform workers, similar to those in more traditional work settings, have concerns about fairness (Song et al., 2020). Fairness issues on digital labour platforms may stem from platform design choices (Griesbach et al., 2019), and management practices and policies related to compensation, distribution of work, and performance assessment (Kalleberg & Dunn, 2016; Kuhn & Maleki, 2017). However, worker perceptions of fairness on digital labour platforms have received scant attention in the literature. Perceived unfair treatment may have adverse effects on the quality of work, workers' engagement, and their intention to remain engaged with the same platform, which is in turn important for customer relationships (Faullant et al., 2017). The gig economy literature is beginning to reveal the implications of platform workers' fairness perceptions on their continuance participation (Liu & Liu, 2019), or turnover

(Ma et al., 2018). Yet, much of what is known about organisational justice comes from studies of traditional employment contexts. To date, there are only a few studies that have investigated worker fairness perceptions of algorithmic management systems in platform work settings (e.g., Deng et al., 2016; Laursen et al., 2021; Pfeiffer & Kawalec, 2020).

Drawing on two currently distinct areas of literature – studies of organisational justice and research addressing algorithm-driven work features on digital labour platforms, this study seeks to investigate fairness perceptions on digital labour platforms by examining the effect of gender, age, and type of platform work on platform worker's perceptions of fairness. This introductory chapter begins by outlining the background of the study (section 1.1). It will then discuss the purpose and significance of the research topic (section 1.2), followed by the study's scope and key definitions (section 1.3). The chapter concludes with an outline of the remaining chapters in the thesis (section 1.4).

1.1 RESEARCH BACKGROUND

The gig economy, typified by digital platforms that connect customers with independent workers/contractors via an app or online platform, has contributed to changes in the nature of work, and transformed the employment landscape across numerous industry sectors (Stewart & Stanford, 2017; Tan et al., 2021). The transformative role of platform organisations, enabled by digital technologies, has been underscored in earlier works, such as Brynjolfsson and McAfee (2014) and Sundararajan (2016). The number of platforms operating globally has increased dramatically in the last 10 years (ILO, 2021). In Australia, 7.1% of people are currently seeking work through digital platforms (McDonald et al., 2019), and participation is expected to rise (Kässi & Lehdonvirta, 2018).

The gig economy has brought both opportunities and risks to individuals who participate in platform work. Digital labour platforms have been credited for operating business models that provide workers with access to alternative sources of income, with low barriers to entry (Choudary, 2018; Industrial Relations Victoria, 2020), and flexibility and autonomy (Graham et al., 2017; Minifie, 2016). Yet, evidence suggests that platform organisations exert a significant degree of control over the labour process (Kenney & Zysman, 2016), using algorithm-driven processes to "reduce the worker's capacity to resist, elude, or challenge the rules and expectations that [the platforms] establish as conditions of participation" (Vallas & Schor, 2020, p. 278). In prior research and reports, concerns have been raised about the risks associated with workforce casualisation (De Stefano, 2016; Kennedy et al., 2017; Macdonald & Charlesworth, 2021), working conditions (Chen, 2018; Goods et al., 2019; Stewart & Stanford, 2017), workers' wellbeing (Duggan et al., 2020), and economic and career stability (Actuaries Institute, 2020; Australian Council of Trade Unions, 2019; Wood et al., 2019). These direct impacts on workers may have far-reaching, long-term consequences, such as the inability to obtain a home loan as a result of a lack of employment contract and income instability (ILO, 2016). Scholars and international agencies have also directed their attention to ethical challenges posed by digital platform work in relation to workplace surveillance and control (Choudary, 2018; de Vaujany et al., 2021; McDonald et al., 2020; Newlands, 2020; Tan et al., 2021; Veen et al., 2019), discrimination (Graham et al., 2017; ILO, 2021; Rosenblat et al., 2017), and social isolation (Dedeoğlu, 2020; Wood et al., 2019).

An accumulation of qualitative evidence shows that the methods used by platforms to algorithmically control the labour process may result in unfavourable experiences and outcomes for workers. In ride-hailing services, for example, platform scheduling alerts drivers with incentives, directing them towards specific schedules that do not take account of, adverse weather conditions (Gregory, 2021; Rosenblat & Stark, 2016), thus reducing worker flexibility and autonomy over when or whether it is safe to work. The mechanisms built into platform functions associated with the allocation of work and performance assessment have also been shown to be opaque (Rosenblat & Stark, 2016; Veen et al., 2019; Williams et al., 2020), bringing concerns about the transparency of the decisions made by the platforms and their impacts upon worker experiences of fairness. For example, Veen et al. (2019) revealed the obscurity of the performance assessment processes on Deliveroo and UberEATS, showing that workers engaged with these platforms have a limited understanding of the basis on which performance is reviewed or future work is allocated. The obscure nature of platforms' performance evaluation systems, which affect worker access to work and earnings, is also raised by Rani and Furrer (2021), whose research focused on workers on microtask platforms, such as Amazon Mechanical Turk and Clickworker. Such insights into the lack of transparency in platforms' design features and practices raise questions of how relevant or appropriate the criteria used by platform algorithms to make decision outcomes (Binns et al., 2018; Robert et al., 2020) or how accurate the decision outcomes are (Shin & Park, 2019), thus the extent to which the platform work features are fair.

There is also growing evidence of discrimination on digital labour platforms. For example, female workers have been found to earn less on average than male workers (Adams & Berg, 2017; Aleksynska et al., 2021; Chen, 2018; Cook et al., 2021). Gender discrimination is pervasive in hiring and performance evaluation on digital labour platforms, as evidenced in a study of online freelancing platforms, such as TaskRabbit and Fiverr (Hannák et al., 2017), Nubelo (Galperin, 2019) and ridesharing platforms (Greenwood et al., 2020), suggesting unequal and potentially unfair treatment of female platform workers. While investigations into the benefits and risks of platform work exist and there is evidence suggesting features of platform work can impact whether workers have fair access to work opportunities and working conditions, our understanding of how platform workers perceive the fairness of their work is underdeveloped.

Considering a growing emphasis on fairness, accountability, and transparency in the algorithmic management of employees (Lepri et al., 2017; Shin & Park, 2019), scholarly attention has been directed to fairness perceptions of algorithmic management in traditional work environments in fields such as personnel selection, performance assessment, and scheduling (Dineen et al., 2004; Newman et al., 2020; Uhde et al., 2020). In a review of stakeholders', including employees', perspectives on algorithmic management, Langer and Landers (2021) found that algorithm-based decisions tend to be perceived by people as less fair than human decisions. Research exploring fairness perceptions in digital platform work however remains limited, both in the number of studies conducted and the breadth of platforms investigated. Despite growing evidence suggesting that the exercise of algorithmic control by digital platforms might not be fair (e.g., Duggan et al., 2020; Kellogg et al., 2020; Rosenblat & Stark, 2016), and concerns about the long-term unfavourable impacts of digital platform work (De Stefano, 2016; Kennedy et al., 2017; Macdonald & Charlesworth, 2021), there is limited discussion of how workers engaged in platform work perceive fairness in the features of their work, including compensation and work distribution outcomes, policies and procedures related to (performance) ratings and reviews, and the levels of control over work processes.

Perceptions of fairness are crucial in organisations as they have been shown to influence employee attitudes and behaviours (Colquitt et al., 2001) as well as their work performance (Cohen-Charash & Spector, 2001; Colquitt et al., 2001). Prior research has suggested that favourable fairness perceptions are directly associated with positive employee behaviours, attitudes, and feelings, which have the potential to enhance organisational performance (Ployhart, 2015). By contrast, perceptions of unfairness or inequitable treatment at work have been regarded as a workplace stressor, and found to elicit negative feelings and emotions, such as anxiety, anger, and frustration (Howard & Cordes, 2010; SimanTov-Nachlieli & Bamberger, 2021), experiences of depression and emotional exhaustion (Eib et al., 2018; Tepper, 2000), and health problems associated with stress (Robbins et al., 2012; Rousseau et al., 2009). Although emerging research has begun to investigate platform workers' fairness perceptions, the use of organisational justice theory in conceptualising worker perceptions of fairness on digital labour platforms has been limited. Organisational justice theory has brought significant insights into how workers, albeit in traditional work settings, evaluate fairness of organisations' policies and procedures, and outcomes. It is therefore an ideal lens through which to explore fairness perceptions among individuals who secure work on digital labour platforms.

Previous studies of digital labour platforms highlight the heterogeneity of work and employment conditions, varied worker characteristics and hence motivation (Dunn, 2020) as well as experiences across different types of platform work (de Groen et al., 2018; Fieseler et al., 2019; Schor, 2017). Digital labour platforms that offer different types of work vary in their approaches to compensation, task distribution, performance assessment, and levels of control afforded to workers (De Stefano, 2016; Duggan et al., 2020; Wood et al., 2019). However, most scholarly attention on platform worker experience and perceptions of algorithmic management focus solely on one or a limited number of leading platforms, sometimes assuming the findings hold for all types of digital labour platforms. Available evidence fails to capture the heterogeneity among digital labour platforms and platform workers (Bajwa et al., 2018; Vallas & Schor, 2020), thus necessitating empirical investigations of a more diverse group of platform workers across a wider range of platforms.

1.2 RESEARCH PURPOSES AND SIGNIFICANCE

This study aims to contribute to the literature on the experience of workers on digital labour platforms, and more specifically, to reveal new knowledge about platform workers' perceived fairness of features of platform work and whether these perceptions differ according to gender, age, and type of platform work. The initial literature review draws on studies of management, organisational justice, and the gig economy. The study offers a theory-driven inquiry into fairness perceptions in the realm of platform work. The study expands our understanding of how demographic factors and type of platform work shape fairness perceptions in the platform work context. The study's focus on worker perceptions of platform work features complements existing scholarship that focuses on platform characteristics, and builds on the work of Wang et al.'s (2020) study which explored individual differences that influence workers' perspectives of fairness in algorithmic management contexts. This study responds to Deng and colleagues' (2016) call for the application of organisational justice theory to explain worker perceptions on digital labour platforms. It also responds to Cohen-Charash and Spector's (2001) call for research on more individual predictors of perceived organisational justice, and the contingencies under which demographic factors influence fairness perceptions, and Lee's (2018) call for incorporating task types into investigations of managerial decisions.

This study undertakes a quantitative analysis of an existing data set obtained through an Australian Research Council-supported project – *Working the gig economy: The organisation of digital platform work* (Project ID: DP180101191), comprising a national prevalence survey – *Digital platform work in Australia* (referred to henceforth as the National Survey) (McDonald et al., 2019). Features of platform work representing distributive and procedural justice dimensions, such as income derived from platform work, are explored by means of factor analysis. A paired samples *t*-test is employed to determine the extent to which platform workers perceive features of their work as fair. Finally, the effects of gender, age, and type of platform work on fairness perceptions are examined using multivariate analysis of variance (MANOVA), followed by descriptive discriminant analysis (DDA) to clarify the nature of any observed group differences.

The purpose of the study is therefore to answer the following research question:

How do workers perceive fairness on digital labour platforms?

Due to the complex and broad nature of the central research question, the study seeks answers to the following sub-research questions:

RQ1: To what extent do platform workers perceive features of the work, such as income derived from platform work, as fair?

RQ2: Do platform workers perceive fairness differently based on their gender, age, or type of platform work?

RQ3: Is there an interaction effect between type of platform work and gender on platform workers' fairness perceptions?

RQ4: Is there an interaction effect between type of platform work and age on platform workers' fairness perceptions?

1.3 SCOPE AND DEFINITIONS

1.3.1 Scope

The gig economy represents an economic system in which digital platforms (e.g., websites and mobile apps) are utilised to match the supply and demand of contingent labour (Cappelli & Keller, 2013; Koutsimpogiorgos et al., 2020). Digital labour platforms are those that connect freelance workers with clients to offer their services by completing on-demand tasks (Duggan et al., 2020). The scope of this study was limited to digital labour platforms that met the parameters set by Codagnone et al. (2016): (1) operate as digital markets for on-demand non-standard work; (2) where a diverse range of services is fulfilled using the labour component, instead of selling goods, licensing creative works, or renting assets; (3) where labour is exchanged for monetary remuneration; (4) where the matching between service requesters and providers is digitally managed, while the fulfilment of the service can be remote or physical; and (5) where decisions relating to labour and money allocation are made by a group of participating buyers and sellers within a price system. These parameters exclude several online platforms.

Parameter (1) excludes online platforms that facilitate matching for traditional work, such as LinkedIn. Parameter (2) excludes capital platforms, such as Etsy, eBay, or AirBnB, which are used by individuals or businesses to sell, rent out, or license goods/assets. Parameter (3) applies to paid platform work where the labour factor is predominant, such as transport and food delivery services on Uber. Parameter (4) pertains to two broadly different types of platform work, namely in-person work, which is performed at a specified location, and internet-based work, which is performed and delivered online. These types of work are discussed in greater detail in section 1.3.2. Finally, parameter (5) is typically applicable to two-sided markets in which a digital platform claims to act as an intermediary, such as Uber, TaskRabbit and Amazon Mechanical Turk.

1.3.2 Definitions of primary types of platform work

Within the digital platforms that mediate the supply of labour, two primary types of work have been identified (De Stefano, 2016; de Groen et al., 2018; Florisson & Mandl, 2018): internet-based work and in-person work (see Figure 1). A key distinction between these two types of work is based on the form of service provision. That is, internet-based work involves tasks that are executed online or remotely, while in-person work involves tasks that are locally performed (De Stefano, 2016; Howcroft & Bergvall-Kareborn, 2019). Furthermore, the internet-based variant tends to involve the provision of medium-to-high skilled labour, as opposed to its in-person counterpart which is typically associated with service provision based on lower skills. A more detailed definition and conceptualisation of in-person and internet-based platform work is discussed below. However, the terms *digital platforms*, *digital labour platforms*, or *platform work* are used in this study to refer to both internet-based and in-person variants. Individuals engaged in both types of platform work have been variously classified as independent contractors, on-demand workers, gig workers, or self-employed freelancers. They will be referred to here as *workers* or *platform workers*, for the sake of simplicity.

Internet-based work consists of tasks or jobs completed online. The work varies in complexity and nature, ranging from “microtasks” – small work activities or tasks, such as tagging photos, valuing emotions, and completing surveys – to larger tasks such as developing logos, or a website for a marketing campaign (Pesole et al., 2018). A typical internet-based work arrangement involves tasks or projects advertised via an online platform by an individual client or business (i.e., requester). Individuals across any geographical location can attempt to fulfill the specified tasks, and often subject to requester satisfaction, are paid for the completed tasks (Berg, 2016). It is worth noting however that internet-based platforms are not homogenous. There are varying approaches to task allocation and payment through, for example, competitive tenders or a first-come-first-served basis (De Stefano, 2016). Commonly cited examples of internet-based platforms are Upwork and Amazon Mechanical Turk.

In-person work (i.e., work on demand via apps) involves traditional and physical tasks, such as transport, cleaning, and running errands, executed locally at a specified location and time (Duggan et al., 2020). Localised platform work is arranged and facilitated through mobile apps (short for 'applications') owned or managed by platform companies that act as an intermediary in establishing minimum performance standards and assigning tasks to individual workers (De Stefano, 2016). Examples of in-person work include ride-hailing and food delivery services on platforms, such as Uber and Deliveroo.

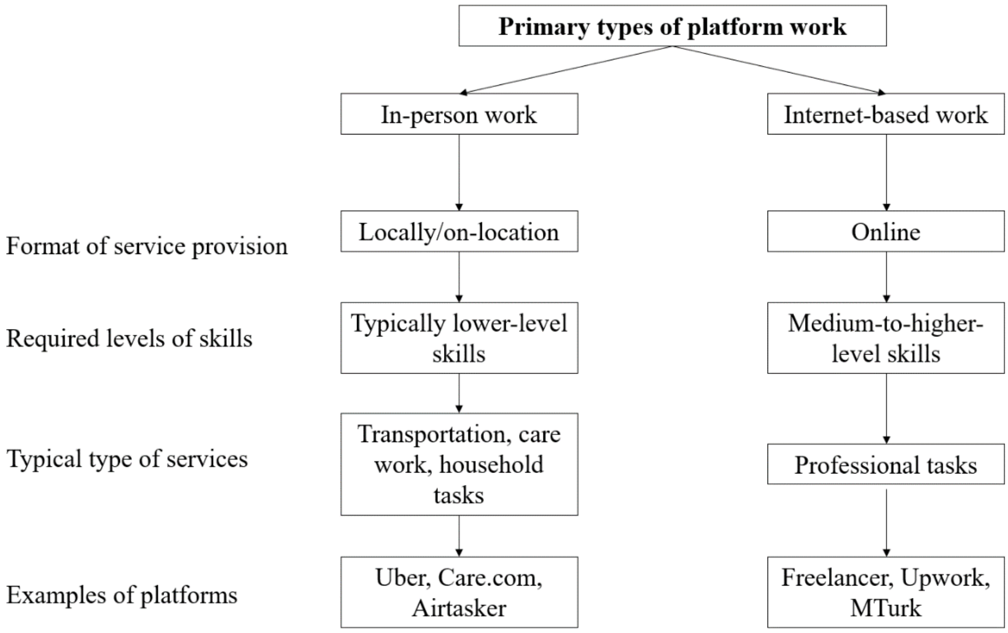

Figure 1. Primary types and characteristics of platform work

1.4 THESIS OUTLINE

The remainder of the thesis proceeds as follows:

Chapter 2 examines the literature concerning digital labour platforms and organisational justice, critically reviewing existing research on algorithmic management and how it affects autonomy and earnings obtained by workers who participate in platform work. The application of organisational justice in investigating fairness perceptions in platform work settings is explained and justified.

Chapter 3 outlines the research design and analytical approaches utilised for the study. The methodological approach is outlined, followed by the description of the sample from which the data were derived. The measurements of the variables under focus are then presented. Results of preliminary data analysis, including missing data and methods used to address the missing data, are outlined. The quantitative analytical techniques used to answer the research questions are also discussed and justified.

Chapter 4 presents the detailed results of the study, drawn from the quantitative analysis of the data. Findings from the factor analysis, paired samples *t*-test, and multivariate analyses are provided.

Chapter 5 provides a discussion of the study findings and their implications. It also outlines the limitations of the study and directions for future research.

Chapter 2: Literature Review

This chapter begins with a discussion about platform work features (section 2.1), reviewing the literature on how algorithmic management on digital labour platforms affects autonomy (section 2.1.1) and earnings (section 2.1.2). It will then provide a rationale for the adoption of organisational justice as a lens to investigate fairness perceptions in the context of platform work (section 2.2), followed by a critical review of organisational justice literature (section 2.3) and fairness perceptions measure (section 2.4). In the final section of this chapter, demographic characteristics, including gender and age, and type of platform work are explored, with a focus on their influence on worker perceptions of fairness (section 2.5).

2.1 FEATURES OF PLATFORM WORK

Previous research has established that workers engage in platform work for various reasons, including flexible and autonomous work, greater work-life balance, and opportunities to earn or supplement their income (Barnes et al., 2015; Kalleberg & Dunn, 2016; McDonald et al., 2021; Pesole et al., 2018). Indeed, the “rhetorical markers” of the gig economy are “freedom, flexibility, and entrepreneurship” (Rosenblat & Stark, 2016, p. 3761). Many platforms promise autonomy, which entails individual task discretion, control over work processes, and worker voice in decision- making (Deng & Joshi, 2016; Goods et al., 2019). On the surface, individuals engaged in platform work are in control of when, where, how, and what particular tasks to undertake. They are generally classified as independent contractors or self-employed freelancers, who are not contractually bound by an employment contract. Platform work might constitute a supplemental income stream or a main source of income, and provide access to work opportunities that may not be otherwise available (Florisson & Mandl, 2018). Workers who are most likely to be engaged in platform work tend to earn lower wages in other forms of paid employment (Balaram et al., 2019; Dunn, 2020; Huws et al., 2017).

However, scholars have raised questions about the actual level of autonomy experienced by platform workers (Jarrahi et al., 2020; Laursen et al., 2021; Lehdonvirta, 2018) and the reality of earnings through platform work (Berg, 2016;

Berger et al., 2018). It has been suggested that autonomy and earnings derived from platform work are often at risk of being reduced by algorithmic management (e.g., Griesbach et al., 2019; Jabagi et al., 2019; Rosenblat, 2018; Shapiro, 2018), which is fundamental to the business model of digital labour platforms. Algorithmic management may encompass both data-driven decision-making entrusted to an algorithmic system and human decision-making aided by algorithmic systems (Gagné et al., 2022), and has been applied to many work contexts beyond platform work (Newman et al., 2020; Parent-Rocheleau & Parker, 2022).

In this study, the term *algorithmic management* is used to refer to the data-driven decision-making procedures which are distinguishable from human decision-making by managers or supervisors. It is often defined as "a system of control where self-learning algorithms are given the responsibility for making and executing decisions affecting labour, thereby limiting human involvement and oversight of the labour process" (Duggan et al., 2020, p. 119). Algorithmic management in platform work is designed to maintain the platform's control over key managerial functions which traditionally were executed by managers or human resource specialists (Kellogg et al., 2020). These functions, as suggested by Parent-Rocheleau and Parker (2022), include monitoring, goal setting, performance management, scheduling, compensation, and job termination (for definitions of these functions, see Table 1).

Table 1: Definitions of key managerial functions executed by algorithmic management on digital labour platforms[1]

Function	**Algorithmic management**
Monitoring	Collect, store, analyse, aggregate, and report any data related to workers' performance and behaviours during their work
Goal setting	Perform task allocation, or establish performance targets
Performance management	Evaluate, rate, compare workers, or provide feedback
Scheduling	Regulate the supply of workers to meet customer demands or send workers scheduling incentives/nudges
Compensation	Determine workers' pay according to various algorithmically managed criteria

[1] Adapted from Parent-Rocheleau & Parker (2022)

Job termination	Make termination decisions and/or announcement

The various algorithmically-determined mechanisms, put in place by digital labour platforms to coordinate, monitor, and compensate a remote workforce (ILO, 2021), might pose significant challenges to participating workers. Unlike workers in more traditional employment settings, workers engaged in platform work interact with an algorithmic system, instead of a human manager. This interaction hinders platform workers' ability to directly influence, discuss or negotiate aspects of their work (Heeks et al., 2021; Möhlmann & Zalmanson, 2017), such as factors that affect their performance or earnings. While management via algorithms may improve transparency and minimise (or remove) human biases in decision-making thanks to its reliance on a predetermined set of governing rules (Hansen & Flyverbom, 2015; Newman et al., 2020), the algorithmic management of labour processes is often characterised by substantially low levels of transparency, which can be attributed to the propriety nature of platform algorithms in a highly competitive market or the changing nature of the data to be collected from workers and clients (Möhlmann & Zalmanson, 2017), rendering an impersonal and inexplicable working environment for platform workers. In their investigation of Uber ride-sharing platform, Rosenblat and Stark (2016) found that the lack of transparency in the algorithmic configuration and practices produce information and power asymmetries in favour of the platform.

Significant power and control in many aspects of platform-mediated labour reside with platform organisations that persist in their role only as an intermediary (Kenney & Zysman, 2016; Prassl, 2018). Positioning themselves as intermediaries that connect the demand for and supply of paid labour, digital labour platforms "shifts economic work-related risk onto workers, thereby reinforcing, and even driving, precarity" (Barratt et al., 2020, p. 1655). Existing evidence suggests that the algorithmic management of workforce on digital labour platforms may impinge on working conditions for workers, thus inducing or exacerbating precarity in terms of uncertainty and instability of work (Anwar & Graham, 2021; Heeks et al., 2021; Spencer, 2018; Sutherland & Jarrahi, 2018). Despite that platform workers are designated as independent contractors, rather than employees, they may not be able to effectively exercise autonomy in their labour process (Fiori, 2017; Glavin et al., 2021; Kalleberg & Vallas, 2017; Rosenblat & Stark, 2016; Vallas & Schor, 2020). As the literature on platform work gradually sheds new light on the role of algorithmic management, significant questions have been raised about the fairness of platform-mediated work. A search of the literature revealed that, while the term *organisational justice* was not necessarily used, findings from several studies highlight features of platform work that are the major causes for concerns. Several algorithmically-driven functions shape platform workers' levels of autonomy (see section 2.1.1) and earning ability (see section 2.1.2).

2.1.1 Autonomy through platform work

Autonomy is a key promise of platform work. Yet, previous studies, predominantly among in-person platform workers, have described how algorithmic monitoring, goal setting, and performance management functions restrict workers' voice, thereby constraining their levels of autonomy. For instance, Goods and colleagues (2019) collected qualitative data from semi-structured interviews with Australia-based Deliveroo and Uber food couriers (i.e., in-person platform work). The authors found that various forms of platform control, including GPS monitoring, work allocation, and performance monitoring, were used to define and control work processes. Since performance metrics, such as acceptance rate and cancellations, affected the allocation of future tasks, riders may feel pressured to maintain high (above 85%) acceptance rates. Electronic monitoring of work processes is also common in internet-based platform work, such as Upwork and Freelancer (D'Cruz & Noronha, 2016; Schörpf et al., 2017), which is likely to reduce workers' perceived autonomy.

Ratings and reviews are regarded as "a major decentralised and scalable management technique that outsources quality control to customers" (van Doorn, 2017, p. 903). Performance assessment on platforms is based on customer ratings and reviews, and other metrics, which are used for making decisions regarding rewards and penalties on platforms, and determination of future tasks (Gerber, 2021; Gregory, 2021; Griesbach et al., 2019; Lehdonvirta, 2018; Wood et al., 2019). Customer ratings are often used in conjunction with other productivity data to allocate tasks to workers (Prassl, 2018). For example, Uber drivers are required to maintain a very high rating or risk deactivation (Rosenblat & Stark, 2016; Wu et al., 2019). High ratings in an in-person work context improve workers' chances of acquiring more work (Rosenblat & Stark, 2016; Wood et al., 2019; Wu et al., 2019). Schörpf et al. (2017) and Williams et al. (2020) revealed that for internet-based platform workers undertaking creative tasks, such as graphic design, high client ratings and positive reviews are important factors in obtaining new work. Unpaid work is often performed in hopes of good reviews (Schörpf et al., 2017).

However, performance assessment algorithms on platforms are not necessarily transparent to workers. The accuracy of information used in appraisal processes, which is critical for procedural justice (Leventhal et al., 1980; Thibaut & Walker, 1975), is a source of concern in platform work. For instance, Rosenblat and Stark (2016) reported that ride-hailing drivers expressed frustration, not just that performance algorithms are invisible and dependent on inaccurate information but also that there is no appeal process to correct erroneous (low) ratings. Low and often unjustifiable ratings on ridesharing platforms are not an isolated case. This issue is pervasive in platform work of various types across multiple sectors and countries (ILO, 2021), bringing the fairness of the platform management process into question.

Research also provides evidence regarding the role of algorithmic scheduling function in orienting workers towards specific schedules, thus constraining workers' autonomy (Jabagi et al., 2019; Lehdonvirta, 2018). The extent of control exerted by digital labour platforms over the work processes is illustrated in a study of professional photographers by McDonald et al. (2021) who found that photographers on platforms, such as iStockphoto, Snappr, and Oneflare, need to adhere to the work structures that are put in place by the platform, including specific time and location of the photo shoot, and delivery schedule. This highlights how the features of photographic platform work may thwart workers' discretion or voice in the creative process. A lack of discretion or ability to influence decision-making may in turn affect workers' perceived fairness. due to its role in procedural justice (Lind et al., 1990; Thibaut & Walker, 1975).

In addition, workers engaged in platform work may be obliged to adjust their schedule during times of high demand, to be on call between tasks, or to become available on short notice, relinquishing their freedom and autonomy. Although workers can choose to work during off-peak hours (e.g., Uber ride-hailing services), they may earn significantly less if they do so (Florisson & Mandl, 2018). This is illustrative of another restriction on worker autonomy. According to Goods et al. (2019), workers' ability to choose the time and location of their work is a low form of autonomy. While this form of autonomy is considered as a major benefit by on-location platform workers, it is limited by their financial necessity (Goods et al., 2019).

Behavioural nudges, such as surge pricing in the case of Uber, are used to incentivise workers to work at certain times and locations of expected high demand. While this scheduling feature is considered by some workers as an advantage, particularly for additional income (Barratt et al., 2020), it is often perceived by others as unreliable and designed to meet passenger demand, rather than maximising worker earnings (Rosenblat & Stark, 2016).

Furthermore, scheduling nudges incentivised food riders to work, even under poor weather conditions or difficult physical demands (Goods et al., 2019; Gregory, 2021), demonstrating how the algorithmic performance management function discouraged workers from exercising their autonomy over work processes, specifically when or whether it is safe to work. Platform constraints on worker autonomy on both in-person and internet-based platforms are also indicated by long and unsocial working hours, and high work intensity (Berg et al., 2018; Schörpf et al., 2017; Wood et al., 2019; Wu et al., 2019). In light of the ILO's Fairwork framework (see Heeks et al., 2021), working conditions shaped by platform algorithms appear to be unfair to workers, as indicated by the issues surrounding work intensification and worker health and safety.

Combined, these studies suggest that algorithmic management contributes to decreased autonomy of platform workers, most apparently in the case of in-person work. Evidence indicates that platform workers are compelled to work long and irregular hours, at times under poor working conditions, posing a threat to their health and safety (Anwar & Graham, 2021; Williams et al., 2022) and that they often work longer hours in order to earn higher incomes (Kuhn & Maleki, 2017; Rani & Furrer, 2021; Wood et al., 2019).

2.1.2 Earnings through platform work

Platform work represents important income-generating opportunities for millions of individuals globally. Research indicates that algorithms used to allocate work, and to manage compensation and job termination can directly affect earnings and job opportunities available to platform workers. Different approaches to the determination of work assignments, pay and other incentives are adopted by digital platforms (De Stefano, 2016). Within the same type of platform work, platforms may differ in clients' and workers' service fees, and utilise different methods for payment (Florisson & Mandl, 2018). In-person labour platforms allocate tasks to workers via an app, such as Uber, or match workers' profiles to jobs posted by clients using platform algorithms, exemplified by platforms providing care work, housekeeping, or repair services, such as TaskRabbit or CareSeekers. Workers who undertake in-person platform work are often paid by the platforms. On internet-based platforms, such as Amazon Mechanical Turk, tasks may be subdivided into smaller units (i.e., micro-task) and distributed by the platform across a large and undefined group of workers. They may involve contest-based work on platforms, such as 99designs, where tasks are requested by an individual or organisation, and performed simultaneously by multiple workers, one of whom is selected and paid for by the task requester (McDonnell et al., 2021).

In addition to customer satisfaction, several other, often hidden, criteria may be used in the determination of pay rates and distribution of future tasks, including the number of tasks completed, quality of completed work, and other productivity data (Griesbach et al., 2019; Kellogg et al., 2020; McDonnell et al., 2021). Unlike traditional employment, workers may be required to pay fees to access work opportunities. Examples of fees associated with platform work are membership fees and commissions from completed tasks (Aloisi, 2016). Similar to performance assessment, work distribution on digital platforms is algorithmically determined, based on mostly invisible and complex inbuilt criteria (Burrell, 2016; Pfeiffer & Kawalec, 2020; Veen et al., 2019). The criteria, which are often of obscure nature and therefore difficult to understand, may be related to the information contained in worker profiles, such as skills and experience (Lehdonvirta, 2018), customer ratings and reviews (Florisson & Mandl, 2018), fees that the worker pays, or other criteria embedded in the platform algorithms (Williams et al., 2020). The complexity and obscurity of the criteria or decision-making input on digital labour platforms bring concerns about worker experience of fairness. That is, the fairness of the procedures and policies by platforms to distribute outcomes, such as algorithmic goal setting (i.e., procedural justice; Colquitt et al., 2005), and the fairness of outcomes, such as an adequate amount of income that is commensurate with worker contribution and fair access to work opportunities (i.e., distributive justice; Cropanzano et al., 2007).

Recent evidence suggests that inadequate pay is common among platform workers. A recent survey based in the United States by the Economic Policy Institute shows platform workers tend to receive low pay, which is sometimes lower than the local minimum wage (Zipperer et al., 2022). This is an indicator of unfairness as outlined in the ILO's Fairwork framework (Heeks et al., 2021). Findings from the Australian National Survey show that many workers do not know how much they earn and the average wage varies by type of platform work (McDonald et al., 2019). Larger tasks, such as contest-based crowdwork, which typically require higher-skilled labour to complete and deliver online, tend to offer more decent pay rates, than those that involve low-skilled work, such as app-based food delivery and micro-task crowdwork (de Groen et al., 2018). As evidenced in Goods et al.'s study, Deliveroo and UberEATS food couriers have no choice but to accept the pay levels specified by the platforms, reporting that the customer fares and fees charged to workers are regularly updated according to demand. Findings from previous studies of platform workers in creative and professional industries also point to workers' perceived inadequacy (or unfairness) of income generated from platform-mediated photographic work, when compared to the workers' contributions such as time and skill (McDonald et al., 2021; Williams, McDonald et al., 2021). Similarly, Berg's (2016) investigation of workers on Amazon Mechanical Turk and CrowdFlower revealed the low-paying and unstable nature of work experienced by internet-based workers. Berg (2016) also found that unpaid working time and a lack of available jobs are the key contributing factors to low and unstable earnings. Workers in the study undertaken by Deng and Joshi (2016) reported frustration with the low payment rate for micro-tasking crowdwork. Compounding challenges related to under-compensation on digital labour platforms are issues surrounding the stability of work and income (Carr et al., 2017; Griesbach et al., 2019; Lehdonvirta, 2018; Veen et al., 2019) due to unpredictable work schedules and customer demands.

Overall, platform workers are exposed to significant risks associated with unpredictable demand and lost income. As discussed earlier, any earnings on digital labour platforms and continuation of work are also subject to and often threatened by algorithmic termination in the event of poor customer ratings (Ravenelle, 2019; Rosenblat, 2018), lowering workers' sense of job security. Williams et al. (2020) revealed that platform-based carers and graphic designers encounter the multi-layered and opaque processes of assigning workers to available work. Regarding algorithmic termination, in her analysis of Airtasker, Minter (2017) notes that, due to the platform's leading market position, a worker who is blocked on Airtasker might effectively be excluded from other task-based platforms. Studies targeted at a specific type of platform workers consistently demonstrate the transfer of responsibility and risks onto workers (Schor et al., 2020; Warren, 2021), raising doubts about fair access to work opportunities on digital labour platforms.

2.2 ORGANISATIONAL JUSTICE THEORY AND DIGITAL PLATFORM WORK

Research on platform algorithms suggests there is an interaction between autonomy and earnings. The issues associated with autonomy and earnings through platform work highlight the importance of a theoretical approach to understand worker's perceived fairness of platform work features. Although findings from previous studies suggest unfairness as a result of algorithmic control exercised by digital platforms (e.g., Duggan et al., 2020; Kellogg et al., 2020; Rosenblat & Stark, 2016), little is currently known about worker perceptions of fairness in this context.

Dimensions of organisational justice have been applied to investigate fairness perceptions in algorithmic management research, however these studies did not investigate digital platform workers. It has been demonstrated that people who are subjected to autonomous algorithm-driven decisions perceive those decisions as less fair, compared to decisions made by humans for personnel selection, performance appraisal, and shift scheduling purposes (Dineen et al., 2004; Newman et al., 2020; Uhde et al., 2020).

Previous research assessing fairness of digital platform work has focused on working conditions on digital platforms against objective criteria of fair work standards (see Graham et al., 2020 for the Fairwork Foundation's criteria of fair work). While evaluating platform work through an objective lens represents an important area of research, such approach does not take into account the distinct characteristics of platform work and worker motivation to participate in this form of work. Despite the important implications of worker fairness perceptions for attitudinal and behavioural outcomes (Colquitt et al., 2001), the gig economy literature reveals little about the fairness perceptions of individuals who turn to digital platforms for work. Very few studies to date have examined perceived fairness on digital labour platforms. For example, a study by Deng et al. (2016) revealed that unfair compensation and governance practices (e.g., platform policies and procedures) elicited strong negative feelings from micro-task crowdworkers. Likewise, in an analysis of crowdworkers in

Germany, Pfeiffer and Kawalec (2020) demonstrated that crowdworkers perceive unfairness in multiple aspects of their work. They observed four major sources of unfairness, namely income and job instability, the opacity of performance evaluation process, obscurities in task briefings, and low payment rates. Similarly, Laursen and colleagues (2021) found that Danish platform workers experienced a lack of control over the important aspects of their work, such as rankings and allocation of tasks, resulting in feelings of unfairness relating to the platform algorithms. These findings indicate that there is a lack of perceived fairness on digital platforms and nuanced aspects of platform work, implicated in its numerous algorithm-driven features. There is a need to gain a deeper understanding of how different cohorts of workers experience platform work (Myhill et al., 2021), such as how they perceive fairness in various features of their work. Understanding workers' perceived fairness on digital labour platforms is pertinent, due to its influence on worker participation and engagement (Faullant et al., 2017; Liu & Liu, 2019), which are pivotal to the success of platforms.

The structure of platform work plays an important role in the study of worker fairness perceptions. Platform work fundamentally differs from traditional employment (Duggan et al., 2020), for which organisational justice theory was originally developed in that it represents flexible short-term working arrangements with low entry barriers and little ongoing mutual commitment between a platform and a worker. Platform workers may reduce their engagement in the work, or withdraw entirely from a platform and no longer offer their labour. Further, workers are motivated to participate in platform work for numerous reasons according to individual worker characteristics (McDonald et al., 2019). A noticeable and growing number of workers participate in this form of work, despite the predominant objective evaluation of platform work as unfair and inferior to traditional employment alternatives. This suggests the essence of worker fairness perceptions in platform work settings may differ markedly from those whose labour is engaged via a formal employment contract. Organisational justice theory can provide insights into workers' subjective evaluations of various aspects of work on digital platforms. These insights contribute to broader discussions on the lived experience of digitally mediated work (Goods et al., 2019; Myhill et al., 2021), and to a more nuanced understanding of potential drivers of entering and engaging in this form of work.

2.3 ORGANISATIONAL JUSTICE THEORY AND FAIRNESS PERCEPTIONS

Organisational justice refers to individuals' perceptions of fairness at work (Colquitt et al., 2005; Cropanzano & Ambrose, 2015). The terms *justice* and *fairness* are used interchangeably in the literature (Colquitt & Rodell, 2015), although attempts have been made to distinguish the two constructs (e.g., Ambrose & Schminke, 2009; Kim & Leung, 2007; Rodell & Colquitt, 2009). Organisational justice and fairness, according to Goldman (2015), can be treated as synonymous. Hence, in the present study, the two terms are operationalised as the same construct. Perceptions of organisational justice are essential to the success of business operations and satisfaction of organisational members (Greenberg, 1990), as they are believed to shape individual attitudes and behaviour (Ouyang et al., 2015). Central to organisational justice research is the investigation of how individuals evaluate their employing organisation's (and its management's) decisions (Cropanzano et al., 2007), and how these decisions are associated with individual behaviour and attitudes towards the organisation (Li et al., 2020).

Organisational justice is based on the transactions or labour exchange between employees and employers. Scholars have attempted to explore organisational justice in the workplace as the perceived fairness of decision outcomes (distributive justice), the perceived fairness of policies, processes, and criteria used by an organisation to allocate outcomes or make decisions (procedural justice), the perceived fairness of the interpersonal treatment one receives in the implementation of decisions and procedures (interpersonal justice), and the perceived fairness or adequacy of explanations related to the decision-making procedures or respective outcomes (informational justice) (Colquitt, 2001; Colquitt et al., 2001). Building on organisational justice theory, other researchers have indicated that individuals may form overall evaluations about an exchange that often involves more than one type of justice, such as outcomes and procedures (Ambrose & Schminke, 2009), and that individuals are unlikely to evaluate outcomes and procedures separately, with (un)fair outcomes perceived to be generated by (un)fair procedures (Ambrose & Arnaud, 2005).

This study recognises that platform workers almost certainly encounter several (un)fair events associated with outcomes and procedures concurrently. Their fairness evaluations are likely to entail what Greenberg (2001) describes as "holistic judgements in which they respond to whatever information is both available and salient" (p. 211). As platform workers work outside of conventional organisations, they often lack interactions with peer workers, and thus, opportunities to compare their reward (e.g., pay) with others (Laursen et al., 2021; Pfeiffer & Kawalec, 2020). In the absence of information regarding the actual distribution of outcomes, the perceived fairness of procedures is likely to assume greater importance as a proxy for the justice appraisal. Hence, this study focuses on overall perceptions of fairness, namely an aggregate of organisational justice dimensional components (Hauenstein et al., 2001), to better capture the holistic worker experiences and judgements of events pertaining to different types of justice (Ambrose & Arnaud, 2005; Ambrose & Schminke, 2009; Greenberg, 2001). 2

This focus is consistent with Colquitt and Shaw's (2005) conceptualisation of overall justice as a global perception, which entails measurement of overall fairness, and is suitable when justice is an endogenous variable (for more in-depth reviews of organisational justice measurement approaches, see Colquitt & Rodell, 2015; Colquitt & Shaw, 2005). Furthermore, measuring overall fairness echoes fairness heuristic or general perceptions of fairness discussed by Lind (2001). A focus on overall perceptions of fairness, rather than specific justice dimensions, allows for a more complete and accurate account of how individuals engaged in platform work evaluate the fairness of their experiences with the work features (Ambrose & Schminke, 2009; Holtz & Harold, 2009).

Overall fairness is rooted in Leventhal's (1980) earlier conceptualisation of the fairness perception, which was suggested to be dictated by distributive and procedural justice rules. Both distributive justice and procedural justice may be relevant to platform work. As mentioned earlier, platform workers by definition do not have a human manager, who is typically the source of interpersonal and informational justice in traditional employment contexts (Colquitt et al., 2001). In the platform work setting, there is no supervisor-subordinate relationship to account for. The application of algorithmic management implies the invisibility of a human manager (Möhlmann & Zalmanson, 2017). Therefore, it seems prudent to focus solely on distributive and procedural justice.

Distributive justice originates from equity theory (Adams, 1965), which postulates that individuals make a comparison between their own outcomes/inputs and those of referent others. In a traditional employment scenario, outcomes are concerned with what employees receive, such as pay, fringe benefits, and some forms of intrinsic rewards, whereas inputs refer to their contributions, including effort, time, cost, and qualifications. While outcomes typically involve compensation, they also entail other resources, such as hiring decisions and performance appraisal, namely "Did the best person get the job?" and "Did the rating received reflect job performance?" (Greenberg, 2011, p. 279) or the decisions related to dispute resolutions (Colquitt et al., 2005). Outcome distributions are deemed to be fair when rewards measure up to contributions (Ambrose & Arnaud, 2005). Distributive justice matters to individuals who secure work on digital platforms as it reflects the appropriateness of rewards (e.g., compensation) workers receive for their labour (e.g., time, effort) (Cropanzano et al., 2007).

Procedural justice relates to the perceived fairness of the policies, processes, and criteria used by an organisation to allocate outcomes (Colquitt et al., 2005; Folger & Konovsky, 1989; Tyler, 1987). The procedural justice dimension initially originated from research on legal disputes (Friedland et al., 1973; Thibaut & Walker, 1975) and soon became relevant in workplace settings (e.g., Lind & Lissak, 1985). While distributive justice is related to the 'ends', procedural justice is related to the 'means' or procedures (Karatepe & Shahriari, 2014). A sense of procedural justice can be fostered by ensuring procedures are consistent, free of bias, and based on accurate information (Leventhal, 1980; Leventhal et al., 1980; Thibaut & Walker, 1975) or by facilitating individuals' voice or influence over the outcome of the procedure (Lind et al., 1990; Thibaut & Walker, 1975). The ability to influence outcomes (i.e., perceived control) plays an important role in judgements of fairness in the respective outcomes (Leventhal, 1976, 1980; Thibaut & Walker, 1975). In the platform work context, procedural justice is important to workers because this form of justice indicates that reward-related decisions (e.g., work opportunities) were made using a just process (e.g., fair scheduling) (Leventhal, 1980; Leventhal et al., 1980).

High correlations between distributive and procedural justice have been reported in previous research (e.g., Cohen-Charash & Spector, 2001; Colquitt et al., 2001; Hauenstein et al., 2001). This is consistent with the 'monistic view' held by Cropanzano and Ambrose (2001) who argued that distributive justice and procedural justice fundamentally are more similar than distinct. The authors postulated that procedures can be evaluated with respect to the outcomes they produce, and that "the same event can be either a process or outcome" depending on the perspective of the observer/assessor (p. 128), suggesting a blurring state of outcomes and processes in a given situation. This effect is ostensibly amplified in platform work. Distributive justice on digital labour platforms may explain workers' evaluation of fairness in, for example, the amount of compensation and the allocation of work. Procedural justice in this context can be reflected in the algorithmic management processes, such as fair performance assessment. As seen in the aforementioned examples of worker experiences with algorithms on digital platforms, rewards in platform work are closely tied to algorithmically determined procedures. Thus, distributive and procedural determinants of fairness in platform work are blurred, with earnings and access to work being determined in many cases by customer ratings and reviews.

2.4 MEASURE OF FAIRNESS PERCEPTIONS

Organisational justice in this study is operationalised as current platform workers' overall fairness perceptions of platform work features. Colquitt and Shaw (2005) outlined a number of choices to be made regarding justice measurement. Using existing data collected through the Australians and the Gig Economy survey (see section 3.1.1 for more information; McDonald et al., 2019), this study followed Colquitt and Shaw's (2005) guidance when deciding items that were deemed to represent fairness perceptions of platform workers. The items used to measure the workers' perceptions (see section 3.2.2) were extracted from the survey and mapped to organisational justice theory. The survey items however were developed based on the platform work literature, not organisational justice theory, and thus have limitations. Nevertheless, while they are bounded specifically in the platform work context, the selected items arguably capture the core conceptualisations of distributive justice and procedural justice.

In line with Colquitt and Shaw (2005), decisions regarding organisational justice measures are concerned with the type of justice, the source of justice, the context of justice, and the measurement approach. As mentioned earlier, this study focuses on two types of justice, namely distributive and procedural, both of which are relevant to platform work. This study argues that the source of justice in platform work is algorithmic management, which is crucial to the operation of digital labour platforms (Gagné et al., 2022). As discussed previously (see section 2.1), algorithmic management refers to a managerial practice whereby algorithms are used to partly or completely automate the oversight and control of workers (Duggan et al., 2020). The justice context of interest in this study relates to decision-making procedures or events that occur via algorithmic management. The chosen items represent both direct and indirect approaches to measuring justice. Direct measures of justice explicitly ask for an evaluation of fairness of an event (Colquitt & Rodell, 2015; Mikula, 2005). An example of a direct item is *The income I earn is fair*. By contrast, indirect measures enquire about "the presence or absence of various events, outcomes, and/or transactions" that are believed to contribute to perceptions of fairness (Cropanzano et al., 2015, p. 285). *I can work the hours I choose* is an example of an indirect item. To ensure measurement repetition, items referencing multiple decision events were selected. For example, *The income I earn is fair* and *The fees, costs or commissions associated with work through the platform are fair* are related to worker earnings. *The rating system on the platform is fair* focuses on performance management, which in turn affects platform workers' access to work opportunities and thus overall earnings (Parent-Rocheleau & Parker, 2022). Furthermore, some items contain the words *reasonable* and *adequate* which are substitutes for the word *fair*, such as *The competition for work is reasonable*. Likewise, multiple inputs in connection with the same decision-making procedure(s) were utilised to provide measurement repetition. For instance, *I can work the hours I choose* and *I can choose my own tasks or projects* concern inputs of time and selected task(s) in relation to platform-based task allocation and scheduling procedures. This decision is summarised in Figure 2, and further discussed in Chapter 3. Research Design. The items used in this study are consistent with Lind's (2001) suggestion for measuring overall fairness; that is, the statements represent platform workers' overall evaluation of the fairness of their experiences with several features of platform work.

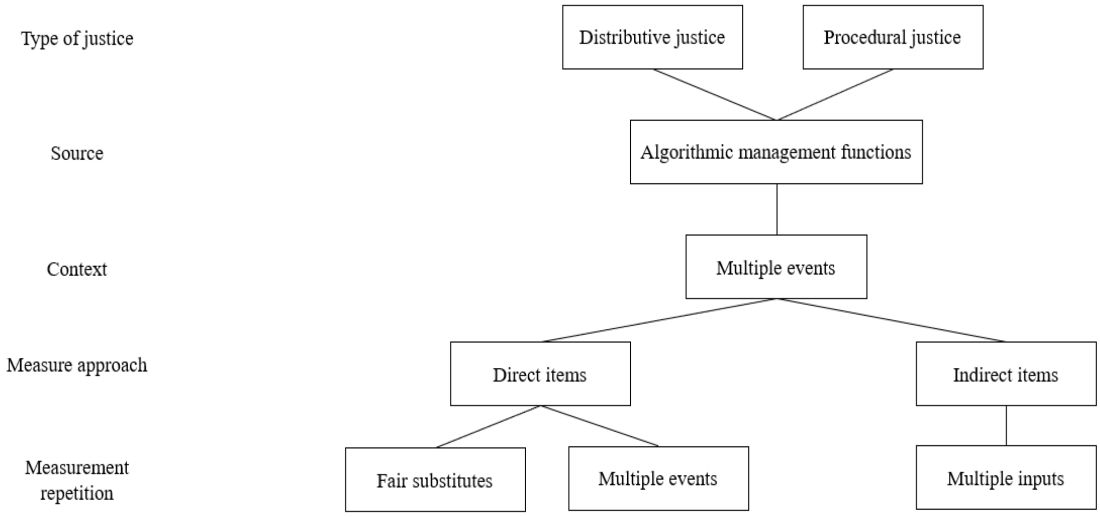

Figure 2. Decisions regarding the measurement of fairness perceptions in the current study

2.5 DEMOGRAPHIC CHARACTERISTICS AND FAIRNESS PERCEPTIONS IN PLATFORM WORK

Participation in platform work and motivations for, and experiences of platform workers have also been found to vary based on demographic characteristics (e.g., gender and age) and across types of platform work (McDonald et al., 2019), with the majority of workers being male and young (Florisson & Mandl, 2018; Kuek et al., 2015). Prior research has shown that discrimination based on demographic attributes is pervasive on digital labour platforms, with platform work features being found responsible for facilitating discrimination against workers of a minority group (Tushev et al., 2022), such as women and older adults. Organisational justice studies have investigated the extent to which fairness perceptions are influenced by demographic attributes, including gender (e.g., Adriaans & Targa, 2022; Cohen-Charash & Spector, 2001; Greenberg & Cohen, 1982) and age (e.g., Cohen-Charash & Spector, 2001; Ghasi et al., 2020). Gender is the most commonly investigated factor. This study explores whether gender and age influence worker perceptions of fairness in the context of platform work. In addition to gender and age, type of platform work may be an influential factor in terms of perceived fairness. Lee (2018) has called for task types to be incorporated into investigations of managerial decisions. In the present study, task types are operationalised as types of platform work (i.e., in-person, internet-based and both), while managerial decisions are related to platform work features.

2.5.1 Type of platform work

Platform work is heterogeneous in terms of management practices, and the nature and complexity of tasks undertaken. Different types of platform work involve different approaches to compensation, distribution of work, performance assessment, and levels of control afforded to workers (De Stefano, 2016; Duggan et al., 2020; Wood et al., 2019). The pricing strategies across platforms also vary, including different fees charged to users (clients/customers and workers) and subscription or membership plans offered by the platform (for an in-depth discussion about platform revenue model, see ILO, 2021).

Additionally, levels of autonomy differ significantly across the platform work types (Durward et al., 2016; de Groen; Florisson & Mandl, 2018; ILO, 2021; Sundararajan, 2016). As suggested by Fieseler et al. (2019), worker experience varies across different types of platform work. For example, in-person platform workers typically have less control over their work, compared with those participating in internet-based work (de Groen et al., 2018; Kost et al., 2020). Within the former type of platform work, perceived unfair treatment may therefore result from app-based monitoring mechanisms (Gandini, 2019). Meanwhile, perceptions of unfairness in internet-based work settings may emanate from a lack of transparency in selection processes (i.e., who is getting the job offer) and unfair monetary distribution (Franke et al., 2013). Furthermore, compared to in-person workers, those engaged in internet-based work perform tasks completely online, and hence are less likely to develop a working relationship with the digital platform organisation (Duggan et al., 2020). Higher-skill workers on "digital platforms with substantial autonomy may not expect [the platform] to care about their well-being", whereas workers offering lower-skill services, such as in localised work, that are more tightly controlled by a platform, may be more likely to consider themselves as employees whose organisation has a responsibility to their welfare (Kuhn & Maleki, 2017, p. 193). Platform workers may also secure both in-person and internet-based work across multiple platforms (De Groen & Maselli, 2016).

Research to date has not yet determined the impact of the type of platform work undertaken on the experience of the workers, including how it shapes their fairness perceptions. The relationship between type of work and perceived fairness remains unclear. Some attempts have been made, in settings outside the gig economy, to understand the perceptions of fairness among different types of workers, though not necessarily through the lens of organisational justice theory. For example, Schalk et al. (2010) investigated the psychological contracts of temporary and permanent workers. The researchers revealed that temporary workers perceived greater fairness in their workplaces than permanent workers. By contrast, De Cuyper et al. (2008) pointed out that individuals employed on a temporary basis are more susceptible to experiencing unfairness at work, than those with permanent contracts. In platform work, processes of algorithmic control differ markedly, affecting the degree of autonomy and earnings afforded by the platform across different types of work (Greenberg & Cohen, 1982). It stands to reason therefore, that type of platform work is likely to have a differential effect of fairness perceptions. Hence, the following hypothesis is proposed:

Hypothesis 1: Type of platform work will have a significant differential effect on workers' perceived fairness of platform work features.

2.5.2 Gender

While the premise of flexible work in the gig economy suggests equal opportunities for men and women (Hannák et al., 2017; Williams, Mayes et al., 2021), there is compelling evidence for gender inequalities on digital labour platforms and the role of algorithmic management in exacerbating gender biases. Similar to the traditional labour market, the platform-based labour market poses challenges for women to access work (ILO, 2021). Research has found that female platform workers earn less on average than their male counterparts, suggesting that the gender pay gap identified in traditional employment settings is sustained in the platform work context (Adams & Berg, 2017; Aleksynska et al., 2021; Chen et al., 2018; Cook et al., 2021). Cook and associates (2021) found a gender earnings gap of between 4% and 7% using a sample of more than a million Uber drivers based in the United States. Others documented a 10-20% gender wage gap on Amazon Mechanical Turk (Adams, 2020; Adams & Berg, 2017; Litman et al., 2020). A study of an online platform by Barzilay and Ben-David (2017) uncovered that women's hourly requested rates were 37% less on average than men's. The hourly rate disparity persisted despite performance ratings, experience, type of work performed or education level. Through an analysis of two crowdwork platforms, Abendroth (2020) found that platform algorithms reinforce gender pay inequalities among crowdworkers by using data that reflect differences in bargaining power between men and women.

Furthermore, digital platform research has found evidence of gender discrimination in hiring and performance evaluation on digital platforms. Gender biases in platform work hiring practices have been evidenced in a study conducted by (Hannák et al., 2017) who collected 13,500 worker profiles, associated customer ratings and reviews, and search algorithms used to locate workers on two major online freelancing platforms – TaskRabbit and Fiverr. The authors found that women receive significantly fewer client reviews than men, which may in turn be detrimental to their rank in search results and access to work opportunities. Likewise, gender stereotypes were uncovered by Galperin (2019) whose study focused on a Spanish online freelance platform Nubelo (since acquired by Freelance.com). Results of this study show that female workers are significantly less likely to be hired for male-dominated job types (e.g., software and web development), but more likely to be favoured in female-dominated job types (e.g., writing and translation) than equally qualified male workers.

Regarding performance evaluation, robust experimental evidence reveals significant gender biases on ridesharing platforms (Greenwood et al., 2020). Specifically, female drivers were found to incur harsher penalties for poor levels of services, relative to male drivers. Additionally, following a low-quality experience, female drivers with high historical quality are more severely penalised than Caucasian male drivers (Greenwood et al., 2020). These studies suggest that female workers typically are disadvantaged by algorithmic features on digital platforms. Hence, it is possible that they will perceive platform work features to be less fair than their male counterparts.

Gender has been theorised to affect perceptions of organisational justice (Greenberg & Cohen, 1982). Gender differences have commanded much attention in justice research and have been demonstrated to influence work-related attitudes (e.g, job satisfaction, organisational commitment; Buchanan, 2005; Foley et al., 2005; Khoreva & Tenhiälä, 2016). Organisational justice studies yield contrasting findings of gender differences. For example, the gender effect is evident in a study undertaken by Tessema et al. (2014). Using a sample of 313 public sector employees, Tessema and colleagues found that female employees perceive distributive justice more positively than their male counterparts. This finding is comparable to those in an experimental work done by Marchegiani et al. (2018) who investigated justice evaluations of performance appraisal. This study found that women react more favourably than men to unfairness in the event of perceived evaluation errors. Gender differences in fairness perceptions were also observed in research conducted by Valet (2018) and Pfeifer and Stephan (2019). Using German panel data, these authors demonstrated that women tend to evaluate their pay as more fair than men do. Based on data collected in 2018-2019 across 28 European countries, Adriaans and Targa (2022) also found disparities for perceived fairness in earnings between men and women. Interestingly, however, these authors found that women do not have more favourable perceptions of their wages than men. Indeed, women in 15 out of 28 countries in the study were found to perceive unfairness to a greater extent than men. This finding is consistent with that of Foley et al. (2005), who found that women have less positive perceptions of distributive and procedural justice.

Conversely, other studies have discovered no significant differential effects of gender on fairness perceptions (Cohen-Charash & Spector, 2001; Nurse & Devonish, 2006; Werner & Ones, 2000), suggesting that men and women perceive justice similarly. Experimental evidence shows that men and women have similar responses when experiencing inequitable treatment from their employers, and suggest that gender differences when it comes to perceptions of fairness are associated with the specific situation (Greenberg & Cohen, 1982), indicating that other factors may act in concert with gender in differentiating perceptions of fairness.

This study examines both the main effect of gender and the gender-type of platform work interaction effect on fairness perceptions of platform work features. Given findings on gender disparities in platform work and mixed results in traditional employment settings, this study anticipates that gender affects digital platform workers' fairness perceptions of platform work features, and this relationship is moderated by type of platform work. This leads to the following hypotheses:

Hypothesis 2a: Female platform workers will have less positive fairness perceptions of platform work features than male platform workers.

Hypothesis 2b: The effect of gender on platform workers' fairness perceptions is moderated by the type of platform work.

2.5.3 Age

Extant studies provide empirical evidence for age-related differences in perceptions of fairness in the workplace. For instance, based on attitudinal data from the British Social Attitudes Survey, Paul (2006) revealed that older employees have less favourable perceptions of fairness in their earnings than younger employees. More recently, Ghasi and associates (2020) explored perceptions of organisational justice among 360 healthcare professionals in Nigeria. They demonstrated that perceptions of distributive (e.g., pay, access to hospital resources, work schedule) and procedural (e.g., ability to appeal management decisions) justice vary significantly across age groups, with older employees having lower perceptions of fairness than their younger peers. Yet, Cohen-Charash and Spector's (2001) meta-analysis found no evidence of age differences in fairness perceptions. In a similar way to gender differences in organisational justice perceptions, as discussed above, study findings in relation to age show mixed results.

The literature beyond organisational justice provides some useful insights into how work motivation differs across the lifespan. One of the earliest systematic reviews of age-related differences in work attitudes and behaviour was conducted by Rhodes (1983). Her review of 185 studies provides some important insights into the influence of age on needs and work values, including that, as individuals age, they tend to attach higher importance to extrinsic job attributes, such as high financial compensation, as opposed to intrinsic rewards, such as development opportunities. A consistent finding was obtained for the negative relationship between age and preference for growth in a meta-analysis by Kooij et al. (2011). Their results however demonstrate an age-related decrease in the salience of extrinsic work-related outcomes, in contrast to Rhodes' findings. Additionally, Kooiji et al. (2011) found that preferences for intrinsic job characteristics, such as security and autonomy, increase with age. That is, jobs that offer higher levels of autonomy and security, rather than pay and benefits, are more important to older workers, compared to younger workers.

Despite their contrasting findings, these studies highlight age-related changes in motivation in traditional work settings. This topic is important to investigate as limited empirical evidence constrains our understanding of the effect of age on fairness perceptions in new work settings, such as platform work. Results from several surveys on the prevalence of digital platform work indicate that younger people (under 35 years) are more likely to participate (e.g., Huws et al., 2017; McDonald et al., 2019; Pesole et al., 2018). Older workers may be less reliant on the income from digital platform work. While it has been suggested that workers secure work on digital platforms for both extrinsic reasons, such as complementing pay, and intrinsic reasons, such as flexibility and autonomy, (e.g., Barnes et al., 2015; Churchill & Craig, 2019; McDonald et al., 2021), supplementary income has been identified as the prime reason for engaging in platform work for workers in all age groups, especially the age group 18-34 years (ILO, 2021). Gig economy literature has indicated that, relative to older workers, younger workers may perceive platform work more favourably. Younger crowdworkers have higher levels of job satisfaction, including pay-related fairness perceptions, than older workers, as reported in O'Higgins and Caro's (2022) analysis of the global crowdwork survey data collected by the International Labour Office in 2015. O'Higgins and Caro noted that the age-related differential in perceptions of crowdwork was attributable to younger workers' lower expectations or their lack of alternative job opportunities. This leads to the following hypothesis.

Hypothesis 3a: Older platform workers will have less positive fairness perceptions of platform work features than younger platform workers.

In line with Greenberg and Cohen (1982), it is further expected that age will interact with type of platform work, in its influence on fairness perceptions. Hence, the following hypothesis is proposed.

Hypothesis 3b: The effect of age on platform workers' fairness perceptions is moderated by the type of platform work.

Chapter 3: Research Design

Chapter 3 describes the research design used to address the research questions guiding this study. The overarching research question was:

How do workers perceive fairness on digital labour platforms?

The sub-research questions were:

RQ1: To what extent do platform workers perceive features of the work, such as income derived from platform work, as fair?

RQ2: Do platform workers perceive fairness differently based on their gender, age, or type of platform work?

RQ3: Is there an interaction effect between type of platform work and gender on platform workers' fairness perceptions?

RQ4: Is there an interaction effect between type of platform work and age on platform workers' fairness perceptions?

This chapter is organised as follows. Section 3.1 covers the method and the sample used in this study. An outline and justification are provided as to how the chosen design offers a suitable research method to answer the research questions. A summary of the sample for the study is also given. The measurements of the variables of interest in the study, including the instrument used to measure fairness perceptions, are described in section 3.2. Section 3.3 details the preliminary data analysis conducted to investigate the amount and extent of missing data, and the methods used to handle the missing data. The analytical techniques used to address the research questions are outlined and justified in section 3.4. Finally, section 3.5 covers ethics.

3.1 METHODOLOGY

3.1.1 Method

This study employed a quantitative survey research methodology to investigate fairness perceptions of digital platform work and whether these perceptions differed on the basis of gender, age, and type of platform work. The study used the data collected for the National Survey (McDonald et al., 2019), which was funded by the

Victorian Government and an Australian Research Council Discovery project: *The organisation of digital platform work* (Project ID: DP180101191). The survey explored the prevalence and contours of digital platform work in Australia, examining the level of participation, the type of platform work or services individuals engage in, and their evaluation of how digital platforms operate, including items relating to their perceptions of the platform functions.

3.1.2 Sample

The target population of the National Survey was adult Australian internet users over the age of 18, who were sampled through a panel survey distributed by the Online Research Unit in March 2019. Of the total 14013 respondents, 988 people were current digital platform workers, who were defined, in the survey, as those who worked or offered services on digital labour platforms at the time of the survey or in the prior 12 months (McDonald et al., 2019). After removing cases with missing values (for details, see section 4.1.1), the sample for this study was 888 current platform workers. The characteristics of the respondents in terms of two relevant demographical variables, namely gender and age, and type of platform work in which they were engaged, are reported in Table 2.

Table 2: Demographic characteristics of the study sample (n = 888)

Variable	**Category**	**Frequency (*n*)**	**Percentage (%)**
Gender	Male	580	65.3
	Female	308	34.7
Age	Younger	469	52.8
	Older	419	47.2
Type of platform work	In-person work	377	42.5
	Internet-based work	270	30.4
	Both	241	27.1

In terms of gender distribution, the majority of the respondents were male (65.3%), compared to females (34.7%). The representation of the age groups was slightly higher for younger workers, aged 18-34, at 52.8% compared to 47.2% for older workers, aged 35-74. The age groupings used in this study are consistent with those used for data analysis in the National Survey. Respondents who were engaging only in in-person platform work made up 42.5% of the sample, with lower representation from internet-based (30.4%) and both (27.1%) types of platform work. In-person work involves traditional and physical tasks that are arranged and facilitated through mobile apps (e.g., Uber, Deliveroo) and executed by independent contractors or freelancers at a specified location. Internet-based work consists of tasks or jobs remotely completed and delivered by a crowd of workers via open websites or online platforms (e.g., Amazon Mechanical Turk).

3.2 MEASURES

3.2.1 Independent variable: Gender, Age, and Type of platform work

The study focused on the following demographic variables as independent variables: gender (male vs. female), age (older vs. younger), and type of platform work (in-person work, internet-based work, and both). These variables were coded in the following way: *gender* as 0 = male, 1 = female, *age* as 0 = older (35-74 years of age), 1 = younger (18-34 years of age), and *type of platform work* as 0 = in-person work, 1 = internet-based work, 2 = both.

3.2.2 Dependent variable: Overall fairness perceptions

To measure overall fairness perceptions of current digital platform workers, the study utilised 15 out of 19 scale items or variables relating to perceptions of digital platform functions from the National Survey (McDonald et al., 2019). These variables were identified as closely reflecting the hypothesised underlying factors representing distributive and procedural justice on digital platforms. Respondents were asked to respond to these variables on a five-point Likert scale between 1 (strongly disagree) and 5 (strongly agree), with the option of 6 (I do not know) and 7 (not applicable). Variable F5, *I can find regular work through the platform despite health issues or disability*, had a high level of not-applicable responses and thus was considered inadequately applicable to the study sample (see section 4.1.1). This variable was excluded from further analysis. The remaining 14 variables, which were subject to further analysis (as described in section 3.4), are presented in Table 3.

Table 3: Scale items

(F1) The income I earn is fair.
(F2) I have the ability to set the price for my services.
(F3) The fees, costs or commissions associated with work through the platform are fair.
(F4) I can find regular work through the platform.
(F6) I can choose my own tasks or projects.
(F7) I can work the hours I choose.
(F8) I can work at the pace I choose.
(F9) I am free to decide how to perform any tasks or projects I accept.
(F10) I can work from home or another place that I choose.
(F11) I can work for myself and be my own boss.
(F12) The rating system on the platform is fair.
(F13) The competition for work is reasonable.
(F14) I receive adequate support to resolve disputes over payments or tasks
(F15) The health and safety conditions are adequate.

3.3 PRELIMINARY DATA ANALYSIS

Data screening was performed through SPSS EXPLORE, FREQUENCIES, and REGRESSION to check on the amount of missing data. Little's Missing Completely at Random (MCAR) test and a Pearson's chi-squared test were conducted to investigate the pattern of missing data. Results of these tests were used to determine the appropriate method for dealing with missing data. Details of the preliminary data analysis are discussed below.

3.3.1 Data screening

Fifteen items from the National Survey were initially considered to reflect justice perceptions. These variables were measured using a five-point Likert scale with the option of 6 being *I do not know* and 7 being *Not applicable* (NA). In the preliminary data analysis, the selected variables were recoded, with 6 being converted to 3 (i.e., Neither agree nor disagree). The rationale was that *I do not know* is an ambiguous response which is conceptually the same as *Neither agree nor disagree*. Answers that were categorised as 7 (i.e., NA) were converted to a missing value as an NA response indicated that the variable or function may not be a feature of that worker's platform, and therefore was not useful in responding to the research questions.

Five cases were removed from the data set on the basis of responses to a question asking for the participant's gender. Specifically, three cases that indicated *intersex/indeterminate* or *other* are insufficient to constitute a separate group for analysis. Two cases that responded *prefer not to answer* were, in effect, missing data. Initial assessment of the extent and patterns of missing data showed that the missing data were concentrated in a small subset of cases. Nine out of 988 cases had more than 70% system-missing values contributing to 9.23% of the missing data overall. Another 86 cases had more than 20% of missing data due to NA (NA-missingness). Therefore, another 95 cases with excessive system- and NA-missingness were removed. Variable-level inspection reported missing data for all variables. Nine out of 15 variables had system-missing data, and all of the variables (F1 to F15) had NA-missing values, as shown in Appendix A. Variable F5, *I can find work through the platform despite health issues or disability,* had 16% of NA-missingness and thus was deleted. An alternative, highly correlated variable F4, *I can find regular work through the platform*, was available to represent the intent of F5. Removing 100 cases with excessive levels of missingness and one variable with a high level of NA-missingness from the dataset resulted in a 6.97% overall decrease in missing data.

3.3.2 Little's MCAR test and Pearson's chi-squared test

To diagnose the overall pattern of missing data on the remaining 14 perception variables, Little's MCAR test was performed. The test had a significance level less than .001, indicating that the missing data process was not completely random (MCAR). Pearson's chi-squared test of contingencies with $\alpha = .05$ was then employed to test for the association between NA-missingness and demographic characteristics including *gender*, *age*, and *type of platform work* (Tabachnick et al., 2019). The chi-squared test was done only for F15, as the item had more than 5 percent of NA-missingness. A dummy variable indicating NA-missingness was created, with a value of zero if the variable had a valid value, and a one if there was a missing value for the variable. Demographic variables are coded as follows: gender (0 = male, 1 = female); age (0 = older workers aged 35-74, 1 = younger workers aged 18-34; and type of platform work (0 = in-person work, 1 = internet-based work, 2 = both).

The result of the chi-squared test (Table 4) showed that significant chi-squared values occurred for NA-missingness on F15 when comparing groups based on gender, $\chi^2 = 4.8$, $df = 1$, p = .029; age $\chi^2 = 10.74$, $df = 1$, $p = .001$; and type of platform work, $\chi^2 = 15.39$, $df = 2$, $p < .001$. This indicated that there were differences between the two groups: observations with and without NA-missing data for F15 on gender, age, and type of platform work. The associations were however small, with Phi coefficients ranging from .07 to .13, making the differences of marginal concern. The missing data process could therefore be classified as missing at random (MAR). The remaining missing data were imputed using the expectation-maximisation algorithm, which allows for unbiased estimates and correct standard errors in MAR situations (Hair, 2019) and maintains the relationships between the variables (Enders, 2003b). This resulted in a useable complete dataset of 888 cases with 14 perceptions variables, two demographic variables and type of platform work variable. The sample size reported in this thesis was sufficient to perform factor analyses (Hair, 2019; Tabachnick et al., 2019).

Table 4: Test of contingencies between demographic variables and NA-missingness on F15

Demographic variables	**χ^2 (*df*)**	***p***	**φ^a**
Gender	4.8 (1)	.029	.07
Age	10.74 (1)	.001	.11
Type of platform work	15.39 (2)	< .001	.13

[a] Phi coefficient

3.4 ANALYSIS

Factor analysis was used for data summarisation with interpretation. Data summarisation was achieved by identifying the underlying factors that represent the original set of variables initially considered to reflect justice perceptions. The factor analysis provided a smaller, more parsimonious set of representative variables for use in subsequent analyses. Paired samples *t*-test was performed to compare group means corresponding to the factors identified in the factor analyses. MANOVA identified differences between groups based on gender, age, and type of platform work on a combination of dependent variables (i.e., overall fairness perceptions). Finally, post hoc comparisons were performed to explore the nature of any observed group differences. Provided below are the details of the analysis.

3.4.1 Factor analysis

The underlying factor structure of the 14 variables was assessed, first, through an exploratory factor analysis (EFA) using the SPSS R-menu extension package (version 2.4.3, Basto & Pereira, 2012), and second, through a confirmatory factor analysis (CFA) using SPSS Amos. The main objective of the EFA was to define the latent factors that adequately represented the 14 variables (Henson & Roberts, 2006). The CFA was then employed to validate the hypothesised factor solution (Hair, 2019).

Prior to performing the EFA, Bartlett's Test of Sphericity and Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy were inspected to assess the overall suitability of the data for conducting factor analysis. The measures of sampling adequacy (MSA) values for each variable were also observed to examine whether the individual variables are sufficiently intercorrelated to generate representative factors (Hair, 2019). Multicollinearity and linearity assumptions of the data were also checked.

The decision regarding the number of factors to retain was made based on the visual scree plot (Cattell, 1966), parallel analysis (Horn, 1965), Minimum Average Partial (MAP) test (Velicer, 1976), Optimal Coordinate method (Raîche et al., 2012), the latent root criterion (i.e., eigenvalues exceeding 1, Kaiser, 1970) and the interpretability of the factor structure. Ordinary least squares estimations with polychoric correlations (as per Gaskin & Happell, 2014; Watkins, 2018), and oblique factor rotation, were employed to extract factors, which were assumed to be closely correlated in measuring perceptions of fairness among current digital platform workers (Tabachnick et al., 2019).

3.4.2 Paired samples *t*-test

Research question 1 asks:

RQ1: To what extent do digital platform workers perceive features of the work, such as income derived from platform work, as fair?

To answer this question, a paired samples *t*-test was used to test any significant difference in platform workers' perceived fairness of the latent factors identified through the factor analyses.

3.4.3 Multivariate analyses

Multivariate tests were performed to answer research questions 2, 3, and 4:

RQ2: Do platform workers perceive fairness differently based on their gender, age, and type of platform work?

RQ3: Is there an interaction effect between type of platform work and gender on platform workers' fairness perceptions?

RQ4: Is there an interaction effect between type of platform work and age on platform workers' fairness perceptions?

The essence of these questions was whether there are differences based on gender, age, and type of platform work with respect to perceptions of fairness in autonomy and earnings. The rationale for conducting multivariate methods, rather than univariate methods, was two-fold. First, multivariate analyses minimise the probability of experiment-wise Type I errors, which could be caused by a series of multiple univariate analyses (Haase & Ellis, 1987; Huberty & Morris, 1989). Second, and most important, multivariate methods consider the dependent variables simultaneously in the analysis, thus preserving the complexity of possible interrelations among the dependent variables (Zientek & Thompson, 2009), and providing a nuanced basis to describe platform workers' perceptions of fairness in the key features of platform work.

Using multivariate analyses was consistent with a fundamental premise that studies in the gig economy should consider the complex nature of features of platform work. This study considered overall fairness perceptions as a latent construct combining multiple variables. Given the multivariate nature of the research questions, multivariate analyses were deemed more appropriate, than univariate analyses, to investigate the relationship (mains and interactions) between the focal demographic variables (i.e., gender, age, and type of platform work) and the outcomes (i.e., fairness perceptions) at the same time. As noted by Tonidandel and Lebreton (2013), "multivariate theories yield multivariate hypotheses which necessitate the use of multivariate statistics and multivariate interpretations of those statistics" (p. 475).

Specifically, a two-way MANOVA was employed as the initial technique when examining the main effects and interactions in the perceived fairness of digital platform work on the basis of gender, age, and type of platform work (N = 888) across the dependent variables of interest (i.e., the variables identified through the factor analyses). Unlike its univariate counterparts, MANOVA forms one or more composite variables by linearly combining the dependent variables of interest. Moderate to strong correlations (e.g., $r = |.60|$) among the latent or dependent variables were required to form meaningful composites (Tabachnick et al., 2019). To this end, MANOVA was used to determine whether a difference in overall fairness perceptions existed among groups of platform workers on the basis of gender, age, and type of platform work.

Following MANOVA, DDA was performed to clarify the nature of any observed group differences, based on the recommendations of several authors (Barton et al., 2016; Smith et al., 2020; Warne, 2014). Specifically, DDA results provided information that explained, if group differences existed, how groups differed on the composite variable(s). Comparable with MANOVA, DDA involved generating linear composite(s) of the dependent variables or discriminant functions (also called canonical variates) that best differentiated the groups and therefore produced measures of overall effect sizes that described the variance accounted for between the grouping variable, such as a demographic variable, and the composite variable (Huberty & Olejnik, 2006). The number of functions, which are analogous to factors in factor analysis, is equal to k (groups) – 1. The first function explains the largest proportion of variance possible. Each subsequent function creates a new and unique composite dependent variable for which the group differences explain as much of the remaining variance (Sherry, 2006). In addition to the overall variance-accounted-for effect sizes, DDA results provided standardised and structure coefficients for each dependent variable to evaluate their relative contribution to group differences on the composite variable(s) (Enders, 2003a). Furthermore, group centroids, which are the means of each group on the composite dependent variable(s) (Sherry, 2006), were examined to determine which groups differed on the composite.

3.5 ETHICS

Ethics approval was gained for the original survey data collection (Approval No. 1900000128). An ethics exemption for this study was sought and granted from QUT Office of Research Ethics and Integrity in line with the National Statement on Ethical

Conduct in Human Research (2007, updated 2018). The current research was exempted from review as it is negligible risk and involves the use of an existing collection of data or records which contain only non-identifiable data about human beings (as per the National Statement on Ethical Conduct in Human Research, paragraph 5.1.22).

Chapter 4: Results

Chapter 4 presents detailed results of the study with respect to the research questions. The overarching question was *How do workers perceive fairness on digital labour platforms?* More specifically, the study set out to answer the following sub-questions:

RQ1: To what extent do platform workers perceive features of the work, such as income derived from platform work, as fair?

RQ2: Do platform workers perceive fairness differently based on their gender, age, or type of platform work?

RQ3: Is there an interaction effect between type of platform work and gender on platform workers' fairness perceptions?

RQ4: Is there an interaction effect between type of platform work and age on platform workers' fairness perceptions?

The chapter commences with the results of the factor analyses regarding the latent factor(s) that represent 14 fairness perceptions variables (see Table 3 for the 14 scale items). This is followed by the results from the paired samples t test, which responds to RQ1. Finally, the results of a multivariate test address the remaining research questions RQ2-4, focusing on differences, based on gender, age, and type of platform work, in platform workers' fairness perceptions.

4.1 FACTOR ANALYSIS

4.1.1 Bartlett's Test of Sphericity and Kaiser-Meyer-Olkin Measure of Sampling Adequacy

The result of Bartlett's Test of Sphericity suggested sufficient correlations existed among the variables to perform a factor analysis, $\chi^2(91) = 5934.296$, $p < .001$ (Allen et al., 2019). The KMO statistic of .930, well above the recommended minimum threshold of .60, indicated that the data were highly suitable for factor analysis (Kaiser, 1970; Kaiser & Rice, 1974; Tabachnick et al., 2019). Results of these tests are summarised in Table 5. The MSA values for each variable were also observed (see Appendix A). Each individual variable achieved an acceptable MSA value above .80, indicating that they were highly adequate for factor analysis (Hair, 2019). Collectively, these measures indicated that the set of 14 variables was appropriate for factor analysis. The polychoric correlation matrix (see Appendix B) was examined for linearity and multicollinearity criteria before conducting factor analysis. The variables that were expected to cluster together in a single factor correlated well (r > .30), except for F2 (Mat Roni & Djajadikerta, 2021), which did not correlate well with F4 (r = .22) and F7 (r = .29), which respectively were expected to load on two factors, indicating departures from linearity. Variable F2 however was further examined for adequacy in the two-factor solution, as discussed below. Given that no correlation estimates exceeded .90, the multicollinearity assumption was not violated.

Table 5: Bartlett's test of sphericity and Kaiser-Meyer-Olkin measure of sampling adequacy for the overall data

Barlett's Test of Sphericity	Approx. Chi-Squared	5934.296
	df	91
	p	< .001
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.930

4.1.2 Exploratory factor analysis

The parallel analysis, MAP, optimal coordinate procedures (see Figure 3), and the latent root criterion, all suggested that two factors should be retained. The scree plot in Figure 3 indicates that two or perhaps three factors may be appropriate when examining the slope of the curve (i.e., identifying the "elbow" or point where the line starts flattening out, which is at the fourth factor). The eigenvalue for the third factor was .937, which was close to the latent root criterion value of 1.0 and therefore considered for retention. However, in a three-factor solution, only one variable (F2) loaded highly on the third factor, indicating that the third factor was poorly defined. Therefore, two factors were retained for further analysis.

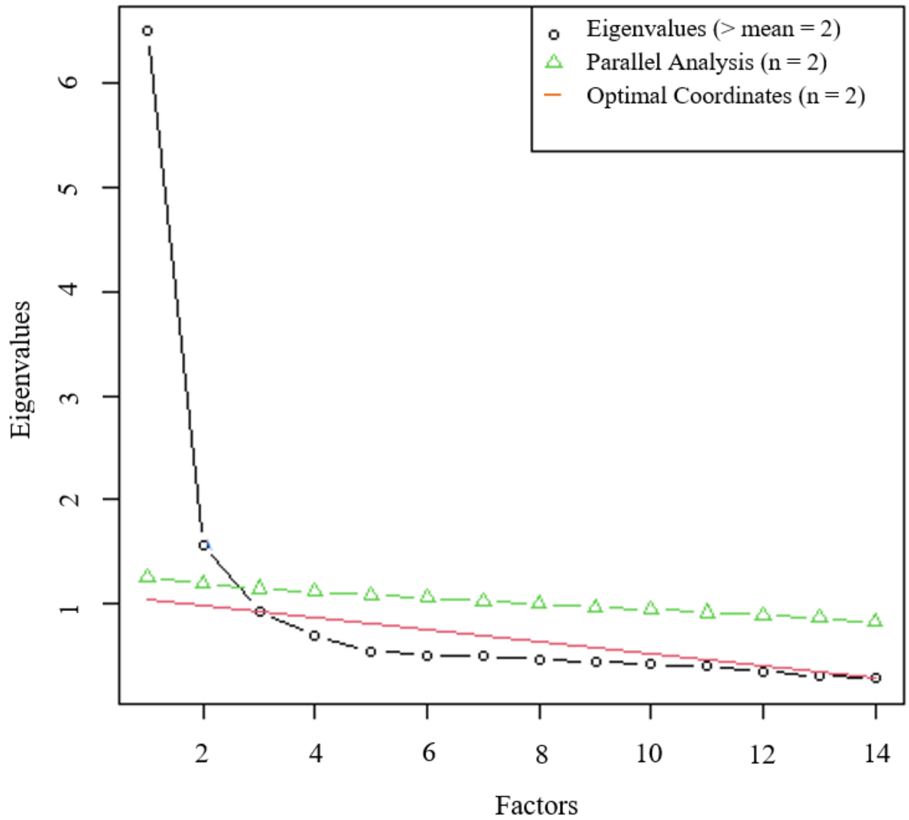

Figure 3. Scree plot, parallel analysis, and optimal coordinates analysis

Appendix C shows the rotated factor matrix and communality coefficients of the full set of 14 variables. Each variable has a significant loading (defined as a loading ast least .50, Mat Roni & Djajadikerta, 2021) on only one factor, except for three variables: F2, *I have the ability to set the price for my services*; F4, *I can find regular work through the platform*; and F15, *The health and safety conditions are adequate*. These variables became candidates for deletion.

F2 loaded at .351 and -.322. on factor 1 and factor 2, respectively. F2 also had a low communality value of .371, which falls below the cut-off value of .40 (Costello & Osborne, 2005), suggesting that this variable has little in common with other items in the analysis. Both F4 and F15 had a factor loading below .50. Furthermore, F4 had a low communality of .293, suggesting a low contribution to the analysis. F2 was removed from the analysis to achieve a clean interpretation of each factor, while F4 and F15 were deleted to improve convergent validity (Mat Roni & Djajadikerta, 2021). The factor structure for the remaining 11 variables, which load on two latent factors, labelled *Autonomy* and *Earnings*, is shown in Figure 4. The labelling of Factor 1 and

Factor 2 occurred through a structured review of the variables (i.e., factor loadings or the correlation of the variable and the factor; Hair, 2019) and related literature. Based on the pattern of factor loadings for the variables (see Appendix D), the top loading variable(s) had a greater impact on the selected factor labels (Watkins, 2018):

- *Factor 1 Autonomy*: (F7) I can work the hours I choose (loading = .840), and (F11) I can work for myself and be own boss (loading = .825).
- *Factor 2 Earnings*: (F3) The fees, costs or commissions associated with work through the platform are fair (loading = .842).

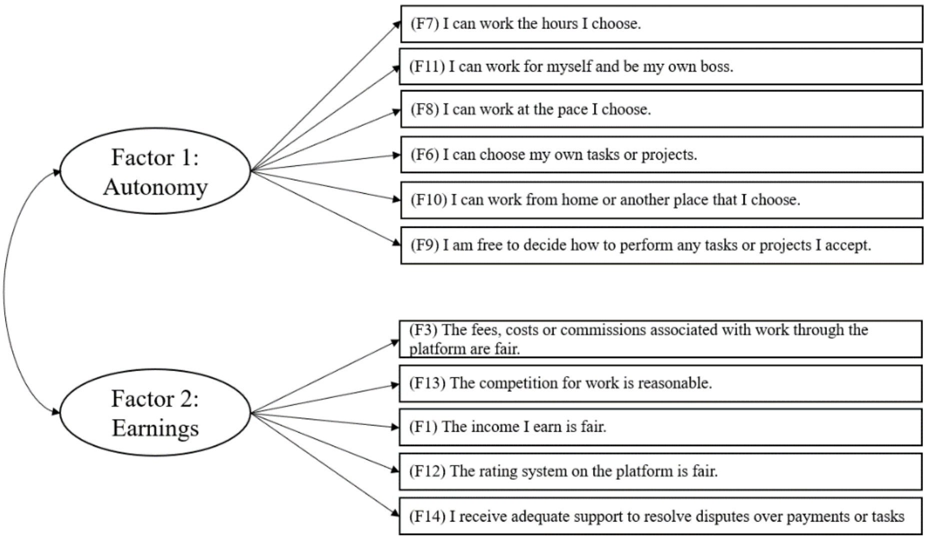

Figure 4. Factor structure of the reduced set of 11 variables

The rotated factor matrix for the remaining variables is shown in Appendix D. Each of the remaining variables has a loading above .60, ensuring practical significance (Hair, 2019), and are reasonable indicators of the respective latent factors. Factor 1 *Autonomy* accounts for six variables, while Factor 2 *Earnings* represents five variables. Factor 1, with an eigenvalue of 5.380, individually captured the most proportion of variance 44.818%. Factor 2, with an eigenvalue of 5.380, explained 9.852% of the variance. In total, these factors explained 54.67% of the variance, providing support for sufficient convergent validity (Mat Roni & Djajadikerta, 2021). Thus, the reduced set of 11 variables relating to worker perceptions of platform functions collectively represents overall fairness perceptions.

4.1.3 Confirmatory factor analysis

The CFA showed good model fit, adding further support to the hypothesised model. Table 6 includes the selected fit statistics from the CFA output. To assess the model fit, the guidelines for acceptable overall fit recommended by Hu and Bentler (1999) were applied, including CFI and TLI values close to .95 or above; SRMR values close to .08 or below; and RMSEA values close to .06 or below. The model CFI and TLI values of .969 and .961, respectively, fell within the range of good fit. Similarly, the SRMR value of .037 and RMSEA value of .053 were also within the range of good fit. Collectively, the majority of the fit indices suggested that the CFA model provided a reasonably good fit. Therefore, it was suitable to proceed to further examination of the model results.

Table 6: CFA fit statistics

Fit Index	**Value**
Chi-square (χ^2)	149.999
Degrees of freedom (*df*)	43
p-value	< .001
Comparative Fit Index (CFI)	.969
Tucker-Lewis Index (TLI)	.961
Standardised Root Mean Square Residual (SRMR)	.037
Root Mean Square Error Of Approximation (RMSEA)	.053

The standardised factor loadings (or regression weights) for the CFA model were observed, using Comrey and Lee's (1992) recommendations: >. 71 = excellent, >.63 = very good, >.55 = good, >.45 = fair, and >.32 = poor. These guidelines are consistent with those suggested by (Hair, 2019), that standardised factor loadings should be at least .50, and ideally .70 or above. Figure 5 shows that the standardised loading estimates range from .59 to .73, linking autonomy to variables F6, F7, F8, F9, F10, and F11. For earnings, the standardised loading values obtained range from .67 to .75, linking to variables F1, F3, F12, F13, and F14. All standardised loading estimates exceeded the .50 recommendation, providing further support for the convergent validity of the model.

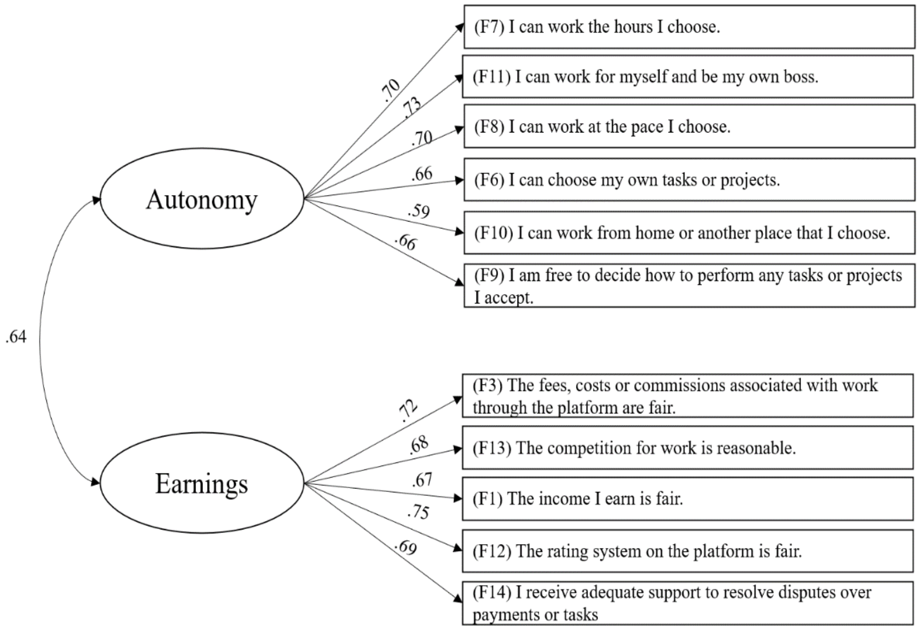

Figure 5. Factor analytic representations of the relationships between each measured variable and the underlying constructs

The means, standard deviations, and correlations of the two factors are shown in Table 7. Cronbach's alpha for the *autonomy* scale and *earnings* scale were both .83, which exceeded the .70 threshold, indicating adequate internal reliability (Lance et al., 2006). *Autonomy* and *earnings* were moderately and positively correlated, $r = .53$, $p < .001$. This correlation fell within the acceptable range for use in MANOVA (see section 4.3) (Hair, 2019).

Table 7: Scale statistics and correlation between Earnings and Autonomy

Scale	**Mean**	***SD***	***α***	Earnings
Autonomy	3.80	.72	.83	.53*
Earnings	3.39	.78	.83	

*$p < .001$

4.2 PAIRED SAMPLES *T*-TEST

Research question 1 asked what features of platform work are considered fair by workers. A paired samples *t*-test with an α of .05 was used to examine mean differences in fairness perceptions of autonomy, $M = 3.80$, $SD = .72$; and fairness perceptions of earnings, $M = 3.39$, $SD = .78$. On average, perceived fairness of autonomy was .41[2] higher than perceived fairness of earnings. This difference was statistically significant, $t(887) = 16.78$, $p < .001$, and fairly large, Cohen's d = .73. Hence, current platform workers perceived greater fairness in relation to features of platform work associated with autonomy than earnings.

4.3 MULTIVARIATE ANALYSES

4.3.1 MANOVA

Research questions 2, 3, and 4 asked whether platform workers perceive fairness differently based on their gender, age, and type of platform work. Fairness perceptions in this study were comprised of perceived fairness of autonomy and perceived fairness of earnings. These questions were answered using MANOVA. Preliminary assumption testing was performed to check for outliners, homogeneity of variance-covariance matrices, and multicollinearity. Multivariate outliers were found in the data (based on maximum Mahalanobis Distances greater than the critical χ^2 value for $df = 2$ at $\alpha = .001$). They were however neglectable, indicated by Cook's Distances less than 1 (Allen et al., 2019). The homogeneity of variance-covariance assumption was tenable as noted by statistically non-significant Box's M ($F(33, 528197) = 1.46$, $p = .04$) and Levene's test for both dependent variables, namely autonomy and earnings, (p's > .05). The preference of a MANOVA over a series of univariate tests was supported by the moderate correlation between autonomy and earnings ($r = .53$, $p < .001$). This correlation fell within the acceptable range for use in MANOVA (Hair, 2019; Tabachnick et al., 2019). The remaining assumptions of MANOVA, such as independence, cell sizes, and linearity, were met. These findings provided support for the robustness of the multivariate test statistics. Table 8 provides a summary of the group profiles on each of fairness perception outcomes across groups of gender, age, and type of platform work.

[2] On a 1-5 scale

Table 8: Descriptive statistics of fairness perception measures (autonomy and earnings) for groups based on gender, age, and type of platform work.

	Fairness perception measures	**Mean**	**SD**	**N**
Male	Autonomy	3.777	.728	580
	Earnings	3.363	.806	580
Female	Autonomy	3.850	.711	308
	Earnings	3.444	.723	308
Younger	Autonomy	3.791	.702	469
	Earnings	3.393	.775	469
Older	Autonomy	3.816	.746	419
	Earnings	3.390	.784	419
In-person work	Autonomy	3.812	.693	377
	Earnings	3.374	.768	377
Internet-based work	Autonomy	3.836	.721	270
	Earnings	3.325	.783	270
Both	Autonomy	3.750	.769	241
	Earnings	3.493	.785	241

Hypothesis 1 stated that type of platform work will have a significant differential effect on workers' perceived fairness of platform work features. The MANOVA showed a significant main effect of *type of platform work* (Pillai's trace = .017, $F(4, 1758) = 3.77$, $p < .01$, partial $\eta^2 = .009$), indicating statistically significant differences in overall fairness perceptions based on type of platform work classifications (i.e., in-person, internet-based, and both). Hypothesis 1 was therefore supported.

Hypothesis 2a proposed that female platform workers will have less positive fairness perceptions of platform work features than male platform workers. Hypothesis 2b stated that the effect of gender on platform workers' fairness perceptions is moderated by the type of platform work. For Hypothesis 2b, the interaction effect between *gender* and *type of platform work* was tested. Neither the main effect of *gender* on *overall fairness perceptions* (Pillai's trace = .002, $F(2, 878) = .95$, $p = .387$, partial $\eta^2 = .002$), nor the interaction effect between *gender* and *type of platform work* (Pillai's trace = .006, $F(4, 1758) = 1.30$, $p = .268$, partial $\eta^2 = .003$) was significant. Results indicated that platform workers do not perceive fairness differently based on gender. Therefore, Hypothesis 2a and Hypothesis 2b were not supported.

Hypothesis 3a stated that older platform workers will have less positive fairness perceptions of platform work features than younger platform workers. Hypothesis 3b proposed that the effect of age on platform workers' fairness perceptions is moderated by the type of platform work. For Hypothesis 3b, the interaction effect between *age* and *type of platform work* was tested. There was no main statistically significant relation between *age* and *overall fairness perceptions* (Pillai's trace =.000, $F(2, 878) = .052$, $p = .949$, partial $\eta^2 = .000$), suggesting no differences with respect to overall fairness perceptions among platform workers based on age. The MANOVA showed no statistically significant interaction effect between *age* and *type of platform work* (Pillai's trace = .002, $F(4, 1758) = .511$, $p = .728$, partial $\eta^2 = .001$). Thus, Hypothesis 3b and Hypothesis 3b were not supported.

In summary, the nonsignificant interaction terms supported the independent effect of type of platform work on workers' overall perceived fairness on digital labour platforms. Overall fairness perceptions of platform workers differed by type of platform work, but not gender or age.

4.3.2 Post hoc DDA

As only the main effect of type of platform work on overall fairness perceptions was significant, DDA was performed accordingly. Two discriminant functions were obtained when examining type of platform work classifications with respect to overall fairness perceptions. Function 1 in this analysis explained a statistically significant amount of variance in this analysis ($p < .01$), while Function 2 did not ($p = .990$). The second function, therefore, was excluded from subsequent analysis. For Function 1, there was a small canonical correlation ($R_c = .136$) with an effect size of $R_c^2 = 1.8\%$. This result indicated that the grouping variable (i.e., type of platform work) accounted for approximately 1.8% of the variance in the composite dependent variable (i.e., overall fairness perceptions linearly created by combining autonomy and earnings) (Wilk's lambda = .981, $\chi^2\,(4) = 16.551$, $p < .01$). The results of the DDA produced comparable results to the MANOVA for type of platform work. Although the effect of group membership based on type of platform work was small, the role of specific dependent variables in the observed differences was examined.

Standardised discriminant function coefficients and structure coefficients for Function 1 (Table 9) were examined to determine which dependent variables (i.e., autonomy and earnings) contributed to the differences in overall fairness perceptions between groups based on type of platform work. Analysis of the coefficients indicated that both autonomy and earnings had an equally strong influence in discriminating the three groups (i.e., in-person, internet-based, and both types of work). Earnings was the more dominant contributor to group differences, accounting for 37% of the variance in the composite. Autonomy played a lesser role in differentiating between the three groups, accounting for 12% of the variance. Earnings was negatively related to autonomy, suggesting that the group differences were explained by the difference between the perceived fairness of autonomy and the perceived fairness of earnings. Given the higher correlation between the earnings variable and the function ($r_s = .61$), a desire for parsimony may lead to an interpretation that only earnings really mattered. That is, differences among type of platform work classifications with respect to overall fairness perceptions were primarily a product of differences in perceived fairness of earnings.

Table 9: Standardised discriminant function coefficients, structure coefficients, and squared structured coefficients for each dependent variable

Dependent Variable	**Standardised coefficient**	r_s	r_s^2
Autonomy	-.93	-.34	.12
Earnings	1.11	.61	.37

r_s = structure coefficients; r_s^2 = squared structure coefficients

Group differences were assessed via group centroids (Table 10). The group centroid for the category *both* (i.e., the group comprised of platform workers doing both in-person and internet-based work) was higher than the two other groups. This indicated that the group differences observed on Function 1 pertaining to perceptions of fairness in autonomy and earnings could be attributed to platform workers doing both types of platform work. Comparing this to the structure coefficients in Table 9, platform workers who engaged in both types of platform work perceived higher fairness of earnings and lower fairness of autonomy than in-person platform workers. This finding was even more pronounced when workers engaged in both types of platform work were compared with internet-based platform workers.

Table 10: Mean of discriminant function scores within a group or Group centroids

Group	**Group centroids**	**SD**	**95% CI**	
			Lower	**Upper**
In-person work	-.04	1.00	-.14	.06
Internet-based work	-.14	1.06	-.27	-.01
Both	.21	.92	.10	.33

SD = Standard deviations of each group on the composite dependent variable; CI = Confidence interval

4.3.3 One-way analysis of variance (ANOVA)

As there were three groups based on type of platform work, the Bonferroni post hoc test via a one-way ANOVA was employed to investigate the difference between the group centroids, based on the guidelines of Barton et al. (2016). The one-way ANOVA was conducted with type of platform work as the independent variable and the saved discriminate functions score from Function 1 as the dependent variable. The results indicated that the in-person group (Mean = -.04) and the internet-based group (Mean = -.14) did not differ statistically (p = .60). That is, in terms of perceptions of fairness in autonomy and earnings, in-person platform workers were similar to internet-based platform workers. The group centroid for workers who engage in both types of platform work (‘both’) (Mean = .21) was higher and statistically differed from those of in-person workers ($p < .01$) and internet-based workers ($p < .001$). These results indicate that the increase in the perceived fairness of earnings and decrease in the perceived fairness of autonomy are significant when workers are engaged in both types of platform work. The changes in perceptions of fairness associated with the platform work features are not significant for those undertaking only one type of work, either in-person or internet-based work. Cohen’s *d* effect sizes were calculated for the post hoc mean comparisons, using the centroids and the standard deviations for each group provided by the ANOVA results (Henson, 2006). These effects were $d = .10$, .26, .35, for the in-person versus internet-based, ‘both’ versus in-person, ‘both’ versus internet-based, respectively.

In summary, the study resulted in two latent factors, labelled *autonomy* and *earnings*, which encompass major features of platform work and collectively represent overall fairness perceptions on digital labour platforms. The results showed platform workers perceive higher levels of fairness in autonomy than earnings, indicating that workers hold different views of each of these features. In addition, platform workers were found to perceive fairness differently based on their type of platform work, namely in-person, internet-based, or both types of work, instead of gender and age. These results indicate that workers engaged in this form of work tend to hold similar perceptions of fairness, regardless of their gender and age, and that different ways of undertaking digitally-mediated work matter in terms of workers’ fairness perceptions. Workers who indicated that they do both in-person and internet-based platform work perceive higher fairness, compared to their counterparts who do only one type of work. Specifically, when undertaking both types of platform work, workers tend to have higher perceived fairness of earnings, but lower perceived fairness of autonomy, than those engaged in solely in-person or internet-based work. These results indicate that those doing both types of platform work are likely to do more work and hours, thus perceiving less fairness in autonomy, in order to earn an amount of income that they consider as fair.

Chapter 5: Discussion and Conclusion

The aim of this study was to investigate worker perceptions of fairness on digital labour platforms, and to examine the impact of three factors – gender, age, and type of platform work – on platform workers' fairness perceptions. Research addressing the experiences of work via digital labour platforms is expanding rapidly. Platform workers are not employees who are entitled to labour protections and benefits, nor do they operate as independent contractors or freelancers (Harris & Krueger, 2015; Josserand & Kaine, 2019), who are genuinely entrepreneurial and enjoy autonomy in their work. Work is managed by an intermediary digital platform, which differentiates platform workers from other contingent labourers (Duggan et al., 2020). While this form of work represents work opportunities for the underemployed or unemployed, it has been subject to critique in the literature for platforms' unfavourable treatment of workers and perceived role in forging labour precarity and exploitation (Tan et al., 2021).

The exponential growth of platform-mediated work creates the need for a better understanding of the perceived fairness associated with platform work features. While fairness perceptions in traditional employment settings have been long investigated and are well documented (e.g., Colquitt et al., 2001; Cropanzano et al., 2007; Cropanzano & Ambrose, 2015), there is much less information about perceived fairness in the platform work context. This study contributes to the growing area of research on the gig economy and digital labour platforms by applying organisational justice theory to investigate platform worker perceptions of fairness. The study utilised data from 888 current platform workers collected via a 2019 nationally representative survey on digital platform work in Australia (McDonald et al., 2019) in order to address *How do workers perceive fairness on digital labour platforms?* In particular, the study set out to answer the following sub-questions:

RQ1: To what extent do platform workers perceive features of the work, such as income derived from platform work, as fair?

RQ2: Do platform workers perceive fairness differently based on their gender, age, or type of platform work?

RQ3: Is there an interaction effect between type of platform work and gender on platform workers' fairness perceptions?

RQ4: Is there an interaction effect between type of platform work and age on platform workers' fairness perceptions?

Analysis of the data was performed using factor analysis, paired sample *t*-test, multivariate analyses, and post hoc comparisons, as described in Chapter 4. The factor analysis of the 14 variables obtained from the National Survey (see Table 3) resulted in the identification of two factors related to the features of platform work – *autonomy* and *earnings*– which represent distributive and procedural justice in platform work settings. Platform worker perceptions of fairness in autonomy and earnings were analysed (section 4.2), followed by an in-depth analysis of the effect of gender, age, and type of platform work on platform workers' fairness perceptions (section 4.3).

This chapter presents a comprehensive discussion of the findings of this study. Section 5.1 discusses the findings related to the key platform work features that emerged from the data – *autonomy* and *earnings* – which encompass distributive and procedural justice in platform work. In section 5.2, findings that address RQ1, which asked *the extent to which platform workers perceive autonomy and earnings as fair*, are discussed. A detailed account of findings in relation to RQs 2-4 which addressed *the effect of gender, age, and type of platform work on fairness perceptions in platform work,* is presented in section 5.3. Theoretical and practical implications of the findings overall are discussed in section 5.4. In section 5.5, the main limitations of the study are acknowledged, followed by suggestions for future research. The final section (section 5.6) provides an overarching conclusion.

5.1 DISTRIBUTIVE AND PROCEDURAL JUSTICE IN PLATFORM WORK – AUTONOMY AND EARNINGS

The rise of digital labour platforms, empowered by innovations in online technology, has directed scholarly attention to investigating worker motivation for participation in platform work (e.g., Barnes et al., 2015; McDonald et al., 2019; Pesole et al., 2018) and job quality in this form of work (e.g., Dunn, 2020; Goods et al., 2019; Wood et al., 2019). Such studies assist in contextualising issues surrounding the fairness of platform work features. Prior research has identified autonomy and earnings as key motivators for individuals to engage in platform work (Churchill et al., 2019;

McDonald et al., 2019). While research on job quality in platform work is still in its infancy, it offers important insights into the central features of platform work, such as income earned and the degree of autonomy experienced by workers. Kalleberg and Dunn (2016), for instance, discussed the quality of jobs on digital labour platforms in terms of control over workers and financial compensation. They argue that platform work differs in the amount of control exercised by the platforms and the income that workers can earn. Qualitative studies in particular (e.g., Dunn, 2020; Goods et al., 2019; Myhill et al., 2021; Wood et al., 2019) have begun to uncover the lived experience of platform workers. Dunn (2020), for example, found that workers on platforms with low barriers to entry, such as ridesharing platforms, experience low wages and high degrees of control exerted by platform operators. In a quantitative study of perceptions of working conditions on crowdworking platforms in Germany, Durward et al. (2020) showed that workers in platform work settings associate adequate financial remuneration and autonomy with fulfilling working conditions. These studies suggest the important role of earnings and autonomy in shaping worker assessment of platform work. The salience of earnings and autonomy in decision-making has also been highlighted in research on platform policies and procedures in relation to algorithmic management. Studies suggest platform workers experience concerns about distributive justice issues (i.e., the fairness of their financial outcomes, Colquitt, 2001; Greenberg, 2011) and procedural justice issues (i.e., the fairness of the processes used by the platform to determine the respective outcomes, Colquitt et al., 2005; Folger & Konovsky, 1989; Tyler, 1987).

Extending this work, the current study applied organisational justice theory to investigate worker perceptions of fairness on digital labour platforms via a large quantitative survey. Using factor analysis, as presented in section 4.1, the findings revealed a two-factor structure for 11 out of the original 14 variables (see Table 3). Factor 1, labelled *Autonomy*, was characterised by 6 variables that represent the extent to which platform workers can control or make decisions about their work processes, such as what tasks to undertake, how long to work, and where to work. Factor 2, labelled *Earnings*, comprised 5 variables representing platform features, such as the competition for work through the platform and the fees, costs or commissions associated with the work. These features influence the amount of income platform workers can earn. Table 11 summarises this factor structure.

Table 11: Summary of Autonomy and Earnings factor structure[3]

Factor 1: Autonomy	(F7) I can work the hours I choose.
	(F11) I can work for myself and be my own boss.
	(F8) I can work at the pace I choose.
	(F6) I can choose my own tasks or projects.
	(F10) I can work from home or another place that I choose.
	(F9) I am free to decide how to perform any tasks or projects I accept.
Factor 2: Earnings	(F3) The fees, costs or commissions associated with work through the platform are fair.
	(F13) The competition for work is reasonable.
	(F1) The income I earn is fair.
	(F12) The rating system on the platform is fair.
	(F14) I receive adequate support to resolve disputes over payments or tasks.

A moderate correlation (*r* = .53) was found between *autonomy* and *earnings*. There are two likely causes for this observed correlation.

Autonomy and *earnings* in platform work may be functionally the same in relation to organisational justice. This perspective is consistent with Cropanzano and Ambrose's (2001) view of distributive justice and procedural justice, which emphasises the blurring effects between these two justice dimensions. Distributive justice (i.e., fairness perceptions of the outcomes) and procedural justice (i.e., fairness perceptions of the processes leading to the outcomes) are often conflated by workers (Ambrose & Arnaud, 2005). In the platform work context, both autonomy and earnings might constitute distributive justice – an end in themselves (i.e., benefits granted to workers) through a decision-making procedure that is algorithmically shaped and controlled by platforms (e.g., monitoring and performance management). For instance,

[3] Three variables that were excluded from further analysis were: (F2) *I have the ability to set the price for my services*; (F4) *I can find regular work through the platform*; (F15) *The health and safety conditions are adequate* (see section 4.1.2 for an in-depth discussion)

variable (F8), *I can work at the pace I choose,* with a high loading of .746 on *autonomy* exemplifies a worker outcome (i.e., how workers do their work), which is largely administered by algorithmic scheduling on platforms. Similarly, variable F12, *The rating system on the platform is fair,* loads highly on *earnings* (loading = .686), indicating the influence of algorithmic performance management on worker compensations. Alternatively, *autonomy* and *earnings* might be considered by workers as a means to an end - a procedure that serves economic and/or socioemotional benefits (Cropanzano & Ambrose, 2001). Workers may consider platform-based earnings as a function of algorithmic compensation procedures by which their economic needs are fulfilled. Likewise, autonomy in platform work might produce a procedural (un)justice, namely platform workers' voice or control (or lack thereof) in the labour process, producing economic and socioemotional outcomes (Cropanzano & Ambrose, 2001). For example, platform workers' perceived autonomy in the determination of schedules, such as when and how long to undertake work, is related to worker voice or participation in setting the terms or influencing the outcomes of the labour arrangements (Lind et al., 1990; Thibaut & Walker, 1975), thus representing a procedural determinant of fairness in platform work.

The observed correlation between *autonomy* and *earnings* in this study also suggests that they are substitutable. According to Lind's (2001) fairness heuristic theory, individuals assimilate different types of fairness-relevant information in a given context to form overall judgements of fairness. This theory proposes that different types of fairness substitute for one another when informing overall fairness perceptions. The substitutability effect occurs in the absence of information. That is, people use any available salient information about a situation to formulate a general impression of how fair the situation is. An investigation into the experiences of platform workers in Australia highlighted the obscure nature of complex and invisible algorithms, which in turn affect workers' autonomy and earnings (McDonald et al., 2019). Coupled with the obscurity of the means of platform control, is the temporal nature of this form of work, which can be characterised by high degrees of volatility in customer demand and fluidity between work and non-work time, especially in the case of in-person platform work (Mäntymäki et al., 2019). This temporality may complicate workers' calculation of earnings derived from platform work (Laursen et al., 2021; McDonald et al., 2019). Given the obscurity of platform work features, the substitutability of different fairness types described by Lind (2001) may help explain the relationship between autonomy and earnings observed.

It could be speculated that information related to autonomy may substitute for information related to earnings, or vice versa, in determining overall fairness perceptions. Platform workers are likely to process information heuristically. They rely on, for instance, the information that is known to them (e.g., the hours or the tasks that they work) to substitute for incomplete information (e.g., when they do not know others' income relative to their own) when assessing the fairness of their work. Similarly, when they find it difficult to interpret platform control mechanisms, such as scheduling and ratings, which affect the levels of flexibility and autonomy (e.g., when and at which pace a given task is to be done) they have over the labour process, they may form their fairness perceptions largely on the basis of compensation-related information (e.g., hourly pay rates for the task).

In summary, the study identified two factors that encompass the primary features of work on digital labour platforms. These factors, labelled *autonomy* and *earnings*, constituted 11 variables in total (see Appendix D), derived from the National Survey, which measure current platform workers' perceptions of the platform functions. Thus, *autonomy* and *earnings* represent important elements of organisational justice in platform work settings. The moderately strong correlation between *autonomy* and *earnings* could be attributed to the blurring effect (Cropanzano & Ambrose, 2001) or the substitutability effect (Lind, 2001) between the two factors. The extent to which platform workers perceive autonomy and earnings of their work as fair is discussed in the next section.

5.2 THE EXTENT TO WHICH PLATFORM WORKERS PERCEIVE AUTONOMY AND EARNINGS AS FAIR

RQ1: To what extent do platform workers perceive features of the work, such as income derived from platform work, as fair?

Despite a moderate correlation between autonomy and earnings, platform workers held different perceptions about the fairness of these features of platform work, with autonomy being considered more fair than earnings. These findings support other evidence from the National Survey results which analysed a separate set of questions regarding worker satisfaction and found that current platform workers were most satisfied with autonomy (e.g., the ability to choose the hours they worked), but less satisfied with earnings potentials on platforms (e.g., fairness of fees and costs, earning a fair income, fairness of rating system) (McDonald et al., 2019). The findings also provide support for prior research demonstrating platform workers express a positive sense of autonomy and flexibility (e.g., D'Cruz & Noronha, 2016; Goods et al., 2019), but at the same time, express perceptions of the precarity of earnings (e.g., Bertolini et al., 2021; Mandl, 2020). The following sections offer some possible explanations for these results.

5.2.1 Perceptions of fairness in autonomy through platform work

Higher perceptions of fairness in relation to autonomy are consistent with workers' favourable views of flexibility and autonomy reported in previous research. Recent studies of app-based platforms such as Deliveroo and Uber in Australia and Scotland found that the workers considered autonomy as an advantage of their work (Goods et al., 2019; Myhill et al., 2021). Similarly, in a study of internet-based workers in Southeast Asian and Sub-Saharan African countries, Wood et al. (2019) argued that platform algorithmic control mechanisms provide workers with significant levels of autonomy and discretion over the temporal and spatial aspects of their work. Wood et al.'s argument echoes earlier research, such as D'Cruz and Noronha's (2016) study of Elance-oDesk (now known as Upwork) workers in India, which showed many workers viewed flexibility on the platform as a positive aspect of their work, and that they supported algorithmic monitoring procedures because it safeguarded them from non-payment. Although previous studies have highlighted the role of algorithmic control in limiting workers from exercising flexibility and autonomy (see section 2.1.1), the optimistic experiences and views of autonomy reported in Wood et al.'s (2019) and D'Cruz and Noronha's (2016) studies may be explained by the characteristics of the targeted samples of workers. Compared to platform workers who live in developed economies, workers in lower- and middle-income countries are likely to face worse career prospects, poorer local working conditions, and greater risks of unemployment and poverty (D'Cruz & Noronha, 2016; Wood et al., 2019). Put another way, platform workers who express favourable views of flexibility and autonomy tend to be vulnerable in their respective local labour market. The sample of platform workers used in the current study comprised more individuals who were students or unemployed and thus likely to be vulnerable in the labour market, and fewer people with other sources of income (i.e., employed or self-employed) (McDonald et al., 2019). Hence, the higher levels of fairness in relation to autonomy observed in the current study may be linked with the workers' labour force status. Platform workers with fewer labour alternatives may be instrumentally motivated by opportunities to earn in platform work for additional income, thus subjectively consider autonomy in this form of work as more fair, despite evidence to suggest they have limited autonomy over their work.

In addition, positively perceived autonomy in the current study may partly be explained by 'softer' forms of workplace control and surveillance (Rosenblat & Stark, 2016; Shapiro, 2018), the intricacies of which platform workers may be unaware. The complexity of platform algorithms and rules signifies the "asymmetric information in the working relationship" between the platform and the worker (Duggan et al., 2020, p. 120), hindering accurate assessments of fairness. Since the structure and management approaches vary across platforms, the levels of autonomy required by and afforded to workers on different platforms vary. Workers may find platform work acceptable to them as it provides the "autonomy to make minute decisions", such as when to work and whether to accept or decline a job (Shapiro, 2018, p. 2965). Goods et al. (2019) described this as a lower form of autonomy, which is more visible to workers. The finding of the current study resonates with observations by Goods et al. (2019) and Myhill et al. (2021), who highlighted the prevalence of individual factors and priorities that shape worker experience and perception of autonomy and control in platform work. Platform work provides workers with short-term temporary work opportunities with purportedly flexible schedules, allowing them to adapt their work to personal circumstances and other commitments such as study. With some flexibility in terms of what, where, and when to work, workers may feel an inflated sense of control over work processes (Spreitzer et al., 2017).

Although the data is unable to confirm this possibility, the more positive fairness of autonomy perceived by platform workers in the current study could also be attributed to an ability to circumvent platform algorithms and rules, and hence retain some autonomy. For example, Wood et al. (2019) provided worker accounts of bypassing the platform's monitoring system by setting up "two screens, I'm watching YouTube while I'm working on the platform…because the screenshot is only for the main [monitor]" (p. 64). Similarly, Jarrahi and Sutherland (2019) found that workers on Upwork substituted the platform messenger with alternative communication and information-sharing tools when working with clients to avoid the platform surveilling conversations. Likewise, Chen (2018) reported the tools leveraged by Didi taxi drivers, including using bot apps or registering their vehicles on multiple devices to manipulate ride-service requests, comparing multiple ride requests and selecting those with the highest fare.

A comparison of this study's findings with those of previous studies confirms that workers on digital labour platforms tend to have a more positive experience and view of autonomy. These findings shed some light on worker motivations for participating in platform work regardless of the objective view on unfairness associated with this form of work. Autonomy through platform work, as shown by the results of this study, consists of workers' ability to make decisions about various aspects of their work on platforms, such as the hours and pace of work. This study adds to growing scholarship on the experience of workers on digital labour platforms, but more importantly, reveals novel insights into platform worker perceptions of fairness regarding autonomy. Despite the finding regarding platform workers' positive fairness perceptions of autonomy, their perceived fairness in earnings was less optimistic.

5.2.2 Perceptions of fairness in earnings through platform work

Compared to autonomy, platform workers indicated lower perceptions of fairness in earnings. This finding may be explained by the fact that earnings through platform work are often low, which is consistently reported in prior studies. Data from the National Survey on digital platform work in Australia showed that many current platform workers earn low wages, with some workers in clerical, data entry, or writing and translation roles likely to earn below $10 per hour. Hourly rates varied from below $10 per hour to more than $100 per hour, but many current platform workers (40%) did not know what they earned (McDonald et al., 2019). Responses to open-ended questions in the National Survey (McDonald et al., 2019, p. 61) further confirm workers' dissatisfaction with earnings derived from platform work, as does a recent report by the Fairwork project which investigated the working conditions of platform workers in the United Kingdom across the ride-hailing, food delivery, courier, and domestic services sectors. The report found many workers were earning below the hourly minimum wage after one hour of work and were not guaranteed to receive at least a living wage after accounting for work-related costs (Bertolini et al., 2021). Similarly, Standford (2018) underscored an alarmingly low estimate of the net hourly rate received by Uber drivers in Australia. Based on his calculation, the average hourly net income for Uber drivers, after subtracting Uber's commission, unpaid waiting time, and all expenses associated with the vehicle, was $14.62, which is below the Australian minimum wage ($18.29 per hour, at the time of the study).

Previous studies of single platforms also provide evidence that low incomes are common among workers across different types of platform work. D'Cruz and Noronha's (2016) analysis of workers on Upwork, for example, noted that workers perceived a downward pressure on their compensation in the bidding process. That is, to improve their chances of getting work, workers may have to pay a premium account fee or offer clients lower pay rates to remain competitive (D'Cruz & Noronha, 2016), which in turn reduces workers' overall earnings. Negative earning experiences were also revealed in a study by Anwar and Graham (2020) who investigated platform-based freelancers in Africa. The authors suggested that workers are under-compensated, taking home only a small portion of the revenue generated from their work. Workers providing location-based services also earn low wages. For many Uber drivers based in Canada, for instance, working on the platform does not generate a decent income due to high operating costs (Peticca-Harris et al., 2020), which is similar to findings from Standford's study of Uber drivers in Australia. It is unsurprising, therefore, that respondents in the current study indicated less favourable fairness perceptions relating to earnings through platform work.

The lower fairness of earnings perceptions of platform workers found in the current study can also be explained in part by unpaid working time. Unpaid working time on digital labour platforms typically involves time spent on training, travelling between jobs (Bertolini et al., 2021), bidding for work, or updating profiles (McDonald et al., 2019). Common in location-based services is unpaid waiting time for the next assignment, which can be lengthy during off-peak periods or low-traffic areas (Standford, 2018). Unpaid overtime doing preparative tasks was found to be the prominent factor contributing to the low hourly pay among crowdworkers (Berg, 2016). As reported in the Australian National Survey, while almost half of the current platform workers were not aware of the exact amount of time they spent on uncompensated work (McDonald et al., 2019), it seems likely that unpaid time would negatively impact their perceptions of fairness in earnings.

Low income on digital labour platforms may be further exacerbated by competition from increasing numbers of platform workers. As noted by, for example, D'Cruz and Noronha (2016) and Goods et al. (2019), work on digital platforms is undertaken in a competitive environment where workers are expendable. Thus, platform workers may, reluctantly or willingly, settle for lower pay rates. Furthermore, workers' ability to obtain a sufficient volume of work is largely constrained by the platform algorithms over which workers have little influence. Availability of work through digital platforms is highly contingent on customer demand and other performance metrics (see for example Rosenblat & Stark, 2016; Williams et al., 2020), resulting in unreliable income for platform workers (Bertolini et al., 2021). The competition among workers on platforms, such as Uber, is described by Barratt et al. (2020, p. 1656) as "a negative-sum-game" in which a worker's gain in piece-rate earnings is equivalent to other workers' loss in terms of income and work opportunities. Part of the reason why platform workers in the current study have less favourable fairness perceptions of their earnings may be that high levels of competition and algorithmic management mechanisms, such as ratings on platforms, exert unreasonable and unfair influence over workers' earning prospects.

The findings of this study provide an important insight into the salient role of earnings in shaping platform workers' fairness perceptions. As mentioned in the literature review, individuals are largely drawn to platform work for flexibility and income-related reasons (e.g., McDonald et al., 2021; Pesole et al., 2018). Exploring task design and financial compensation in crowd work contexts, Durward et al. (2020) found that crowd workers care about, first and foremost, their financial compensation, suggesting the fundamental role of earnings in influencing worker perceptions of working conditions. For the workers in the current study, while flexibility and autonomy were important motivators, their key motivation for undertaking platform work was to earn supplementary income, as shown by the National Survey (McDonald et al., 2019). It appears that platform workers in the current study were more concerned about the income obtained from platform work than they were about the flexibility and autonomy afforded by the platform, and thus more sensitive to and critical of negative features affecting their pay.

In summary, this study found that workers on digital labour platforms perceive higher levels of fairness in relation to autonomy than earnings. These findings support previous research that shows some contrasting experiences and views of autonomy and earnings through platform work. That is, the levels of flexibility and autonomy workers have over their work are often perceived favourably. By contrast, wages and earning potential on digital labour platforms are often the target of less favourable sentiments among workers. In the following section, the effect of gender, age, and type of platform work on worker perceptions of fairness is discussed.

5.3 THE EFFECT OF GENDER, AGE, AND TYPE OF PLATFORM WORK ON FAIRNESS PERCEPTIONS IN PLATFORM WORK

This section is structured as first, a brief summary of the research questions and hypotheses, and second, a detailed discussion of the effect of gender, age, and type of platform work on fairness perceptions.

RQ2: Do platform workers perceive fairness differently based on their gender, age, and type of platform work?

With respect to RQ2, three hypotheses were made:

Hypothesis 1: Type of platform work will have a significant differential effect on workers' perceived fairness of platform work features.

Type of platform work (in-person, internet-based, or both) was expected to have a significant differential effect on worker perceptions of fairness associated with the features of platform work, given the heterogeneity of digital labour platforms discussed in prior research. It has been suggested that platforms vary in terms of the algorithmic mechanisms and strategies to coordinate, administer, and compensate workers. It has also been shown that not only the nature and complexity of tasks but also levels of autonomy and earnings vary across different types of platform work (Durward et al., 2016; de Groen et al., 2018; Florisson & Mandl, 2018; ILO, 2021; Sundararajan, 2016).

Hypothesis 1 was supported. The findings demonstrated a significant difference in that workers who were engaged in both in-person and internet-based platform work concurrently, expressed more favourable perceptions concerning the fairness of work, compared to those engaged in only one type of work.

Further analysis showed that higher fairness perceptions of earnings among platform workers doing both in-person and internet-based work contributed to their overall perceptions of fairness. Perceived fairness in autonomy however decreased when workers were doing both types of work (see Figure 6). The overall levels of fairness perceptions did not exhibit statistically significant differences between in-person workers and internet-based workers.

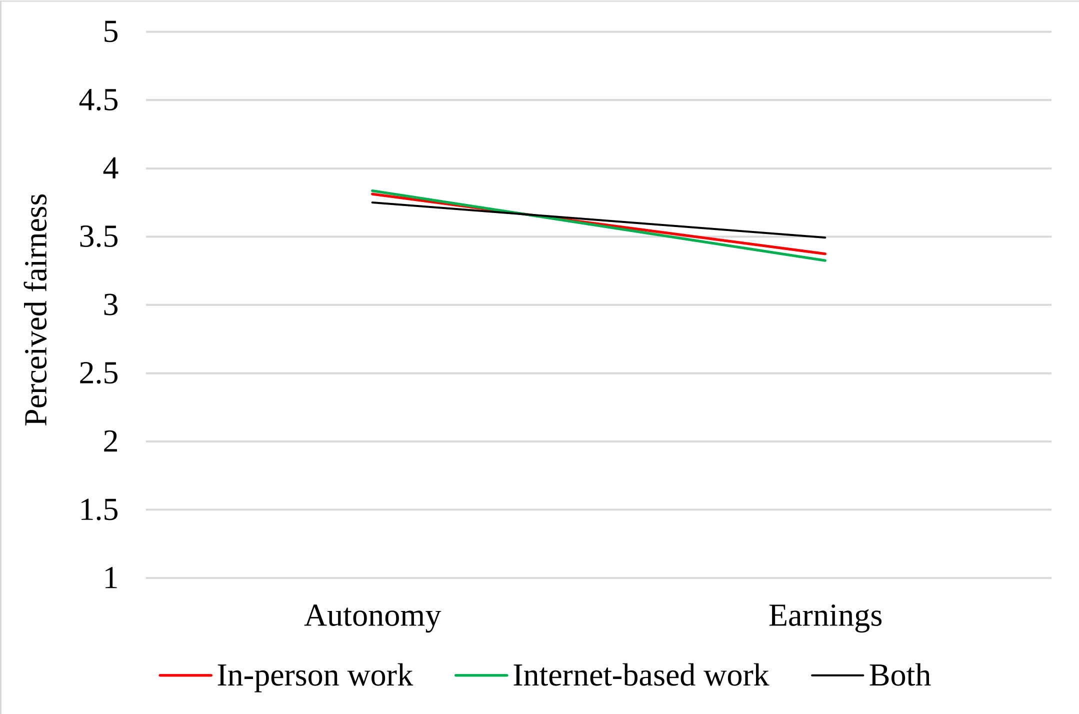

Figure 6. Perceived fairness in autonomy and earnings by type of platform work

Hypothesis 2a: Female platform workers will have less positive fairness perceptions of platform work features than male platform workers.

Female platform workers were expected to have less positive fairness perceptions, compared to male platform workers. This expectation was based on evidence that gender discrimination is pervasive in platform work. Women participating in platform work have been found to earn less on average than men (e.g., Adams & Berg, 2017; Aleksynska et al., 2021; Chen, 2018; Cook et al., 2021). Bias against women has also been demonstrated in hiring and performance evaluations on digital labour platforms, as evidenced in a study of online freelancing platforms, such as TaskRabbit and Fiverr (Hannák et al., 2017), Nubelo (Galperin, 2019) and ridesharing platforms (Greenwood et al., 2020).

Hypothesis 2a was not supported. The findings revealed that gender did not significantly affect platform workers' perceptions of fairness. Regardless of gender, workers responded similarly to questions about the fairness of platform work.

Hypothesis 3a: Older platform workers will have less positive fairness perceptions of platform work features than younger platform workers.

Older platform workers were expected to have lower fairness perceptions of platform work than younger platform workers. This hypothesis was based on prior research suggesting older workers tend to be less satisfied with platform work (O'Higgins & Caro, 2022) and that there are age-related differences in work attitudes and behaviour (e.g., Kooij et al., 2011). However, in a similar way to gender, age was not significantly influential on perceptions of fairness.

Hypothesis 3a was not supported. The findings showed that older and younger platform workers did not differ in their perceptions of fairness in relation to autonomy and earnings.

The remaining research questions in this study are:

RQ3: Is there an interaction effect between type of platform work and gender on platform workers' fairness perceptions?

RQ4: Is there an interaction effect between type of platform work and age on platform workers' fairness perceptions?

Two hypotheses were made in response to RQ3 and RQ4:

Hypothesis 2b: The effect of gender on platform workers' fairness perceptions is moderated by the type of platform work.

Hypothesis 3b: The effect of age on platform workers' fairness perceptions is moderated by the type of platform work.

Evidence on the effect of gender and age on fairness perceptions in the organisational justice literature is mixed. Prior research has suggested that differences in perceptions of fairness based on gender are linked to specific circumstances (Greenberg & Cohen, 1982). The current study, therefore, hypothesised that other factors, such as type of platform work, may operate alongside demographic attributes, such as gender or age, in their impacts on fairness perceptions.

Hypotheses 2b and 3b were not supported. The findings demonstrated that type of platform work did not moderate the main effect of gender or age on fairness perceptions.

The following sections provide a discussion about the main effect of type of platform work (section 5.3.1), gender (section 5.3.2), and age (section 5.3.3) on workers' fairness perceptions on digital labour platforms.

5.3.1 Type of platform work

Two main types of platform work have been identified in previous research: in-person work and internet-based work (De Stefano, 2016; de Groen et al., 2018; Florisson & Mandl, 2018). The former involves tasks that are locally performed whereas the latter entails tasks that are executed online or remotely (see section 1.3). In this study, three types of platform workers were examined: (1) in-person workers, (2) internet-based workers, and (3) both (i.e., workers who undertake both in-person and internet-based work).

An important finding of this study was that type of platform work influences platform workers' perceptions of fairness. In-person workers and internet-based workers indicated similar levels of fairness perceptions, although they are different from those doing both types of work in terms of their perceived fairness. However, workers who indicated they engaged in both in-person and internet-based work had higher overall perceptions of fairness than their counterparts who did only one type of work. However, due to the small effect size of type of platform work, these findings must be interpreted with caution. Differences in perceived fairness between individuals engaged in both types of platform work and those in one exclusively could be attributed to the perceived fairness in earnings. Taken together with earlier observations about workers being drawn to platform work primarily for income-related reasons and that they were concerned about earnings, it is possible that earnings was a salient factor in workers' overall perceptions of fairness.

When doing both types of platform work, workers are likely to be able to access more work opportunities, which might be lacking otherwise. The Australian National Survey (McDonald et al., 2019) showed that many workers work across multiple platforms at once and undertake both types of work simultaneously. Of the 1827 respondents who had undertaken platform work, 33.1% had, at some point, engaged in both in-person and internet-based types of work (McDonald et al., 2019). It would be expected that those who participate in both types of platform work may be performing more tasks or services and working more hours, and thus, be able to diversify their income streams. For example, some might provide not only highly skilled professional platform services but also micro jobs and possibly localised unskilled ride-hailing platform services (Pesole et al., 2018). It may also be the case that when operating simultaneously across in-person and internet-based platforms, workers become more experienced in navigating platform functions, such as algorithmic scheduling, or find ways to accumulate higher overall ratings/reputation scores (see section 2.1), enabling them to obtain more work opportunities. Workers who undertake both types of platform work may therefore be able to maximise their financial rewards, in turn shaping their perception of fairness in their aggregate earnings from platform work.

Participation in both types of platform work, however, was associated with a reduction in fairness perceptions of autonomy. The observed reduction in the perceived fairness of autonomy could be attributed to the inability to disconnect from work and to capitalise on the scheduling flexibility of platform work (Peticca-Harris et al., 2020). To earn an income that is believed to be fair, platform workers tend to put in more hours (Wood et al., 2019). Workers who undertake both types of work monitor multiple platforms and juggle multiple schedules. These workers possibly do more unpaid work, such as travelling between jobs, doing preparatory work, or spending more time bidding for jobs (Berg, 2016; Bertolini et al., 2021). Individuals who are engaged in both types of platform work may in theory have significant flexibility in scheduling their work, like any other workers doing either in-person or internet-based work. However, in practice, their participation in both types of work, whether it be borne out of choice or necessity, appears to undermine their freedom in work scheduling, which in turn could have contributed to their lower perceived fairness in autonomy.

In summary, this study demonstrated that workers undertaking both in-person and internet-based platform work concurrently perceived higher overall fairness, compared with those doing only one type of work. In particular, individuals engaged in both types of platform work had higher perceived fairness of earnings, but lower perceived fairness of autonomy than those doing either in-person work or internet-based work. While type of platform work was found to make a significant difference in workers' perceived fairness in autonomy and earnings through platform work, gender and age were not found to be influential factors.

5.3.2 Gender

Based on evidence of the gender earnings gap and biases against women in platform work (Cook et al., 2021; Greenwood et al., 2020), female platform workers were expected to have less favourable perceptions of fairness in relation to the platform work features examined in this study. Contrary to expectations, this study did not find any significant differences in platform workers' fairness perceptions by gender. The findings revealed that female and male platform workers have similar perceptions of fairness in the autonomy and earnings features of platforms. This accords with previous organisational justice studies conducted in traditional employment settings (Cohen-Charash & Spector, 2001; Nurse & Devonish, 2006; Werner & Ones, 2000), which showed no significant gender effect on fairness perceptions.

There are two possible explanations for this result. The similar fairness perceptions shared by women and men in this study may partly be explained by the gender segregations of the digital platform labour market, with several job categories male or female-dominated. As evidenced in the National Survey, women are more likely to work in traditionally female-dominated jobs, such as care work; while men are more likely to work in jobs that are predominantly male work settings, such as transport and food delivery (McDonald et al., 2019). According to distributive justice theory, individuals make a comparison between their own outcomes/inputs and those of referent others (Cropanzano et al., 2007). As men and women are concentrated in certain platform-based jobs, it seems possible that they might be using same-gender referent standards. Female platform workers in female-dominated jobs are likely to compare themselves to other women doing the same jobs, who might not be aware of gender-based differentiated treatment by the platforms. Comparisons with other women in the same occupation might conceal the presence of, if any, gender inequity, which in turn results in comparable, rather than divergent, overall perceptions of fairness. That fairness perceptions are similar for both genders on digital labour platforms may also be attributed to the frequency of engagement with digital platforms to seek or undertake work, which can be considered as a proxy for input or contribution (e.g., time, effort). Data from the National Survey confirms that women are less frequently engaged in platform work than men (McDonald et al., 2019). In light of distributive justice theory (Cropanzano et al., 2007), the lower frequency of engagement could lead to lower expected outcomes. It seems possible that female platform workers consider fairness in terms of the outcomes, such as pay or work opportunities, relative to their contributions. Due to their lower contribution in terms of engaging with platform work, they do not perceive an inequity of outcomes. More research is needed to understand why men and women in platform work settings do not differ in their overall perceived fairness, despite the objective gender differences on digital labour platforms.

5.3.3 Age

Similar to gender, age was expected to affect platform workers' fairness perceptions. It was hypothesised that older platform workers will have lower fairness perceptions of platform work features than younger platform workers, given evidence of age-related differences in work attitudes and behaviour (e.g., Kooij et al., 2011) and that older workers are less satisfied with work through platforms (O'Higgins & Caro, 2022). This study however found no significant difference in perceived fairness in platform-based autonomy and earnings between older and younger workers. This finding is contrary to previous studies in traditional employment relationships which have found that older workers have lower perceptions of fairness than younger workers (Ghasi et al., 2020; Paul, 2006). The finding however is consistent with Cohen-Charash and Spector's meta-analysis of organisational justice studies (2001), which showed no significant differences in fairness perceptions when analysed against age. Based on this finding, Cohen-Charash and Spector (2001) anticipated the interactive relationships between demographic variables, such as age, and other variables as predictors of perceived fairness. Thus, further research would be required to determine if this result is related to other factors, such as education level, which may interact with age in shaping the perceptions outcomes of interest. For example, the differences in fairness perceptions between older and younger platform workers may vary significantly only for those with a better education background. Older workers with higher education levels may have higher expectations and are more critical of platform practices and associated work features, and thus might have less favourable perceptions of fairness.

5.4 IMPLICATIONS

In summary, investigating the impact of gender, age, and type of platform work showed that platform worker perceptions of fairness in features of their work differ only based on their type of platform work. Specifically, those who are engaged in both in-person and internet-based work were found to have higher overall perceptions of fairness than their counterparts who undertake only one type of work. More importantly, the perceived fairness in earnings was shown to be a major contributing factor in the higher overall fairness perceptions. Participation in both in-person and internet-based work is likely to allow workers to increase their earning potential by, for example, undertaking more tasks and accruing experiences operating across platforms, which in turn promote a more positive sense of fairness in earnings. Doing so however suggests that workers tend to be simultaneously monitoring several platforms and performing several tasks/projects, including uncompensated work. Their flexibility and autonomy are likely to rely on and be tailored to the various tasks and schedules they are engaged with, thus lowering their perceived fairness in autonomy through platform work. The theoretical and practical implications of these findings are discussed in this section.

5.4.1 Theoretical implications

This study contributes to the growing area of research on the gig economy and digital labour platforms by applying organisational justice theory. The theoretical contributions are threefold. The first contribution relates to how workers perceive fairness on digital labour platforms. *Autonomy* and *earnings* represent major features of platform work that contribute to distributive and procedural justice on digital labour platforms. The evidence suggests that *autonomy* and *earnings* may be functionally similar or substitutable in relation to organisational justice since both of these factors are about outcomes or benefits (i.e., distributive justice) determined by algorithmic management procedures on platforms and/or functions of the algorithmic management procedures (i.e., procedural justice). In platform work settings, autonomy and earnings representing different justice-relevant information may substitute for each other through overall fairness perceptions. That is, platform workers may rely on available and salient information in place of insufficient information when forming a general assessment of fairness associated with the features of their work. The understanding of platform workers' overall fairness perceptions afforded by the results is important in a number of aspects.

This finding suggests components of organisational justice in the platform work context need not or perhaps cannot be separated. As argued by Ambrose and Arnaud (2005), individuals are unlikely to evaluate outcomes and procedures separately, with (un)fair outcomes perceived to be generated by (un)fair procedures. It is possible that platform workers base their fairness evaluations on the outcomes they are afforded (both autonomy and earnings) and/or the procedures they experience (e.g., algorithmic monitoring systems), and that workers considered their experience operating on digital labour platforms in general, using the information available to them. Given the possible blurring or substitutability effects between autonomy and earnings, it is less clear what features of platform work represent which organisational justice components. The complex relationship between autonomy and earnings through platform work do not map neatly onto existing theoretical frameworks of organisational justice.

Platform work is distinctive from traditional employment settings for which organisational justice theory was originally developed, in that it typically involves the use of algorithmic management to complement or replace human oversight (Duggan et al., 2020). Organisational justice in traditional employment relationships is largely premised on workers' justice perceptions in relation to a human manager. However, in platform work settings, work is algorithmically managed by, instead of a human manager, a platform with which workers interact (Duggan et al., 2020; Möhlmann & Zalmanson, 2017). The findings in this study support the view of the complex and nuanced experiences of workers undertaking platform work that differs substantially from traditional employment (Goods et al., 2019; Myhill et al., 2021). Thus, this study makes a major contribution to research on platform worker perceptions by showing that, while existing evidence suggests platform work is tightly managed and controlled, workers were found to have a positive view of the level of flexibility and autonomy in platform work. In addition, the study offers valuable insights into the role of earnings in shaping workers' fairness perceptions in platform work settings. Generating a supplementary income has been identified as a salient factor driving worker participation on digital labour platforms (Churchill & Craig, 2019; McDonald et al., 2019). The current study extends this research by showing that earnings play a fundamental role in influencing platform workers' perceptions of what constitutes fair work features. The results imply that, if workers can earn a fair amount of income, their overall perceptions of fairness are likely to be favourable.

This study has also raised an important question about the utility of applying interpersonal and informational justice types (Colquitt, 2001; Colquitt et al., 2001) to understand platform workers' fairness perceptions. While organisational justice can be similarly understood as workers' assessment of how they are treated by the organisation (Colquitt et al., 2005; Cropanzano & Ambrose, 2015), interpersonal and informational justice dimensions might not be relevant in the absence of platform workers' interactions with human managers. This study provided evidence that organisational justice may work differently in the context of platform work than in traditional employment settings, indicating the need for theoretical advancement.

The second contribution is concerned with type of platform work. The study demonstrated that type of platform work is an important factor to consider when assessing organisational justice. Given the rise in new, potentially more precarious modes of work, the evidence presented suggests that organisational justice may vary according to different ways of undertaking work. This finding complements those of earlier studies that show heterogeneity of work and working conditions, and varying worker characteristics, motivation, and experience across platforms and types of work (Dunn, 2020; de Groen et al., 2018; Fieseler et al., 2019; Schor, 2017). While a few studies have explored platform worker perceptions of fairness (Deng et al., 2016; Laursen et al., 2021; Pfeiffer & Kawalec, 2020), they focus on a specific type of platform work – internet-based work, or a small subset of location- and internet-based platforms. The current study analysed data collected on a wide range of different platforms across various work categories, such as transport and food delivery, caring, microtasking, and professional services. Therefore, it provides the first comprehensive investigation of platform workers' perceptions of fairness and a comparison of the perceived fairness among workers across different types of work.

5.4.2 Practical implications

A large body of evidence has demonstrated that fairness perceptions influence several important employee outcomes in traditional employment relationships, such as work performance (Cohen-Charash & Spector, 2001; Colquitt et al., 2001), job satisfaction, and turnover (Colquitt et al., 2001). In a more recent review of organisational justice literature, Fortin and colleagues (2014) reiterated the pivotal impact fairness perceptions have on workers' attitudes and behaviours. Similarly, investigations into the platform work context have suggested that perceived fairness is critical for workers' performance as well as ongoing engagement and participation (Faullant et al., 2017; Liu & Liu, 2019; Meng-Meng et al., 2020; Wu et al., 2021). The current study provides insights for advancing nascent research on worker perceptions in digitally-mediated work contexts, with a number of practical implications.

Worker perceptions of fairness on digital labour platforms are strongly influenced by their perceived fairness in earnings. Previous research has shown that fair monetary compensation led to higher work quality in online platform work settings (Litman et al., 2014), and that fairness perceptions drive worker engagement and participation (Faullant et al., 2017; Liu & Liu, 2019; Meng-Meng et al., 2020; Wu et al., 2021), which in turn are critical to the operations of digital labour platforms. Not only does the success and sustainability of digital labour platforms depend on the output/service quality, but it is also largely subject to the active and continuous participation of workers (Boons et al., 2015; Choudary, 2018; Wu et al., 2021). Commenting on the business model of digital labour platforms, Choudary (2018) noted that both consumers and workers are needed to maintain an efficient and profitable marketplace via platforms. Therefore, it may be in the best interest of platforms to take critical interventions to ensure that worker compensation is commensurate with their contribution (Song et al., 2020), to enhance perceptions of fairness in platform work.

There is an ongoing debate worldwide on the application of minimum wage standards and social protections to platform workers and associated regulatory challenges (Stewart & Stanford, 2017), which is outside the scope of this study. Yet, by uncovering the salience of earnings to worker fairness perceptions, the study recognises the proactive role that platform organisations can play in finding an equitable solution to better protect workers who are often placed in vulnerable and precarious positions. Platform-based mechanisms should proactively promote worker interest through, for example, protecting workers against under- or non-payment (Song et al., 2020). Sufficient financial compensation plays an important role in signalling appreciation of worker contribution (Durward et al., 2020). Previous research has shown that individuals use minimum wage as an indicator of what is regarded as a fair wage (Falk et al., 2006). This information can be used to develop targeted interventions aimed at setting minimum standards of pay (Fieseler et al., 2019; Todolí-Signes, 2017) and ensuring workers are capable of genuinely negotiating pay rates. Ensuring fair compensation to workers will benefit platforms by shielding them from poor performance and turnover. If workers believe the compensation for their efforts is not fair on a platform, this may lead to lower quality of work (Faullant et al., 2017), or moving to another platform (Ma et al., 2016; Ma et al., 2018), which are likely to be detrimental to the operations of platform organisations.

The findings further highlight the unfavourable implications of undertaking both in-person and internet-based work for fairness perceptions. Undertaking both types of platform work has conflicting effects on worker perceptions of fairness in their earnings and exercise of autonomy. Many workers are bound, whether by choice or necessity, to maintain participation across in-person and internet-based platforms in order to earn an income that they consider as fair. This finding casts doubt upon the actual fairness of earnings and autonomy through platform work. Insights from this study may be of assistance to policymakers by illuminating where improvements and development of strategies are needed to create a fair, responsible, and sustainable digital marketplace for both workers and businesses. In Australia, there are a number of important policy considerations as outlined in a recent report of the inquiry into the on-demand workforce (Industrial Relations Victoria, 2020). These include changes to workplace relations regulations, work status for workers who are not employees, and support systems for non-employee workers, giving them access to better choice, certainty, and fairness of work. Continued and collective efforts between the Australian Government, platform organisations, and other stakeholders, including workers, are needed to address industry-wide opportunities and challenges.

5.5 LIMITATIONS AND FUTURE RESEARCH

While the current study makes clear contributions to theory and practice, there are possible limitations and remaining questions that should be addressed in future investigations. The study used available secondary data from an Australian Survey on participation in digital platform work (McDonald et al., 2019). While this approach allowed timely and cost-effective access to a large sample size, one primary limitation is that the survey may not have captured all platform work features that are salient to workers. Another limitation is that the survey variables used to form the measure of fairness perceptions in this study were not developed using organisational justice theory. This may have led to ambiguity in what the statements refer to, and thus impacted the validity of the findings. However, the in-depth review of the survey data and related literature, and subsequent mapping of survey items to organisational justice dimensions, compensated for the absence of theoretically-informed survey items.

Future work should consider extending organisational justice theory to take into account digitally-mediated work and other emerging forms of work. A natural progression of the current study is to revisit existing measures of organisational justice, exploring more variables that represent justice in the context of platform-mediated work. The variables eliminated in this study due to low factor loadings (i.e., below .50) and low communality (i.e., below .40) (see section 4.1.2) may represent potential additional aspects of organisational justice in platform work which could be represented by additional variables. For example, variable (F4), *I can find regular work through the platform,* with a low communality (see section 4.1.2) makes it a prime candidate for future revision of justice measure in exploring perceived fairness in the platform work context.

Digital labour platforms are constantly evolving marketplaces where a wide range of factors may affect worker perceptions of fairness. Further research on platform work could usefully determine the relationship between perceived fairness in earnings and perceived fairness in autonomy. In addition to distributive and procedural justice dimensions, survey items that tap into interpersonal and informational justice dimensions should be developed. For example, future research should examine the level of information available to workers and their associated perceptions of fairness, and whether interpersonal justice is relevant to the context of algorithmic management on digital labour platforms.

The generalisability of the results in this study is to some extent limited. The study used the data that comes from an Australian nationally representative sample, collected in 2019. The results of the study can be considered as snapshots of digital labour platforms in general. Given that regulatory frameworks concerning platform work vary across different countries, future research could replicate this study in different national contexts, providing opportunities for benchmarking the current findings in Australia and exploring distinctive results in different cultural and regulatory jurisdictions.

Future studies should also further examine the impact of demographic factors, including gender and age when considering workers' perceived fairness on digital labour platforms. While this study found that neither gender nor age significantly affected worker perceptions of fairness in autonomy and earnings, there might be other contingencies under which gender or age affect fairness perceptions beyond those examined in this study. Additional work needs to be done to determine whether other demographic attributes, such as education level, are strong enough to affect fairness perceptions as well as how they might operate with gender or age in shaping worker perceptions. Research could further investigate the role of type of platform work in worker perceptions of fairness, in particular applying moderation and mediation analyses for a more in-depth understanding of the effect of platform work type. The moderating effect of education level, for example, may provide insights into the potential variability of the main effect of type of platform work. The mediating effect of the role of motivation to work, or the level of dependency on income from platform work, may provide a partial explanation of why the type of platform work affects the fairness perception outcomes.

5.6 CONCLUSION

This study was designed to investigate worker perceptions of fairness on digital labour platforms and to determine the effect of gender, age, and type of platform work on platform workers' perceptions of fairness. The study, therefore, contributes to the literature in the fields of management, organisational justice, and the gig economy, and advances knowledge on organisational justice in the context of platform work.

The study identified two key features of platform work – *autonomy* and *earnings*, which encompass important components of distributive and procedural justice on digital labour platforms. Based on a statistical analysis of the data, the study has also demonstrated that platform workers perceive higher levels of fairness in autonomy than earnings. One of the more significant findings to emerge from this study is that while gender or age might play an influential role in perceived fairness in traditional employment contexts, these factors may not matter in digital platform work. The differences in platform workers' perceived fairness in autonomy and earnings occur when analysed against type of platform work. Thus, the study enhances the literature by comparing the perceptions of fairness between in-person workers, internet-based workers, and those doing both types of work.

The study demonstrated that significant changes in perceived fairness in autonomy and earnings through platform work occur when workers engage in both types of work. Particularly, workers who undertake both in-person and internet-based types of work have higher overall perceptions of fairness than those who do only one type of work. When doing both types of work, workers perceive higher fairness in their earnings, and lower fairness in their autonomy through platform work, compared to their counterparts who are engaged in either in-person or internet-based work. Overall, this study expands our understanding of the experience of workers on digital labour platforms, their perceived fairness of features of platform work, and the extent to which type of work affects fairness perceptions on digital labour platforms.

Appendices

APPENDIX A

Kaiser-Meyer-Olkin Measure of Sampling Adequacy (MSA) value for each item

Variable number and statements	MSA value
(F1) The income I earn is fair.	.913
(F2) I have the ability to set the price for my services.	.890
(F3) The fees, costs or commissions associated with work through the platform are fair.	.922
(F4) I can find regular work through the platform.	.935
(F6) I can choose my own tasks or projects.	.962
(F7) I can work the hours I choose.	.894
(F8) I can work at the pace I choose.	.931
(F9) I am free to decide how to perform any tasks or projects I accept.	.934
(F10) I can work from home or another place that I choose.	.945
(F11) I can work for myself and be my own boss.	.921
(F12) The rating system on the platform is fair.	.950
(F13) The competition for work is reasonable.	.931
(F14) I receive adequate support to resolve disputes over payments or tasks	.937
(F15) The health and safety conditions are adequate.	.960

APPENDIX B

Polychoric correlations between 14 variables

	F1	F2	F3	F4	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15
F1	_	.51	.59	.40	.37	.27	.33	.37	.33	.31	.54	.51	.48	.43
F2	.51	_	.40	.22	.44	.29	.33	.54	.46	.44	.43	.36	.37	.40
F3	.59	.40	_	.38	.36	.27	.30	.39	.30	.29	.57	.54	.56	.50
F4	.40	.22	.38	_	.32	.31	.35	.33	.20	.32	.40	.47	.43	.31
F6	.37	.44	.36	.32	_	.53	.52	.55	.49	.54	.44	.37	.36	.41
F7	.27	.29	.27	.31	.53	_	.62	.49	.46	.66	.38	.29	.37	.42
F8	.33	.33	.30	.35	.52	.62	_	.54	.48	.56	.44	.34	.36	.40
F9	.37	.54	.39	.33	.55	.49	.54	_	.49	.56	.46	.42	.36	.41
F10	.33	.46	.30	.20	.49	.46	.48	.49	_	.52	.36	.25	.34	.38
F11	.31	.44	.29	.32	.54	.66	.56	.56	.52	_	.41	.36	.37	.44
F12	.54	.43	.57	.40	.44	.38	.44	.46	.36	.41	_	.57	.59	.51
F13	.51	.36	.54	.47	.37	.29	.34	.42	.25	.36	.57	_	.53	.40
F14	.48	.37	.56	.43	.36	.37	.36	.36	.34	.37	.59	.53	_	.51
F15	.43	.40	.50	.31	.41	.47	.40	.41	.38	.44	.51	.40	.51	_

APPENDIX C

Oblique-rotated factor matrix: Full set of 14 variables

Variable number and statements	Oblique-rotated loadings[a]		
	Factor		
	1	2	h^2
(F3) The fees, costs or commissions associated with work through the platform are fair.	**.856**	.129	.610
(F1) The income I earn is fair.	**.748**	.033	.529
(F13) The competition for work is reasonable.	**.739**	.027	.522
(F14) I receive adequate support to resolve disputes over payments or tasks	**.703**	-.035	.527
(F12) The rating system on the platform is fair.	**.695**	-.111	.593
(F4) I can find regular work through the platform.	.479	-.092	.293
(F15) The health and safety conditions are adequate.	.460	-.259	.429
(F2) I have the ability to set the price for my services.	.351	-.322	.371
(F11) I can work for myself and be my own boss.	-.047	**-.830**	.642
(F7) I can work the hours I choose.	-.098	**-.823**	.585
(F8) I can work at the pace I choose.	.012	**-.731**	.545
(F10) I can work from home or another place that I choose.	.027	**-.641**	.433
(F6) I can choose my own tasks or projects.	.118	**-.636**	.514
(F9) I am free to decide how to perform any tasks or projects I accept.	.169	**-.612**	.533

[a] Factor loadings greater than .50 are in bold and variables sorted by loadings on each factor; h^2 = Communality coefficients

APPENDIX D

Oblique-rotated factor matrix: Reduced set of 11 variables

Variable number and statements	Oblique-rotated loadings[a]		
	Factor		
	1	**2**	***h^2***
(F7) I can work the hours I choose.	**.840**	-.106	.609
(F11) I can work for myself and be my own boss.	**.825**	-.049	.634
(F8) I can work at the pace I choose.	**.746**	.007	.563
(F6) I can choose my own tasks or projects.	**.636**	.118	.510
(F10) I can work from home or another place that I choose.	**.621**	.039	.417
(F9) I am free to decide how to perform any tasks or projects I accept.	**.604**	.168	.516
(F3) The fees, costs or commissions associated with work through the platform are fair.	-.099	**.842**	.618
(F13) The competition for work is reasonable.	.016	**.713**	.522
(F1) The income I earn is fair.	-.001	**.713**	.507
(F12) The rating system on the platform is fair.	.138	**.686**	.604
(F14) I receive adequate support to resolve disputes over payments or tasks	.076	**.667**	.513
Eigenvalues	5.380	1.521	-
Total variance explained (extracted) %	44.818	9.852	-

[a] Factor loadings greater than .50 are in bold and variables sorted by loadings on each factor

h^2 = Communality coefficients

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