Fairness in Algorithmic Management: Bringing Platform-Workers into the Fold

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Abstract

On digital labor platforms, algorithms execute a range of decisions including work assignments, performance evaluation, etc. Although algorithmic decision-making is a key feature of platform work, our understanding of how people perceive decisions made by algorithms – particularly in terms of the fairness of their processes and outcomes – remains underdeveloped. The impacts of such perceptions on job satisfaction and perceived organizational support (POS) are also still under exploration with some scholars challenging the possibility of POS among transient platform workers. In this paper, we explored the impacts of the perceived procedural and distributive fairness of algorithms operating in a paradigmatic context of algorithmic management, namely Uber. Drawing on the Theory of Organizational Justice, and a survey of 435 Uber drivers, we not only find that independent platform workers can experience POS, but that the fairness of managerial algorithms (in particular their outcomes) can play a critical role in stimulating such perceptions.

1. Introduction

Over the last decade, the use of algorithmic decision-makers and AI-based decision-making by organizations and governments has grown steadily. This movement has sparked increasing concerns about the fairness and ethicality of algorithmic decision-makers given their wide range of applications across all areas of society from our social media feeds to our health and justice systems [1, 2, 3].

A novel aspect of this trend is the use of algorithms to manage digital platform workers – a phenomenon known as "algorithmic management". On one hand, digital labor platforms like Uber have disrupted several service industries by leveraging self-learning algorithms to harness and optimize large, distributed, and fluid workforces [3, 4, 5]. On the other hand, despite their efficiency, algorithms operating on labor platforms often lack transparency, a situation that reduces workers' autonomy and threatens their ability to ascertain the fairness of an algorithm's decision-making processes and outcomes [6]. The latter is problematic given that perceptions of fairness are known to drive job satisfaction and to reduce turnover intentions [7]. These relationships are important given reports that over half of gig-workers are unsatisfied with their jobs and intend to leave [8], a fact that threatens the long-term viability of a platform business model via the phenomenon of network effects.

In recent years, the study of the fairness of managerial algorithms and their impacts on workers on platforms has captured the attention of scholars from various disciplines and fields ranging from information systems (IS) to computer-human behaviour to human resource management (HRM). Although this nascent area of research is growing, it is still unknown whether platform-based work and new managerial tactics—such as the use of algorithmic management and people analytics—can provide a welcoming and sustainable environment for workers [9]. Moreover, the role that the perceived fairness of managerial algorithms plays in job satisfaction and POS is underexplored.

Addressing these research gaps is important, given that algorithmic management is extending beyond gig-work and many traditional organizations are tapping digital labor platforms to fill vacant positions, reduce costs, and stay agile in an uncertain economy and a period of recovery following covid-19 and the Great Resignation [10, 11]. Despite this, various scholars contend that research in this area has been constrained by a view that existing organizational theories and related strategies hold "little relevance in the context of gig work" due to "the transactional nature of gig work and the lack of formal employment relationships" [12, p. 3997]. At the same time, others have suggested that new theories specific to platform work will be required to explain previously well-understood phenomena [11, 13]. Amid conflicting viewpoints, more comprehensive research exploring how workers perceive the fairness managerial algorithms is required to understand whether theories of organizational support and organizational justice can be used to advance our knowledge of

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platform workers' reality and our ability to create a healthier and more sustainable future of work.

In this paper, we take a socio-technical perspective of algorithmic fairness [14] to highlight the role that technologically-mediated managerial practices can play in driving job satisfaction and perceptions of organizational support among independent platforms workers. Our paper is structured as follows. First, we discuss the role of managerial algorithms in our research context. Next, we introduce our lens—the Theory of Organizational Justice (TOJ)—and our two dimensions of algorithmic fairness (procedural and distributive fairness). Then, we present our theoretical development, followed by our methodology and analyses. We conclude by discussing our results and contributions, as well as future research avenues.

2. Role of managerial algorithms

According to extant research, including a meta-analysis of alternative and temporary agency workers, extending human resource (HR) practices to contingent workers is likely to increase job satisfaction. Despite such findings, there remain limitations to how such practices can be applied to platform-based workers [15].

Unlike the traditional dyadic employee-employer relationship, app-based work-relationships are triadic in nature, where a platform owner, such as Uber, serves as an intermediary between customers and workers [3, 11, 16, 17]. In the gig-economy, intermediaries rely on platforms powered by algorithms that organize, facilitate, and broker services provided by a large and dispersed workforce. On platforms like Uber, algorithms are responsible for matching workers and customers, monitoring and evaluating workers' performance, as well as implementing other HR decisions like rewards and punishments [4, 18]. Platform workers interact with the managerial algorithm through a digital interface (e.g., an application) where they receive instructions from the algorithm [14].This practice is known as algorithmic management, which is defined as the use of software algorithms and surrounding institutional devices (e.g., platforms) that assume managerial functions [4]. We define managerial algorithms as algorithms that assume managerial tasks typically executed by human managers (e.g., job assignments, performance evaluations, rewards, etc.).

Given that the platform owner is the only party with full access to and control over the platform's data, processes, and rules, a managerial algorithm "can be understood as an automated manifestation of the interests of the platform" owner [19, p. 9]. Thus, platform owners are largely responsible for determining working conditions and workers' experiences through the design of their managerial algorithms which workers tend to perceive as their bosses [20] (as cited by [14]).

3. Organizational justice and platform work

In the emerging literature, it is recognized that platform workers' perceptions of fairness are expected to be shaped by the features of the labor platform and its governing algorithms [3]. To further understand how workers perceive the fairness of managerial algorithms and the impacts of those perceptions, we build on the theory of organizational justice (TOJ). The TOJ is concerned with fairness in the workplace. It has been widely employed in the fields of management and IS [14] to understand the psychological mechanisms by which people form judgments of fairness, as well as their responses to these perceptions [21]. It is important to recognize that the TOJ conceptualizes employment as the trade of time and effort by an employee for tangible benefits and rewards, such as promotions, pay, recognition, and any other job-related resources that assist employees in their tasks or that maintain overall well-being [22]. In this transactional view of employment, employees who perceive fair treatment from the organization and its agents are more likely to "feel a sense of obligation to create a good act in return" [22, p. 2]. Thus, by prompting the norm of reciprocity, justice perceptions have been found to be a key driver of employees' attitudes such as job satisfaction and organizational commitment; justice perceptions have also been positively linked to organizational citizenship behavior, innovative work behavior, and job performance. Conversely, diminished perceptions of justice are found to lead to dissatisfaction and negative feelings among employees, as well as withdrawal, sabotaging, and/or destructive behaviors [23, 24, 25].

TOJ scholars have identified three types of organizational events that people evaluate regarding their fairness, namely: decision-making processes; outcomes; and interpersonal treatment. These events are commonly viewed as three dimensions of organizational justice (OJ): procedural; distributive; and interactional justice, as defined in Table 1 [22, 26].

Event	Dimension and definition
Decision-making processes	**Procedural justice** concerns the fairness of the approaches used to determine how resources such as pay, promotions, and job assignments are distributed.
Outcomes	**Distributive justice** concerns the fairness of the outcomes received by an employee (e.g., pay, promotion, status, performance evaluations, etc.)
Inter-personal treatment	**Interactional justice** concerns the treatment that an employee receives as decisions are made; it refers to the degree to which those affected by the decision are treated with dignity and respect.

Table 1: Organizational justice dimensions

In this paper we adopt the two-factor model of OJ, which includes both procedural and distributive justice. In addition to being the most commonly used [22], the two-factor model can predict a range of outcomes such as job satisfaction and organizational commitment, as well as both agent- and system-referenced evaluations of authority like POS[1] [7]. Moreover, per Colquitt et al. [7], in studies like ours, where justice is the independent variable or antecedent to a justice-based outcome (e.g., behavioral or attitudinal changes resulting from fair or unfair treatment), including all of the dimensions of justice has diminishing returns and is not useful.

In the context of algorithmically-managed work contexts – where many managerial and decision-making processes become reduced into a set of opaque algorithmic processes that are complex and inaccessible to the typical worker – it is timely and important to capture the perceived fairness of outcomes (distributive fairness) alongside procedural justice [27, 15, 28]. As such, in the context of emerging algorithmically managed work, it is possible that perceptions of distributive fairness might play a greater role in driving outcomes than in traditional organizations.

4. Theoretical development

In this study, we restrict ourselves to the context of algorithmically managed platform work. Specifically, we focus on workers participating on platforms that operate as digital marketplaces for alternative work where the services exchanged on the platform are both remunerated and labor-intensive (e.g., Uber). Within this scope, we further limit our focus to workers participating on highly centralized platforms that exercise extensive control over task allocation and performance evaluations via algorithms. In accordance with TOJ, the decisions executed by the algorithms operating on these platforms relate to the allocation of key organizational resources (e.g., job assignments, pay, rewards). In focusing on an extreme case of algorithmic control, we aim to isolate workers' perceptions of fairness to those deriving solely from managerial algorithms with little to no interference from other parties (e.g., customers or human managers).

Lastly, this study focuses on a single organizational resource and decision, namely: job assignments or the 'matching' of workers with customers. Algorithmic matching on digital labor platforms can be defined as "the algorithmically mediated coordination of interactions between demand and supply" (p. 2005). Per Möhlmann et al. [20], one of the key functions of the algorithms operating on digital labor platforms like Uber is to create improved scalable marketplaces through a data-driven process of matching supply and demand. To ensure fast and accurate matching, the algorithms are fed with input and output data [20].

As an example, on the Uber platform, data points like "user profiles, ride requests, locations, and time availabilities" are initially used to match riders and drivers [20, p. 2005]. Next performance data—in the form of customer ratings—is used "to draw inferences about drivers' performance and feed the matching algorithms to ensure the best possible experiences for riders" [ibid.]. Notably, on the Uber platform, the matching algorithm also leverages dynamic pricing mechanisms to maximize economic efficiency in matching supply and demand.

According to a recent study, one in four online gig-workers find how their jobs are assigned to be unfair [29]. On ride-sharing platforms, the fairness of matching has been an ongoing preoccupation as platforms like Uber aim to balance wait times, revenues, and fairness [30]. Thus, increasing the perceived fairness of matching algorithms may present a key opportunity for platform intermediaries to increase satisfaction and reduce turnover. As such, we focus on the perceived procedural and distributive fairness of algorithmically made matching decisions.

We define ***perceived procedural fairness*** as a platform worker's perception concerning the fairness of the algorithmic processes applied to determine how job assignments are distributed (the matching process between customers and workers) [26]. We define ***perceived distributive fairness*** as a platform worker's perception of the fairness of the algorithmically-determined job assignments or matching outcomes.

4.1. POS and algorithmic fairness

Perceived organizational support (POS) is the degree to which employees believe that their organization values their contributions, cares about their well-being, and fulfills their socioemotional needs [31]. The concept of POS derives from Organizational Support Theory (OST) which explains employer-employee relationships through the lens of social exchange theory (SET) [15, 32, 33]. Specifically, "OST invokes social exchange theory [by conceptualizing employment] as the trade of effort and loyalty by the employee for tangible benefits and social resources from the organization" [23, p. 1857]. Although SET and POS originated to explain traditional employment relationships, recent research has found that organizations should seek to establish transparent and

[1] In the OJ literature, an agent-referenced evaluation of authority would entail focusing on a person, such as one's supervisor, whereas a system-referenced evaluation would refer to focusing on management in general [7].

supportive relationships with all types of employees – both internal and external, such as freelancers and platform workers [15, 34].

Amid discussions on the application of SET in the context of a new era of workplace relationships and digitized workplaces, and the need to rethink the variables and boundaries of such theories [34], we propose that POS can be engendered among platform workers through their exchanges with a platform algorithm. Per the literature, POS can be prompted by both the fairness of organizational procedures and one's treatment by organizational agents such as a human manager or colleague [23, 25]. Thus, procedural fairness can be both a function of an organization, such as through a formalized decision-making system, or of a decision-making agent, such as a human manager which involves an employee in the decision-making process [7]. Where managerial algorithms operate on and enact a set of previously developed rules and instructions embodying an organization's policies and procedures, we suggest that such algorithms can be considered both as embodiments of procedural justice, and as organizational agents demonstrating fairness (or unfairness) in their decision-making processes [19, 11].

Where organizational procedures are considered by workers to be highly discretionary as well as essential to their long-term interests and well-being, procedural fairness has been found to be one of the strongest drivers of POS in two meta-analyses [23, 25]. Thus, we put forth Hypothesis 1 (H1): *The perceived procedural fairness of algorithmic matching decisions will be positively related to POS.*

According to equity theory (Adams, 1965), workers evaluate the fairness of organizational outcomes by examining: (i) whether resource allocations are equally applied; and (ii) whether the ratio between their received outcomes and their contributions to the organization [26, 35]. In the context of our research, the job opportunities a worker receives serve as the basis for distributive justice perceptions.

It is well-recognized that managerial algorithms operating on digital labor platforms punish workers for failing to maintain benchmark levels of key performance indicators by restricting work opportunities. Conversely, well-performing workers are rewarded with improved work opportunities and access [36, 4, 19, 28]. Importantly, platform-workers typically have access to a dashboard where they can view their tasks completed, ratings and feedback, as well as other key performance indicators [19]. Thus, in view of how managerial algorithms allocate work, it is plausible and likely that platform-workers will concern themselves with the distributive justice of such outcomes.

Where distributive justice concerns the allocation of organizational resources, distributive justice leads employees to make inferences regarding the willingness of the platform organization to support or reward them. Such inferences engender beliefs that the organization values their contributions and cares about their well-being, thereby leading to perceptions of organizational support [23, 25]. Thus, we put forth Hypothesis 2 (H2): *The perceived distributive fairness of algorithmic matching decisions will be positively related to POS.*

4.2. Job satisfaction and algorithmic fairness

Job satisfaction refers to an employee's overall affective evaluation of their job situation and their overall sense of well-being at work [25]. The link between procedural justice and job satisfaction has been studied frequently [7]. Specifically, research on the influence of procedural justice on job satisfaction suggests that when employees question the fairness of the procedures affecting them, they experience reduced job satisfaction and motivation. Conversely, when employees feel that they are treated fairly by the organization, they are motivated to show positive attitude and behavior like job satisfaction.

According to the relational model of procedural justice, when employees consider organizational procedures and personal treatment to be objective and impartial, procedural fairness conveys positive identity clues like dignity and organizational regard which bolster one's self-image and morale. Based on such identity clues, workers appraise the organization more positively and experience more job satisfaction [35].

The strong, positive correlation between procedural fairness and job satisfaction is well-established [22, 26] as confirmed in Colquitt et al.'s [7] meta-analytic review. In the context of platform work, we expect the relationship between procedural justice and job satisfaction to hold true for the decisions executed by managerial algorithms as the resources allocated through these decisions are analogous to those studied in traditional work contexts (e.g., compensation, evaluation, and – in the case of our study – work allocation) [26]. Thus, we put forth Hypothesis 3 (H3): *The perceived procedural fairness of algorithmic matching decisions will be positively related to job satisfaction.*

Within the organizational behavior literature, there is a significant body of knowledge that suggests that the "perceived fairness of outcomes exerts a strong influence on how employees react to a variety of aspects of organizational life" [37, p. 1830]. According to the personal outcomes model of distributive justice, people are concerned with the fairness of resource distributions as they believe that fair distributions will result in favorable distributions [37, 38]. Based on this model, distributive justice has been found to be an important predictor of workplace attitudes and behaviors, as well as a dominant predictor of job satisfaction and turnover intentions [7, 26, 37, 22].

Following the extant literature, we predict that platform-workers who perceive their job allocations as fair and just, as well as representative of their work efforts will experience greater happiness and job satisfaction [22]. Conversely, when they perceive that job opportunities are unfair and do not match their contributions and efforts, we predict that they will experience a poor fit between themselves and their work environment leading to a reduction in job satisfaction [7, 37]. Thus, we put forth Hypothesis 4 (H4): *The perceived distributive fairness of algorithmic matching decisions will be positively related to job satisfaction.*

4.3. POS and job satisfaction

An individual's affect and behavior are influenced by their opinions and beliefs about the fundamental processes that constitute their organization. Among these beliefs is POS. In traditional work contexts, the link between POS and job satisfaction is well-established and further confirmed by two meta-analyses conducted by Rhoades and Eisenberger [25] and Kurtessis et al. [23]. Specifically, POS has been found to be strongly related to job satisfaction ($\rho = .65$) such that employees with enjoy high levels of POS appear to be more satisfied with their jobs as compared with those with lower organizational support [23].

The mechanism underlying this outcome lies in the theory of social exchange and the norm of reciprocity. Research suggests that employees treated favorably will (i) care about an organization's well-being and feel liable to support the organization in reaching its objectives; as well as (ii) feel an expectation that their increased performance will be recognized and rewarded. Accordingly, organizations that demonstrate support towards workers not only fulfill socioemotional needs, but also increase the anticipation of help when needed, and strengthen reward expectancies as well as self-efficacy thereby enhancing job satisfaction. Thus, where a gig-organization's managerial algorithm "can be understood as an automated manifestation of the interests of the platform organizer" [27, p. 9], we suggest that perceptions of support driven by a managerial algorithm will lead to job satisfaction. Thus, we put forth Hypothesis 5 (H5): *POS will be positively related to job satisfaction.*

5. Methodology

To test our model, a cross-sectional online survey was conducted with North American Uber drivers (n=435) over a period of three months. Uber was selected as the site for data collection on the basis that it represents a paradigmatic instance of algorithmic management where self-learning algorithms optimize the allocation of tasks using existing data on worker availability, travel times, road conditions, and/or customer habits [5, 11, 36]. Canadian drivers were paid 5.00 CAD and U.S. drivers were paid 4.00 USD.

5.1. Sample: Recruitment and description

To qualify for participation, potential respondents needed to have worked on the Uber platform for at least one month over the last year to ensure respondents had sufficient familiarity and experience with the platform, as well as its functions and features. Respondents were recruited online via Facebook Uber driver groups, a commonly utilized source for Uber-specific studies (e.g., [36, 39]), and Prolific a crowdwork platform like MTurk. Post-hoc analyses indicated no major differences between the data sources thereby allowing us to amalgamate the two datasets following other researchers' approaches (c.f. [36, 4, 39]).

Descriptive statistics for our sample were as follows. Most respondents (62.1%) were from the U.S. Nearly one third (28.5%) of respondents were female, which is representative of the Uber driver population [40]. Most respondents were also younger than 45 years old, specifically: participants aged 18-24 represented 24.4% of the sample; those aged 25-34 represented 44.4% of the sample; and those aged 35-44 represented 21.6% of the sample. Our sample was relatively well-educated with 73.8% of respondents having at least a post-secondary degree. Most respondents worked part-time for Uber (92.9%) and worked at least one other job (61.8%). With respect to platform tenure, respondents' average tenure with Uber was 34 months. Lastly, in terms of platform experience and work intensity, 39.3% of respondents had completed less than 100 rides on the platform; 34.3% completed 100-499; 22.5% completed 500-4999; while only 4% completed more than 5000.

5.2. Measures

To measure perceptions of algorithmic fairness, we adapted Colquitt's [26] extensively validated measure of OJ ($\alpha = 0.93$). Colquitt's instrument has been used (c.f. 39) to explore fairness on home-sharing platforms such as Airbnb. The scale includes seven items to measure procedural justice and four items to measure distributive justice; all items were measured on a 7-point Likert-scale (1 = to an extremely small extent, 7 = to an extremely large extent). Adapted items include: "*Do you consider that the app's matching procedures are based on accurate information?*" (Procedural justice); "*Are your ride opportunities justified, given your performance?*" (Distributive justice).

Following Eisenberger et al. [32], we measured job satisfaction using four items from Quinn and Shepard's Overall Job Satisfaction index (α = 0.79), a facet-free job satisfaction scale measured on a 7-point Likert-scale (1 = strongly disagree, 7 = strongly agree). Exemplar items include: "*All in all, I am very satisfied with my current job as an Uber driver*" and "*Knowing what I know now, if I had to decide all over again whether to drive for Uber, I would."* To measure POS, we used Eisenberger et al.'s [31] short form Survey of Perceived Organizational Support (α = 0.97), which consists of eight items measuring POS on a 7-point Likert-scale (1 = strongly disagree, 7 = strongly agree). A sample item included: ''*Uber really cares about my well-being*.''

Based on prior research, we controlled for age [41]; based on Lee [7], and the mechanisms underlying POS, we controlled for people's level of knowledge about algorithms and the extent to which they attribute decisions taken on the platform to an algorithm.

5.3. Data quality assessment

Prior to analyses, we assessed our data's statistical quality and its suitability for structural equation modelling. Using SPSS 26, an initial data quality check showed all scores for skewness and kurtosis to be within the -2 and +2 range (skewness range: -0.801 and 0.904; kurtosis range: -1.146 and 1.637), suggesting no serious departures from the normality assumption. Using Cook's D values [42], no outliers were found in our data set. Lastly, we ran the Kaiser-Meyer-Olkin Measure of Sampling Adequacy test and Bartlett's Test of Sphericity. For both tests, our data surpasses the required thresholds with a KMO value of 0.970 and a significant ($p < 0.0001$) Bartlett's Test of Sphericity.

6. Results and analyses

For our analyses, we employed the partial least squares (PLS) structural equation modelling (SEM) technique using Smart PLS 3.2.3. This technique is well suited to research focused on prediction where the identification of relationships is a central purpose [43]. The technique is also useful when theory is less developed, and when seeking to explain key target constructs and/or to identify key driver constructs [44, 45]. As the theory of POS has yet to be explored and even understood to be possible in the context of algorithmic management [5, 15, 34], PLS-SEM was chosen given its utility when "theory is less developed" [45]. Beyond its utility for evaluating propositions and exploring crucial links between core concepts, PLS-SEM has been used by scholars, including IS scholars (c.f. [46]), to study OJ and fairness.

6.1. Measurement model

As a first step, confirmatory factor analysis (CFA) was used to examine our measurement model and to confirm the good psychometric properties of our scales. Through a series of iterations, we eliminated items with low loadings on all factors or high loadings on more than one factor (e.g., high cross-loading). Following best practice, we retained items that clearly loaded onto a single appropriate factor, with a minimum loading of 0.7, and that demonstrated a difference of 0.20 between their primary and alternative factor loadings [47]. Next, we assessed the internal consistency, as well as the convergent and discriminant validity of the constructs in our model. Results are found in Table 2.

	CA	CR	PF	DF	JS	POS	VIF	
							JS	POS
PF	0.87	0.91	**0.85**				2.10	1.95
DF	0.91	0.94	0.69	**0.92**			2.32	1.90
JS	0.88	0.93	0.59	0.71	**0.89**		End.	End.
POS	0.86	0.90	0.61	0.67	0.69	**0.84**	1.99	End.

- PF – Procedural fairness; DF – Distributive fairness; JS – job satisfaction; CA – Cronbach's α; CR – Composite reliability; VIF – Variance inflation factor; End. - Endogenous
- The bold values in the diagonal (correlational) cells are the square root of the AVE for the corresponding constructs.

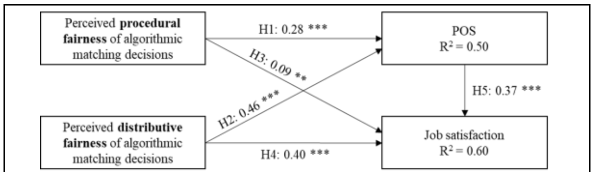
Table 2: Convergent & discriminant validity statistics

Convergent validity was assessed by calculating the reliability of the constructs in our model as measured by Cronbach alpha (α), composite reliability (CR), and finally Rho_A. Where all values for the reliability statistics exceeded the threshold of 0.7, convergent validity was confirmed [45]. Convergent validity was further assessed by the square root of the AVEs for all constructs, which were above the minimum level of 0.50. Variance inflation factors (VIF) were analyzed for the items (outer model) and the constructs (inner model; see Table 2 for inner VIF values). All VIF values were well-below the 3.3 threshold, which confirms sufficient construct validity by a lack of multicollinearity and that common method bias is not a major issue [48].

Discriminant validity was assessed using the Fornell-Larcker criterion. As per Table 2, the square root of the AVE for all constructs were all greater than their correlations with other variables, thus confirming satisfactory discriminant validity [42]. As an additional test of discriminant validity, we also calculated the Heterotrait-Monotrait ratio (HTMT) which were all below the threshold of 0.85 [49]. Lastly, to assess the fitness of our measurement model, we examined the saturated model and the Standardized Root Mean Square (SRMR) at a 95% bootstrap quantile. Our SRMR is 0.067, which is far below the threshold of 0.8 and indicating a well-fitting measurement model [45].

6.2. Structural model

Given the satisfactory results for the fit, reliability and validity of our measurement model, our next step was to analyze our structural model. To do so, we used a bootstrapping procedure to assess the significance of the path coefficients and predictive power of the model. A one-tail test was used given the strong theoretical evidence supporting positive relationships across our five hypotheses (H1-H5). Results are found in Figure 1.



- p-values: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$
- Controlled for age, algorithmic knowledge, and algorithmic attribution

Figure 1: Results of research model test

Following best practices, we examined several empirical thresholds for: statistical significance, effect sizes, and R^2. First, with the exception the path from procedural fairness to job satisfaction (H2), all paths are at least 0.20 [50]. Next, we examined the statistical significance of the path coefficients by applying Hair, et al.'s [51] guidelines: specifically, a minimum threshold of 1.65 for the t-statistics values at $p < 0.05$ confidence interval. As shown in Figure 1, all paths are statistically significant at $p < 0.001$ except for H3 at $p < 0.01$.

We next examined R^2 for both of our endogenous variables. Per established guidelines, R^2 values of 0.75, 0.50, and 0.25 reflect substantial, moderate, and weak values respectively [45, 48]. Our analyses indicate moderate values for job satisfaction and POS. Moreover, bootstrapping results from the significance test of the R^2 values are statistically significant as indicated by the t-statistics and p-values in Table 3.

Endogenous constructs	R^2	t-statistic	p value
Job satisfaction	0.60	20.75 ***	0.000
POS	0.50	14.12 ***	0.000
Hypotheses	f^2	**t-statistic**	**p value**
H1: PF → POS	0.078	2.51 **	0.006
H2: DF → POS	0.222	3.48 ***	0.000
H3: PF → Job satisfaction	0.009	0.97	0.166
H4: DF → Job satisfaction	0.177	3.55 ***	0.000
H5: POS → Job Satisfaction	0.172	3.74 ***	0.000

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$

Table 3: R^2 and f^2 values with statistical significance

Although f^2 and Q^2 statistics are less frequently reported, these structural model metrics enable the accurate interpretation of a model's results [45]. Thus, we next examined effect sizes using the f^2 statistic. Per established guidelines, f^2 values of 0.020 to 0.150 indicate weak effects; f^2 values of 0.150 to 0.350 indicate medium effects; and f^2 values of 0.350 or greater indicate large effects [52, p. 11]. Our analyses indicate medium effects for the distributive fairness of matching to POS and job satisfaction, as well as for POS to job satisfaction. The procedural fairness of matching to POS is a weak effect. Lastly, as indicated by the t-statistic and p-values in Table 3, bootstrapping results from the significance test of the f^2 values are statistically significant for all relationships except for the procedural fairness of matching to job satisfaction.

Next, we examined the Q^2 statistic, which is used to evaluate the predictive relevance and strength of a structural model. These statistics are generated using the PLS Predict function. Results are reported in Table 4. Per established guidelines, Q^2 values above zero indicate that the model is well-constructed and has predictive relevance. Specifically, Q^2 values higher than 0, 0.25 and 0.50 depict small, medium, and large predictive relevance of the PLS-path model [53]. Predictive relevance and accuracy were confirmed by our Q^2 values in Table 4, which were all greater than 0, and therefore meaningful. To derive Q^2 values for the latent variables in our model, we employed a blindfolding approach with an omission distance of 7, as recommended by Hair et al. [45]. This procedure yielded Q^2 values of 0.472 (Job satisfaction) and 0.333 (POS) which suggest near-large and medium predictive relevance for our constructs, respectively.

Endogenous items	Q^2	Q^2 meaning
JS4	0.417	Med-large
JS1	0.500	Large
JS3	0.335	Medium
POS6	0.488	Large
POS8	0.402	Medium
POS2	0.191	Small
POS3	0.230	Small
Job sat. (JS)	0.472	Med-large
POS	0.333	Medium

Table 4: Predictive power analyses

7. Discussion

Understanding the precise impact of algorithms on the experiences and outcomes of platform workers is of paramount importance. Knowing what impact these algorithms have on platform workers' jobs can provide valuable insights into the interplay between algorithms and worker dynamics, as well as a deeper understanding of the impact on the broader ecosystem of platform work.Various IS scholars have called for the exploration of the sociotechnical aspects of algorithms on managerial practices [11]. This paper tests how perceptions of algorithmic decision-makers' fairness impact workers' perceptions of job satisfaction and POS. In doing so, we addressed calls for research investigating the impacts of algorithmic management and the perceived fairness of managerial algorithms in real-world settings [4, 15].

In accordance with H1 and H2, we found positive and significant coefficient paths linking the perceived procedural fairness of algorithmic matching decisions (β=0.28, p<0.001) to POS, and the perceived distributive fairness of algorithmic matching decisions (β=0.46, p<0.001) to POS. We did not find support for H3, as the coefficient path linking the perceived procedural fairness of algorithmic matching decisions to job satisfaction was found to be on the verge of non-significant (β=0.09, p<0.09). Regarding H4, we found a positive significant path coefficient linking the perceived distributive fairness of algorithmic matching decisions (β=0.46, p<0.001) to job satisfaction (β=0.40, p<0.001). In accordance with H5 and extant literature, POS was found to be a strong statistically significant predictor of job satisfaction (β=0.37, p<0.001).

With respect to effect sizes independent of sample size, we find that workers' perceptions of distributive fairness on POS (f^2=0.222) and job satisfaction (f^2=0.177) play the more important roles in our model.

7.1. Scholarly implications and contributions

Except for H2, our hypotheses are aligned with prior research in the areas of social exchange, justice, and organizational support. Despite such alignment, these findings are novel given that the possibility of POS in transactional work-contexts such as gig- and platform-work has been challenged by some scholars [15]. Thus, we contribute to recent scholarship highlighting the need for cultivating relationships and human capital practices in non-standard and platform-based work contexts [5]. Our work also underscores the importance that managerial algorithms can play not only as series of codes used to enact organizational policies but as organizational agents that can impact the relationships that independent and transient platform workers form with platform-based organizations.

It is also important to highlight the ways in which our findings deviate from the existing literature. In the extant literature, procedural justice has consistently been shown to have higher contributions to POS than other dimensions of justice [23, 25]; it has also been shown to have stronger effects than distributive justice on system-referenced variables such as organizational commitment and trust in management, as well as job satisfaction [26, 38]. These established findings do not hold in our research model, as distributive justice was found to have higher and more significant effects on both of our dependent variables; moreover, procedural fairness was not found to have a significant effect on job satisfaction. The reason for this finding likely lies in the unique context of algorithmic management and the opacity of the matching algorithm on the Uber platform.

As previously mentioned, in algorithmically managed work environments, many managerial and decision-making processes are reduced into a set of opaque algorithmic processes that are inaccessible to most workers [15, 28]. Where workers cannot ascertain the fairness of procedures due to algorithmic opacity, it is plausible that workers' evaluations of the fairness of the outcomes of such decisions become more valuable, and thus play a greater role in explaining downstream effects on job satisfaction and POS.

This assumption is further supported through an analysis of the items that were dropped from our procedural justice scale due to low factor loadings. A factor loading for a variable measures how much the variable (or item) contributes to the factor (or focal construct). Notably, items such as: "*Do you consider that the app's matching procedures are applied consistently?"* (PF4) and "*Do you consider that the app's matching procedures are free of bias?"* (PF5) were dropped as such items tend to require insight into the "black box" of the algorithm itself. Conversely, the procedural fairness items that were retained related to a worker's participation in the process which, despite an algorithm's opacity, a worker can ascertain (e.g., *Are you able to express your views and feelings during the app's matching procedures?"* (PF1) and *"Are you able to appeal the rides assigned to you by the app?* (PF3)).

7.2. Practical implications and contributions

Our work demonstrates that platform organizations can leverage well-designed algorithms to engender POS and to drive job satisfaction among independent platform-workers despite their transience and limited attachment to the organization. Notably, recent research has suggested that low-skill workers who are more actively managed by a platform firm tend to perceive themselves as employees and are more likely to expect a platform-provider to care about their well-being. As such, perceptions of organizational support could have important consequences for gig-workers working on highly centralized platforms such as Uber [15]. Such findings are also relevant for traditional organizations as they increasingly adopt algorithms to oversee and manage their workforces, and as they build contingent workforces into their organizational strategies.

Our research also sheds light on how organizations can create more fair managerial algorithms. To do so, we conducted an importance-performance map analysis (IPMA) (See Figure 2). Whereas "standard PLS-SEM analyses provide information on the relative importance of constructs in explaining other constructs in the structural model", the IPMA method "extends the results of PLS-SEM by also taking the performance of each construct into account" (SmartPLS, n.d.). The IPMA is relevant for managers (or in our context designers of managerial algorithms) as it helps identify which actions to prioritize given limited resources.

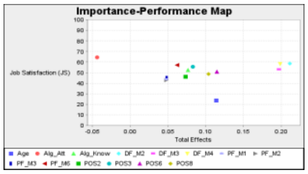


Figure 2: IPMA analysis

As previously elaborated, distributive fairness seems to play an important compensatory role in two-factor models of fairness when concerning workers' perceptions of the fairness of opaque managerial algorithms. Based on our IPMA, we can guide platform organizations seeking to increase job satisfaction by bolstering perceptions of distributive fairness. Specifically, our analyses suggest focusing on ensuring that work opportunities generated via the matching algorithm are considered by workers to be appropriate for the work they have completed (DF2) and their performance (DF4) two variables that tend to be openly accessible on digital labor platforms. In doing so, organizations can compensate for the negative impacts of opacity on workers' perceptions of procedural justice on job satisfaction and POS. This can be a useful strategy where disclosing an algorithm may not be feasible (as in the case of proprietary knowledge or a self-learning AI) or useful due to its complexity.

8. Limitations and Future Research

In this paper, we focused our inquiry on the perceptions of algorithmic fairness of gig-workers performing work on highly centralized platforms. Due to the novelty of our research context, we limited our conceptualization of justice to the two-factor model applied to the context of matching (work allocation) decisions. Given these limitations, we encourage scholars to expand upon our work by integrating other dimensions of justice, like interactional justice, into the research model. We also suggest that future scholars explore how perceptions of fairness differ based on the decision-type executed by an algorithm. Algorithms operating on digital labor platforms enact a wide range of decisions beyond matching and performance evaluation, including rewards and penalty decisions. Prior research (e.g., [6, 24]) suggests that fairness perceptions of algorithmic decision makers were impacted by the type of decision made by the algorithm and whether people thought that an algorithm was equipped to take such decisions. Thus, the fairness of different decision-types merits further exploration.

Future work research should seek to test workers' perceptions of the platform organization's role and the positioning of its online service impacts their perceptions of fairness. In their qualitative study, Fieseler et al. [3] found that perceptions of fairness were impacted by whether workers perceived the platform provider as a mere service facilitator or as an "ersatz employer", and whether the platform was proposed to workers as a computational service or as a platform mediating human work. Quantifying such perceptions and their impacts should provide important conceptual and practical insights into how platform work is experienced. Lastly, exploring perceptions of unfairness, as well as how to attenuate such feelings, is another valuable future area of research opportunity for scholars to pursue.

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