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Fair Dealings with Algorithms? Analyzing the Perceived Procedural Fairness of Managerial Algorithms and their Impacts on Gig-Workers

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Abstract

Using Organizational Justice Theory, this study examines gig-workers' perceptions of the fairness of managerial algorithms and their impacts on perceived organizational support (POS) and job satisfaction. Through a survey of 435 Uber drivers, we find that the perceived fairness of algorithmic decisions (both matching and performance evaluation decisions) is positively and significantly related to job satisfaction and POS. We also find that certain indicators of perceived algorithmic fairness are unique to the type of decision made and whether it is perceived to require mechanical or human skills. In answering calls to study the impacts of algorithmic fairness in real-world settings, we find that managerial algorithms play a key role in shaping gig-workers' attitudes as technological artefacts and organizational agents. Recommendations are provided to enhance perceived algorithmic fairness to address challenges in the gig-economy, like high turnover, by increasing satisfaction and POS.

1. Introduction

The adoption of algorithms as decision-makers has experienced consistent growth in both the private and public sectors over recent years. Yet as these technologies have become more advanced and complex, their increasing reach has ignited growing concern about their fairness and ethicality as decision-makers [1]. As an example, in 2020, the 'robo-firing' of Uber drivers by algorithms sparked public outrage, over a lack of transparency and human intervention, as well as legal action in the European Union (EU).

The use of decision-making algorithms by Uber, and other organizations, to manage workers is known as 'algorithmic management' (herein AM). It is a relatively nascent phenomenon prevalent in the gig-economy where companies, like Lyft, rely on algorithms to oversee and optimize large, distributed, and fluid workforces on their platforms. Despite the efficiencies of this advanced technology and form of management, managerial algorithms are known to reduce workers' autonomy and their ability to ascertain the algorithm's fairness [2, 3] due to the opacity of their processes. As such, various studies have indicated that algorithmic management can negatively affect worker's conditions, livelihood, wellbeing, and satisfaction which can account for high-turnover rates on platforms [1, 4, 5]. Thus, for gig-organizations, reaping the full rewards of AM and ensuring their long-term viability may require remedying the negative impacts of AM on workers by improving the perceived fairness of the system [1, 6].

While gig-workers expect fairness—especially when managed by technologies that are "supposedly more 'objective' than humans" [1, p. 196]—our understanding of the perceived fairness of managerial algorithms and whether such perceptions can engender POS among transient gig-workers in the absence of human managers remains nascent [5, 7]. Moreover, "predicting what will be perceived as 'fair' and how AM practices shape [such] perceptions remains [sic] a challenge" [1, p. 196]. This paper seeks to address these research gaps—among others—by exploring two different types of AM decisions, their links to job satisfaction and POS, as well as nuances across the fairness indicators unique to each type of AM decision. Through these efforts, we aim to understand the role that technologically-mediated managerial practices play in cultivating better job experiences for gig-workers.

As applications of AM reach beyond the gig-economy to full-time employees, gaining a deeper understanding of AM is important to both scholars and practitioners [5]. Moreover, from a societal perspective, a better understanding of AM and the impacts of its perceived fairness on workers may aid policymakers in ensuring good working conditions for platform workers [1]. Our paper is structured accordingly: First, we briefly discuss our research context. After, we present our theoretical lens, Organizational Justice Theory (OJT), followed by our theoretical development. Next, we detail our research methodology, data, and analyses. We conclude by discussing our results and contributions, as well as future research avenues.

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2. Gig-work and algorithmic management

In contrast to the standard dyadic employee-employer relationship, app-based work-relationships in the gig-economy involve at least three parties. On digital labor work platforms, a platform provider (like Uber or Upwork) serves as an intermediary facilitating the coordination of clients and platform workers. In certain instances, suppliers (e.g., restaurant partners, in the case of SkipTheDishes) may act as a fourth party [8].

In the gig-economy, the algorithms powering these digital labor platforms are responsible for matching gig-workers with clients, assigning work, monitoring and evaluating gig-workers' performance, as well as implementing other managerial decisions such as rewards and punishments, all without the need for face-to-face, human interaction [3, 8]. Instead, gig-workers receive instructions from and interact with a managerial algorithm through a digital interface (e.g., an app) [1]. This practice is known as algorithmic management (AM), which Möhlmann et al. [9] define as "the large-scale collection and use of data on a platform to develop and improve learning algorithms that carry out coordination and control functions traditionally performed by managers" (p. 2001). Per Möhlmann et al., AM can be conceptualized as comprising of two key dimensions, namely: algorithmic matching (defined as the algorithmically mediated coordination of platform supply and demand), and algorithmic control (defined as the algorithmic monitoring of workers' behavior to ensure quality service and alignment with the platform provider's goals).

Given that a platform provider is the only one of the four parties (i.e., platform provider, workers, clients, suppliers) with complete access to and control over the platform's data, processes, and rules, platform providers play a key role in determining working conditions as well as gig-workers' experiences through the design of their matching and control-based algorithms [5, 8, 9].

3. Organizational justice and AM

Recent work suggests that gig-workers' perceptions of fairness tend to be shaped by the features and functions of a labor platform and by its governing algorithms [10]. To better understand how gig-workers perceive the fairness of managerial algorithms and their resulting impacts, we adopt a socio-technical perspective of algorithmic fairness [1], and we leverage OJT as a theoretical lens [11].

Organizational justice refers to employees' perceptions of fairness in the workplace. According to scholars, organizational justice is conceptualized as having multiple dimensions, namely: procedural, distributive, interactional, interpersonal, and informational justice [12]. Although some studies examining the fairness of managerial algorithms have confounded all of the dimensions into a single aggregate measure [13], given its importance relative to the other dimensions[1] [12], we focus on procedural justice.

Procedural justice concerns the fairness of the approaches used to determine how organizational resources such as pay, promotions, and job assignments are allocated. Importantly, procedural justice has been conceptualized as having both structural and social aspects. Per the literature, structural aspects concern the formal rules and policies that pertain to decisions impacting employees, like giving adequate notice of decisions before they are implemented and the use of accurate information in the decision-making process. Social aspects concern the quality of interpersonal treatment during the resource allocation process, such as: treating employees with dignity and respect; providing information concerning how decisions were made; and providing opportunities for employees to be actively involved in the development and application of organizational procedures [14]. Given these conceptualizations, procedural justice can be both a function of the organization (such as through a formal decision-making system) or a function of a decision-making agent (such as a manager who involves an employee in the decision-making process) [12].

Accordingly, in the context of AM, 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 managerial algorithms can be considered both as embodiments of procedural justice, and as organizational agents demonstrating fairness in their decision-making processes [6, 5]. This is aligned with recent work which suggests that individuals do indeed attribute managerial algorithms to the organizations that chose them [3, 15] and that workers tend to perceive such algorithms as their bosses [9] (as cited by [1]).

Before proceeding to the next section, we note that the terms 'justice' and 'fairness' have been used interchangeably in the OJT literature [1]. In this study, we follow Schulze et al. [1] and adopt the term 'fairness' which concerns the appraisal of normative 'justice' standards. As we are focused on gig-workers' perspectives and their subjective assessment of justice, we herein use the terms 'fairness' and 'fair' to discuss AM and algorithmically made decisions in our study.

[1] As compared to the other justice dimensions, procedural justice has been shown to have higher contributions to POS and job satisfaction, the two dependent variables in our study, than its counterparts [10, 22].

3.1. AM fairness and decision-types

Whereas many OJT studies do not focus on the allocation of a specific resource or subsume different resource types under a single allocation decision [16], in this study, we explicitly specify two unique resource allocation decisions, namely: matching decisions and performance evaluation decisions. Our design choice was based on experimental work by Lee [3] which found that the perceived fairness of managerial algorithms was shaped by the type of decision executed and whether people thought that an algorithm was equipped to take such decisions. More specifically, Lee [3] identified two types of managerial decisions attributed to algorithms, namely: those requiring 'mechanical skills' and those requiring 'human skills.' According to Lee, mechanical-skills decisions reflected decisions like work assignment and scheduling, which rely heavily on the processing of quantitative data to generate objective measures. Lee further defined human-skills decisions as those that require subjective judgment and emotional capability, like hiring and work evaluation.

In comparing their perceived fairness, Lee [3] found that when algorithms allocated work (a task considered to require mechanical skills), such decisions were perceived as at least as fair as the human-made decisions. Participants attributed the fairness of such decisions to the perceived efficiency and objectivity of the algorithm. However, when algorithms evaluated workers (a task considered to require human skills), people tended to view such decisions as less fair than the human-made decisions based on perceptions that algorithms lack "intuition, only measure quantifiable metrics, and cannot evaluate social interaction or handle exceptions" [p. 12].

Relatedly, Newman et al. [17] found that the fairness of algorithmically made personnel decisions were impacted by people's views of algorithms as reductionist entities, primarily leveraging quantitative data in the decision-making process. Similarly, recent work exploring the perceived fairness of AI hiring evaluations suggested that perceptions of AI fairness were sensitive to one's beliefs of an AI's capacities as a rationalistic entity lacking human bias and instincts [15]. Collectively, these studies underscore that perceptions of fairness will differ based on the type of decisions made by a managerial algorithm, and that gaining a deeper understanding of the mechanisms driving workers' perceptions of fairness requires isolating and studying different decision-types.

For these reasons, we sought to study gig-workers' perceptions of fairness for two types of algorithmic decisions prevalent on digital labor platforms, namely: matching decisions and performance evaluation decisions. In this study, we define matching decisions as the decisions made by a managerial algorithm to connect a platform client with a platform worker; we define performance evaluation decisions as the decisions made by a managerial algorithm to determine a workers' performance rating. These focal decisions correspond to Möhlmann et al.'s [9] two dimensions of AM. Specifically, our matching decision-type corresponds to their *algorithmic matching* dimension, while our performance evaluation decision-type corresponds to their *algorithmic control* dimension. Following Lee [3], matching decisions were selected to represent decisions requiring mechanical skills whereas performance evaluation decisions were selected to represent decisions requiring human skills. See Figure 1 for our research model.

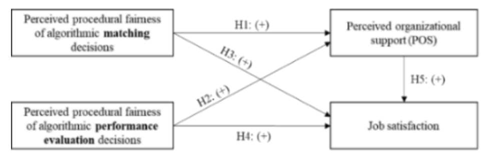


Figure 1: Research model

3.2 Perceived AM fairness and POS

POS is the degree to which employees believe that their "organization values their contributions and cares about their well-being" [18, p. 11]. Both POS and OJT are rooted in social exchange theory (SET) which conceptualizes employment as the trade of time and effort by an employee for tangible benefits and rewards, such as pay, promotions, and other job-related resources. Although SET and POS were conceived to explain traditional employment relationships, recent works have called for organizations to cultivate transparent and supportive relationships with all types of workers regardless of whether they are internal or external (e.g., freelancers and gig-workers) [19, 20].

Amid calls for a renewed focus on SET in the context of digitized workplaces, and the need to rethink the variables and boundaries of SET and related theories [20], we propose that POS can be engendered among transient gig-workers through their exchanges with a platform algorithm. Our proposition is rooted in the mechanism underlying the formation of POS; specifically, perceptions of organizational support are driven by the tendency for people to assign humanlike characteristics to their organizations and to attribute the actions taken by its agents (e.g., managers) as an indication of the organization's intent towards them.

Where organizational procedures are considered by employees 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. More specifically, the perception of fairness in organizational procedures helps to foster a positive organizational climate. When workers consider the systems in place to be just and impartial, they are more likely to believe that the organization is principled, supportive, and values their contributions [21].

In the context of AM – where a platform provider is the only party with full access to and control over the platform's data, processes, and rules – a gig-organization's algorithm(s) "can be understood as an automated manifestation of the interests of the platform organizer" [22, p. 9]. Thus, where gig-workers view a managerial algorithm as a materialization of the organization's interests and discretionary organizational procedures, we expect the perceived procedural fairness of algorithmic decisions to be positively related to POS.

Based on Lee's [3] work, we model our hypotheses as two unique hypotheses to capture the distinct effects of mechanical skills decisions (matching) and human skills decisions (performance evaluation) on POS.

H1*: Perceptions of procedural fairness for algorithmic matching decisions will be positively related to POS.*

H2*: Perceptions of procedural fairness for algorithmic performance evaluation decisions will be positively related to POS.*

3.3 Perceived AM fairness and job satisfaction

Job satisfaction denotes an employee's overall affective evaluation of their job circumstances and their overall sense of well-being at work [14]. Prior research suggests that job satisfaction largely reflects perceptions of organizational fairness. According to the relational model of procedural justice, when employees question the fairness of the procedures affecting them, they experience reduced job satisfaction. Conversely, instances of procedural fairness convey positive identity clues like organizational regard and dignity which lead to improved self-image and morale. Based on these clues, workers appraise the organization more positively and experience more job satisfaction [23].

The strong and positive correlation between procedural fairness and job satisfaction has been confirmed by two meta-analyses [12, 21]. We expect this relationship to apply to the decisions executed by managerial algorithms, as the resources allocated by these decision-makers are analogous to those in studies conducted in traditional work contexts. Using the same logic applied in H1 and H2, we model our hypotheses separately to capture the distinct effects of each decision-type on job satisfaction.

H3*: Perceptions of procedural fairness for algorithmic matching decisions will be positively related to job satisfaction.*

H4*: Perceptions of procedural fairness for algorithmic performance evaluation decisions will be positively related to job satisfaction.*

3.4 POS and job satisfaction

The concept of POS derives from Organizational Support Theory (OST). Explaining employer-employee relationships through the lens of social exchange theory, OST assumes that workers ascertain an organization's readiness to reward their work efforts and to meet their socioemotional needs by developing a set of global beliefs concerning an organization's support. Thus, according to OST, employees treated favorably will: (i) care about an organization's well-being and feel an obligation to help the organization reach its objectives; as well as (ii) feel an expectation that their increased performance will be recognized and rewarded [14].

By stimulating the norm of reciprocity, POS should not only fulfill socioemotional needs, but also increase the anticipation of help, and strengthen reward expectancies and self-efficacy thereby enhancing job satisfaction. In essence, POS creates an environment where employees feel acknowledged, valued, and equipped to perform their roles which contributes to heightened job satisfaction. This relationship is well-established in traditional work contexts and has been confirmed by two meta-analyses [21, 14].

Where a gig-organization's managerial algorithm can be understood as a series of code that embody the interests and intents of the platform organizer [22], we suggest that perceptions of support engendered by a managerial algorithm will lead to job satisfaction. Therefore, we put forth Hypothesis 5:

H5*: POS will be positively related to job satisfaction.*

4. Methodology

To evaluate our model, we conducted an online (cross-sectional) survey with Uber drivers from North America (n=435). Per Möhlmann and Zalmanson [24], the Uber platform is an exemplar of an algorithmically managed work context. More specifically, the platform is a highly centralized system where a managerial algorithm plays a significant role in automating and controlling most exchanges. More specifically, the Uber algorithm is responsible for tasks such as matching drivers with riders and monitoring and assessing their performance in addition to other managerial functions.

4.1 Participant recruitment and statistics

To qualify for our study, potential participants were required to have worked on the Uber platform for at least one (1) month over the last year to ensure they had sufficient familiarity and experience with the platform, including its features and functions. Participants were recruited online via Prolific (a crowdwork platform) and Facebook Uber driver groups, a commonly utilized source for Uber-specific studies (e.g., [24, 25]). The two datasets were amalgamated following other researchers' approaches (c.f. [24, 25]). However, prior to doing so, post-hoc analyses were conducted to ensure no major differences between the data sources.

Most participants were American (62.1%). Close to one in three of our participants (28.5%) were female, which is representative of the Uber driver population [5]. Most participants were younger than 45 years old, specifically: participants aged 18-24 accounted for 24.4% of the sample; those aged 25-34 accounted for 44.4%; and those aged 35-44 accounted for 21.6% of the sample. Our sample was well-educated; nearly three-quarters (73.8%) of participants had at least a post-secondary degree. Most participants worked part-time for Uber (92.9%) and worked at least one other job (61.8%). Average tenure with Uber was 34 months. In terms of platform experience and work intensity, 39.3% of participants had completed less than 100 rides on the platform; 34.3% completed 100-499; 22.5% completed 500-4999; and only 4% completed more than 5000.

4.2 Survey measures

To measure perceptions of algorithmic fairness, we used Colquitt's [11] measure of organizational justice ($\alpha = 0.93$). The scale includes seven (7) items to measure procedural fairness which we adapted to assess the perceived algorithmic fairness of two decisions on the Uber platform: matching decisions and performance evaluations decisions. Sample items included: "*Have you been able to express your views and feelings during the matching procedure?"* (e.g., procedural fairness item for matching); "*Do you consider that the app's evaluation procedures are based on accurate information?*" (e.g., procedural fairness item for evaluation). All items were measured on a 7-point Likert-scale (1 = to an extremely small extent, 7 = to an extremely large extent).

Based on Eisenberger et al. [26], we measured job satisfaction using four items from Quinn and Shepard's Overall Job Satisfaction index, a facet-free job satisfaction scale measured ($\alpha = 0.79$). A sample item included was: *"All in all, I am very satisfied with my current job."* To measure POS, we used Eisenberger et al.'s [18] Survey of Perceived Organizational Support. The short (8-item) version of the scale was used ($\alpha = 0.97$). Sample items included: *"The organization really cares about my well-being"* and "*The organization fails to appreciate any extra effort from me*' (R)." Job satisfaction and POS were measured on a 7-point Likert-scale (1 = strongly disagree, 7 = strongly agree).

Based on previous job satisfaction research (e.g., [27]), we controlled for age in our survey[2]. We also controlled for people's varying levels of knowledge about algorithms which could impact their perceptions of the fairness of algorithmic decisions. To measure participants' Algorithmic Knowledge, we asked: *"Please rate your knowledge of algorithms"* (1 = no knowledge at all, 7 = expert knowledge). Finally, we also controlled for the extent to which people attribute platform decisions to an algorithm [3]. To measure Algorithmic Attribution, we asked participants: "*To what extent do you attribute the actions and decisions of the Uber app to an algorithm?*" (1 = to an extremely small extent, 7 = to an extremely large extent)[3].

4.3 Data quality assessment

Prior to our analyses, we assessed the quality of our data and its suitability for structural equation modelling using SPSS 26. An initial data-quality check suggested no significant departures of the normality assumption, as indicated by our skewness scores (-0.801 and 0.904) and our kurtosis scores (-1.146 and 1.637) which respect the -2 and +2 ranges [28]. Cook's D values were used to identify any potential outliers, but none were detected. All values were below 1—the threshold suggested by Stevens [29]. Finally, we conducted the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy test and Bartlett's Test of Sphericity. Our data surpassed the thresholds for both tests with a KMO value of 0.970 and a significant Bartlett's Test ($p<0.0001$).

5. Analyses and results

To conduct our analyses, the partial least squares (PLS) structural equation modelling (SEM) technique was employed using SmartPLS 3.2.3. PLS path modeling is well-suited to research aimed at prediction where the identification of relationships is the central purpose of one's work. As our research goals include the evaluation of propositions and the exploration of links between core concepts, PLS-SEM is well-aligned with

[2] Previous research has consistently shown a small positive correlation between age and job satisfaction.

[3] A copy of our complete instrument has been made available online at this address: https://bit.ly/HICSS_Appendix

our needs [30, 31]. PLS-SEM has also been used by other IS scholars to study justice and fairness (c.f. [32])

5.1 Measurement model

Confirmatory factor analysis (CFA), a multivariate statistical procedure, was used to examine our measurement model and to confirm the psychometric properties of our scales. First, through an iterative process, we eliminated all items with low loadings on all factors and/or high cross-loadings. Through this process, we retained items with a minimum loading of 0.7, that clearly loaded onto a single appropriate factor, and that demonstrated a difference of 0.20 between their primary and alternative factor loadings [33]. Our measurement model is found in Figure 2[4].

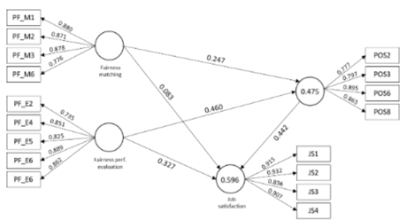


Figure 2: Measurement model

As a next step, we evaluated internal consistency, as well as the validity (both convergent and discriminant) of our constructs (See Tables 1 and Table 2). To assess convergent validity, the reliability of our constructs was measured by Cronbach alpha (α), composite reliability (CR), and finally Rho_A. All reliability statistics surpassed the threshold of 0.7, affirming convergent validity. Additionally, the average variance extracted (AVE) for all constructs exceeded the minimum requirement of 0.5, further confirming convergent validity [34]. Variance inflation factors, or VIF, were analyzed for both our items (the outer model) and our constructs (the inner model). All VIF values for the inner model were well-below the 3.3 threshold, indicating sufficient construct validity by a lack of multicollinearity. Lastly, we concluded that common method bias (CMB) was not a significant issue [35].

To evaluate discriminant validity, we employed the Fornell-Larcker criterion. As per Table 2, the square-root of the AVE for each construct was higher than its highest correlation with any other construct, thereby ensuring satisfactory discriminant validity [28]. To further test discriminant validity, we also calculated the Heterotrait-Monotrait ratio (HTMT). All HTMT values were less than 1 and the more stringent threshold of 0.85, thus further confirming discriminant validity between our reflective constructs [35].

								VIF	
	N	Mean	Std. Dev.	CA	rho_A	CR	AVE	JS	POS
Fairness (P. Evaluation)	435	4.024	1.472	0.890	0.897	0.919	0.696	2.792	2.391
Fairness (Matching)	435	4.722	1.516	0.874	0.875	0.914	0.727	2.500	2.386
Job Satisfaction (JS)	435	3.838	1.391	0.920	0.929	0.944	0.807	Endogenous	Endogenous
POS	435	4.159	1.369	0.856	0.879	0.902	0.697	1.903	Endogenous

Notes: SD (standard deviation); CA (Cronbach alpha); CR (composite reliability); AVE (average variance extracted); VIF (variance inflation factor)

Table 1: Reliability and convergent validity statistics

	Square root AVE				HTMT			
	Fairness Perf. Evaluation	Fairness Matching	JS	POS	Fairness Perf. Evaluation	Fairness Matching	JS	POS
Fairness (Perf. Evaluation)	**0.834**							
Fairness (Matching)	0.754	**0.852**			0.849			
Job Satisfaction (JS)	0.683	0.603	**0.899**		0.749	0.661		
POS	0.661	0.613	0.714	**0.835**	0.741	0.685	0.786	

Table 2: Discriminant validity statistics

Lastly, to evaluate the fit of our measurement model, we examined the saturated model and assessed the Standardized Root Mean Square Residual (SRMR) at a 95% bootstrap quantile. With an SRMR value of 0.066, which is well-below the threshold of 0.8, we concluded a well-fitting measurement model [31].

5.2 Structural model

To examine our structural model, we utilized a bootstrapping procedure to assess the significance of the path coefficients and the predictive power of our model. Given the strong theoretical support for positive relationships among our hypotheses (H1-H5), we conducted a one-tail test. Following recommended practices, we examined multiple empirical thresholds for statistical significance, effect sizes, and R^2.

H	Focal constructs and relationships	Path coef.	t-statistic	p value
H1	Fairness (Matching) → POS	0.247	4.009 ***	0.000
H2	Fairness (Perf. Evaluation) → POS	0.460	7.898 ***	0.000
H3	Fairness (Matching) → Job Satisfaction (JS)	0.083	1.858 *	0.032
H4	Fairness (Perf. Evaluation) → Job Satisfaction (JS)	0.327	5.532 ***	0.000
H5	POS → Job Satisfaction (JS)	0.442	9.672 ***	0.000
	Controls	Path coef.	t-statistic	p value
	Age → Job Satisfaction (JS)	0.056	1.644 *	0.050
	Age → POS	0.020	0.514	0.304
	Algorithmic Knowledge → Job Satisfaction (JS)	0.035	0.979	0.164
	Algorithmic Knowledge → POS	0.089	2.3650 **	0.009
	Attribution →Job Satisfaction (JS)	-0.030	0.791	0.215
	Attribution → POS	-0.052	1.312	0.095

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

Table 3: Path coefficients and statistical significance

First, as recommended by Chin [36], all hypothesized paths were at least 0.20 – with the exception of the path from Fairness (Matching) to Job satisfaction (H3). Next, statistical significance of all path coefficients was assessed by applying Hair, et al.'s (2011) guidelines which requires a minimum threshold of 1.65 for the t-statistics values at $p < 0.05$ confidence interval. Apart from our control variables, all paths demonstrated statistical significance (see Table 3).

[4] For legibility reasons, we have not included the controls nor their paths in the model. For further details, see Table 3.

Next, we evaluated the R^2 values for both of our endogenous variables. Per Hair et al. [31], R^2 values of 0.25, 0.50, and 0.75 signify weak, moderate, and substantial levels respectively. Based on these thresholds, our analysis revealed moderate R^2 values for job satisfaction and near-moderate values for POS. Additionally, bootstrapping results of the significance test for our R^2 values were shown to be statistically significant (see t-statistic and p-values in Table 4).

Endogenous constructs	R^2	t-statistic	p value
Job satisfaction	0.596	19.457 ***	0.000
POS	0.475	14.282 ***	0.000
Focal constructs and relationships	**f^2**	**t-statistic**	**p value**
Fairness (Matching) → POS	0.048	1.812 *	0.035
Fairness (Evaluation) → POS	0.168	3.522 ***	0.000
Fairness (Matching) → Job Satisfaction (JS)	0.007	0.855	0.196
Fairness (Evaluation) → Job Satisfaction (JS)	0.095	2.454 **	0.007
POS → Job Satisfaction (JS)	0.254	4.243 ***	0.000
Controls			
Age → Job Satisfaction (JS)	0.008	0.756	0.225
Age → POS	0.001	0.142	0.443
Algorithmic Knowledge → Job Satisfaction (JS)	0.002	0.368	0.350
Algorithmic Knowledge → POS	0.012	1.095	0.137
Attribution → Job Satisfaction (JS)	0.002	0.301	0.382
Attribution → POS	0.004	0.572	0.284

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

Table 4: R^2 and f^2 values with statistical significance

Whereas f^2 and Q^2 statistics are reported less frequently, these structural model metrics ensure the accurate interpretation of a model's results [31]. We therefore assessed the effect size using the f^2 statistic (a measure of the magnitude of an effect that is independent of sample size). Per established guidelines for f^2, values of 0.020-0.150 signify weak effects; values of 0.150-0.350 signify medium effects; and values of 0.350 or greater signify large effects [35]. Accordingly, we find medium effects for the fairness of performance evaluation decisions to POS, and for POS (as a mediator) to job satisfaction. All other effects, except for fairness of matching to job satisfaction, were weak. Lastly, as signaled by the t-statistic and p-values in Table 4, bootstrapping results for the significance tests of f^2 values for all relationships were statistically significant except for the fairness of matching to job satisfaction.

			RMSE	
Endogenous Items	**Q^2_predict**	**Interpretation Q^2**	**PLS**	**LM**
JS1	0.443	Medium-Large	1.302	1.305
JS2	0.441	Medium-Large	1.285	1.299
JS3	0.295	Medium	1.321	1.323
JS4	0.355	Medium	1.377	1.388
POS2	0.171	Small	1.656	1.661
POS3	0.231	Medium	1.523	1.497
POS6	0.445	Medium-Large	1.292	1.304
POS8	0.399	Medium	1.373	1.382
Endogenous variables (using Blindfolding technique)				
Job Satisfaction (JS)	0.470	Medium-Large	n/a	n/a
POS	0.317	Medium	n/a	n/a

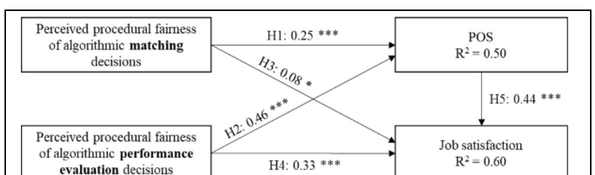
Table 5: Predictive power analyses

Next, we assessed Q^2 (see Table 5). Per established guidelines for Q^2, values over zero signify that a model is well-constructed and has predictive relevance. More specifically, Q^2 values greater than 0, 0.25 and 0.50 indicate small, medium, and large predictive relevance for a PLS-path model [34]. All Q^2 values for our items were greater than 0 and meaningful. Our Q^2 results confirm the predictive relevance and accuracy of our model. For the latent variables in our model, we employed the blindfolding approach to derive Q^2 values. Using Hair et al.'s [31] recommended omission distance of 7, the blindfolding approach yielded Q^2 values of 0.470 for job satisfaction and 0.317 for POS. As all but two of our Q^2 values for both our items and endogenous constructs exceeded 0.25 – and with many values near or greater than 0.4 – our results indicate the medium to high predictive relevance for our model.

Lastly, as part of our analysis of predictive power, we conducted a comparative analysis of whether the PLS analysis yields higher or lower prediction errors in terms of root mean squared error (RMSE) versus the LM analysis. Per Hair et al.'s guidelines [34], our model is considered to have a high out-of-sample predictive power for job satisfaction and moderate power for POS.

6. Discussion

Insofar as gig-workers are not passive recipients of algorithmic management [22], and knowing that people tend to build "diverse mental models and folk theories" [3, p. 2] about how algorithms operate, despite how they actually work, understanding how gig-workers perceive managerial algorithms and the fairness of their decisions is of great importance. In this study, we examined how gig-workers perceive the fairness of decisions made by algorithms on digital labor platforms using Organizational Justice Theory. Through a survey of 435 Uber drivers, we found that the perceived procedural fairness of both algorithmic matching decisions and performance evaluation decisions were positively related to POS and job satisfaction (see Figure 2). Interestingly, the path coefficients from the perceived fairness of performance evaluation decisions to POS (0.46***) and to job satisfaction (0.33***) were greater than those from the perceived fairness of matching decisions to POS (0.25***) and to job satisfaction (0.08*). These results lead us to believe that the impacts of perceptions of algorithmic fairness may differ based on the decision enacted by an algorithm. Our results also demonstrate positive and significant relationships between POS and job satisfaction (see Figure 2). We now discuss the scholarly and practical contributions of our findings.



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

Figure 2: Research model results

6.1 Research contributions

Our work offers several scholarly contributions. Firstly, by exploring AM fairness in the unique context of the gig-economy, our study answers calls for research investigating perceptions of AM and AI fairness and their impacts in real-world settings [3, 15]. Moreover, by measuring fairness perceptions across two types of decisions, we adopt an under-utilized methodological approach that provides unique insights into how gig-workers perceive managerial algorithms and form perceptions of their fairness [16].

Specifically, by analyzing the items retained for each of the fairness constructs in our measurement model, we were able to begin drawing conclusions on the mechanisms driving perceptions of algorithms' procedural fairness. As a reminder, the items used to measure fairness in our model were eliminated based on their factor loadings[5]. All but two factor loadings for our fairness constructs exceeded 0.8, making them good representations of the factor and thus of practical significance. Accordingly, based on the remaining indicators, one can draw conclusions on the relative importance of indicators driving perceptions of algorithms' procedural fairness. Notably, the ability to influence the outcome of the decision-making process as well as the belief of an algorithm's use of accurate information were the only two indicators common to both matching and performance evaluation decisions.

As expected, we identified differences in the importance of the other fairness indicators across the two decision-types. On the one hand, the ability to appeal outcomes and to express one's views emerged as important indicators of fairness for matching decisions, but not for performance evaluation decisions. In the context of our research, these findings suggest that the opacity or transparency of an algorithmic decision-making process plays an important role in forming perceptions. On the Uber platform, the matching algorithm is significantly opaquer than its performance evaluation algorithm, which is based on readily available and accessible data such as customer ratings, as well as cancellation and acceptance rates [8]. Due to the opacity of the matching decision process, a worker's ability to ascertain the trustworthiness and fairness of such decisions may be threatened [24, 37].

Where a decision-making process, like the matching decision, lacks transparency, one's ability to express one's views and the ability to appeal decisions is likely to increase in importance. Per de Fine Licht and de Fine Licht [38], when algorithmic decision-making processes are transparent, this may motivate those impacted to "act as good losers" when faced with unfavorable decisions (e.g., they may be more likely to accept the decision and move on). However, where such decisions lack transparency, those impacted may be less likely to 'move on' and may instead look to their ability to voice their opinions and/or appeal decisions. Thus, our analysis reinforces the roles that the ability to express one's views and to appeal decisions play as indicators of fairness for opaque algorithmic decisions.

On the other hand, consistency, lack of bias, and the adherence to moral and ethical standards emerged as important indicators of fairness for performance evaluation decisions, but not for matching decisions. Such distinctions in perception might be attributed to whether algorithms are perceived as capable of making such decisions, as suggested in prior research [3, 15, 39]. Notably, the importance of the "lack of bias" and "moral and ethical" fairness indicators in performance evaluation decisions aligns with prior findings which found that perceptions of AI fairness (in human-skills decisions) are sensitive to one's beliefs of an AI's capacities as a rationalistic entity lacking human bias and instincts – two elements often necessary in the management of humans – as well as beliefs concerning an algorithm's moral authenticity [39].

Lastly, our work demonstrated that engendering POS among transient gig-workers through perceptions of algorithmic fairness is both possible, and desirable for platform providers, given the relationship between POS and job satisfaction. Establishing the possibility of platform-generated POS among gig-workers' is important given that some scholars and practitioners have questioned its feasibility and relevance as a human resource strategy in the gig-economy, while others have stressed the importance of creating transparent and supportive relationships for internal and external workers alike [19, 20, 40].

As an unexpected finding, we found that the perceived fairness of performance evaluation decisions emerged as a more important factor than the perceived fairness of matching decisions with regards to their impacts on our dependent variables (POS and job satisfaction), as measured by the path coefficients in our structural model. This finding suggests that despite concerns surrounding the capacities of algorithms and AI-systems to execute decisions requiring human skills [3, 39], gig-workers still accept such decisions as indications of the organization's goodwill and intent towards them. Moreover, it is possible that performance evaluation decisions emerged as a relatively more important factor in our model due to gig-workers' perceptions of their discretionary nature. As a reminder,

[5] A factor loading for a variable measures how much the variable (or item) contributes to the factor (or focal construct).

procedural fairness has been found to be one of the strongest drivers of POS and job satisfaction since organizational procedures are generally considered by workers to be highly discretionary as well as essential to their long-term interests and well-being [21]. Based on OST research, matching (or mechanical skills) decisions might have played a less important role in our model if the decision is perceived as being rooted in efficiencies and less discretionary in nature than performance evaluation (human skills) decisions which, on the Uber platform, are linked to rewards and recognition.

6.2 Implications for practice

Our study offers various practical contributions. First, it highlights that gig-organizations can promote job satisfaction by ensuring that managerial algorithms are perceived as treating workers fairly. Our research also confirms that perceptions of organizational support are indeed experienced by independent gig-workers, despite their transience and limited attachment to the organization, and that perceptions of organizational support play a key role in supporting gig-workers' job satisfaction. Such findings can aid gig-organizations to retain gig-workers given that fairness, job satisfaction, and POS are positively linked to intentions to stay [21].

Notably, unlike freelancers marketing higher-skill services on digital platforms with substantial autonomy, low-skill workers who are more actively managed by a platform's managerial algorithm tend to perceive themselves as employees and are more likely to expect a platform-provider to care about their well-being. Thus, POS could have important consequences for gig-workers performing work on highly centralized platforms like Uber [19]. Moreover, engendering POS among gig-workers could help attenuate the negative impacts associated with the inherent stress of such arrangements resulting from "being treated as a commodity rather than a person" [13].

Ensuring that gig-workers perceive managerial algorithms as based on accurate information, as well as upholding moral and ethical standards, requires addressing the issue of algorithmic opacity on digital labor platforms [40]. To address this common issue, gig-organizations can opt to explain to gig-workers the intent and goals of the managerial algorithm, as well as communicate the basis for the inclusion, exclusion, or optimization of various inputs to the algorithm. In cases where disclosing an algorithm's properties and processes is impossible, gig-organizations can submit themselves to routinized third-party algorithmic audits which can provide indications of an algorithm's objectivity, accuracy, and consistency [37].

Lastly, where certain indicators of perceived algorithmic fairness were unique to the type of decision made (and whether it is perceived to require mechanical or human skills), it is likely that the successful adoption of managerial algorithms in organizations may require the use of 'framing techniques' [17] by organizational leaders to emphasize different aspects of an algorithm's functions and capacities according to the decision-type assigned to the managerial algorithm. Our factor-loading analyses further suggest that regardless of the decision-type, organizational leaders should ensure that those affected by the algorithm perceive it as based on accurate information and sense that they can influence the decision-making outcome. As such, in addition to the importance of transparency, ensuring that workers are not treated as passive recipients of AM can support perceptions of algorithmic fairness across different types of algorithmically made personnel decisions.

6.3 Limitations and future work

Given the novelty of our research, we focused specifically on gig-workers' perceptions of the procedural fairness of algorithms operating on the Uber platform. These limitations offer various future research opportunities. First, future studies could incorporate additional dimensions of fairness within our research model. In algorithmically managed work contexts, managerial and decision-making processes are often reduced to opaque algorithms that are complex and inaccessible – leaving workers unable to ascertain the fairness of such procedures [19]. In such instances, integrating the distributive dimension of fairness (which examines outcomes of procedures) could offer new insights into how workers perceive algorithmic fairness.

Second, future studies could extend our findings by examining workers' perceptions of fairness in relation to different types of algorithmic decisions. Managerial algorithms are increasingly responsible for handling a wide array of tasks beyond job assignments and performance evaluations. Managerial algorithms and various forms of AI have been tasked with recruitment and hiring in traditional organizations. Where such practices have been met with outcry and complaints by the public and researchers regarding their fairness, exploring the fairness of decision types, within and across platforms, as well as in traditional work contexts, is a promising area for further investigation [15]. This research stream offers many opportunities, and we hope that IS scholars will continue exploring how people experience algorithmically managed work.

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8. References

[1] L. Schulze, et al., "Fairness in Algorithmic Management: How Practices Promote Fairness and Redress Unfairness on Digital Labor Platforms," HICSS, 2023.

[2] M. K. Lee, et al., "Working with Machines: The Impact of Algorithmic, Data-Driven Management on Human Workers," *ACM SIGCHI Conference*, 2015.

[3] M. Lee, "Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management," *Big Data & Society,* 5(1), pp. 1-16, 2018.

[4] K. Kellogg, et al., "Algorithms at work: The new contested terrain of control," *Academy of Management Annals,* 14(1), 366–410, p. 14, 2020.

[5] N. Jabagi, et al., "Perceived Organizational Support in the Face of Algorithmic Management: A Conceptual Model," HICSS, pp.4001-4010, 2020.

[6] A. McDonnell, et al., "Technologically mediated human resource management in the gig economy," *The International Journal of Human Resource Management,* 32(19), pp. 3995-4015, 2021.

[7] N. Jabagi, et al., "Unlocking Perceived Algorithmic Autonomy-Support: Scale Development and Validation," ICIS, pp.1-17, 2021.

[8] J. Duggan, U. Sherman, R. Carbery and A. McDonnel, "Algorithmic management and app-work in the gigeconomy: A research agenda for employment relations and HRM," *Human Resource Management Journal,* no. 1, pp. 1-19, 2019.

[9] M. Möhlmann, et al., "Algorithmic Management of Work on Online Labor Platforms: When Matching Meets Control," *MIS Quarterly,* 45(4), pp. 1999-2022, 2021.

[10] C. Fieseler, E. Bucher and C. Hoffmann, "Unfairness by design? The perceived fairness of digital labor on crowdworking platforms," *Journal of Business Ethics,* 156(10), 2019, pp. 987-1005, 2018.

[11] J. A. Colquitt, "On the Dimensionality of Organizational Justice: A Construct Validation of a Measure," *Journal of Applied Psychology,* 86(1), pp. 386-400, 2001.

[12] J. Colquitt, et al., "Justice at the millennium: A meta-analytic review of 25 years of organizational justice research.," *Journal of Applied Psychology,* 86, pp. 425-445, 2001.

[13] D. Cross and J. Swart, "The (ir)relevance of human resource management in independent work: Challenging assumptions," *Human Resource Management Journal,* 32, p. 232–246, 2022.

[14] L. Rhoades and R. Eisenberger, "Perceived organizational support: a review of the literature," *Journal Applied Psychology,* 87, pp. 698-714, 2002.

[15] A. Mirowska and L. Mesnet, "Preferring the devil you know: Potential applicant reactions to artificial intelligence evaluation of interviews," *HRMJ,* 32, pp. 364-383, 2022.

[16] B. Hu and S. Han, "Distributive Justice: Investigating the Impact of Resource Focus and Resource Valence," *Journal of Business and Psychology,* pp. 1-28, 2020.

[17] D. Newman, N.J. Fast, and D. Harmon, "When eliminating bias isn't fair: Algorithmic reductionism and procedural justice in human resource decisions," *Organizational Behavior and Human Decision Processes,* vol. 160, pp. 149-167, 2020.

[18] R. Eisenberger, et al., "Perceived organizational support," *Journal of Applied Psychology,* 71, pp. 500-507, 1986.

[19] K. Kuhn and A. Maleki, "Micro-entrepreneurs, dependent contractors, and instaserfs: understanding online labor platform workforces," *AOM Perspectives,* 31(3), pp. 183-200, 2017.

[20] L. Chernyak-Hai and E. Rabenu, "The New Era Workplace Relationships: Is Social Exchange Theory Still Relevant?," *Industrial and Organizational Psychology,* 11(3), pp. 456-481, 2018.

[21] J. N. Kurtessis, et al., "Perceived Organizational Support: A Meta-Analytic Evaluation of Organizational Support Theory," *Journal of Management,* 43(6), pp. 1854-1884, 2017.

[22] M. H. Jarrahi and W. Sutherland, "Algorithmic Management and Algorithmic Competencies: Understanding and Appropriating Algorithms in Gig work," *iConference*, 2018.

[23] S. Blader and T. Tyler, "Relational Models of Procedural Justice," in *The Oxford Handbook of Justice in the Workplace*, Oxford, Oxford University Press, 2015, p. 351–369.

[24] M. Möhlmann and L. Zalmanson, "Hands on the wheel: Navigating algorithmic management and Uber drivers," ICIS, 2017.

[25] G. Newlands and C. Lutz, "Fairness, Legitimacy, and the Regulation of Home-Sharing Platforms," *International Journal of Contemporary Hospitality Management.,* 32(10), pp. 3177-3197, 2020.

[26] R. Eisenberger, et al., "Perceived organizational support, discretionary treatment, and job satisfaction," *Journal of Applied Psychology,* 82, pp. 812-820, 1997.

[27] J. Hackman and G. Oldham, "Motivation through the design of work: test of a theory," *Organizational Behavior and Human Performance,* 16(2), pp. 250-279, 1976.

[28] S. Moussawi and M. Koufaris, "Perceived Intelligence and Perceived Anthropomorphism of Personal Intelligent Agents: Scale Development and Validation," HICSS, 2019.

[29] J. Stevens, Applied multivariate statistics for the social sciences (2nd ed.), L. Erlbaum Associates, 1992.

[30] D. L. Goodhue, W. Lewis and R. Thompson, "Does PLS Have Advantages for Small Sample Size or Non- Normal Data?," *MIS Quarterly,* 36(3), p. 981–1001, 2012.

[31] J. Hair, et al., A Primer on Partial Least Squares Structural Equation Modeling, 2nd ed., Sage Publishing, 2017.

[32] D. Mirchandani and A. Lederer, "Autonomy and procedural justice in strategic systems planning," *Information Systems Journal,* 24(1), pp. 29-59, 2014.

[33] N. Roberts and J. Thatcher, "Conceptualizing and Testing Formative Constructs: Tutorial and Annotated Example," *The DATA BASE for Advances in IS,* 40(3), pp. 9-31, 2009.

[34] J. Hair, et al., "When to use and how to report the results of PLS-SEM," *European Business Review,* 31(1), pp. 2-24, 2019.

[35] J. Benitez, et al., "How to performa and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research," *Information & Management,* 57(2), pp. 1-15, 2020.

[36] W. Chin, "Issues and Opinion on Structural Equation Modeling," *MIS Quarterly,* 22(1), pp. vii-xvi, 1998.

[37] J. Burrell, "How the machine 'thinks': Understanding opacity in machine learning algorithms," *Big Data & Society,* 3(1), p. 1–12, 2016.

[38] K. de Fine Licht and J. de Fine Licht, "Artificial intelligence, transparency, and public decision-making," *AI & SOCIETY,* 35, pp. 917-926, 2020.

[39] A. Jago, "Algorithms and authenticity," *Academy of Management Discoveries,* 5(1), pp. 38-56, 2019.

[40] J. Meijerink, et al., "Algorithmic human resource management: Synthesizing developments and cross-disciplinary insights on digital HRM," *IJHRM,* 32(12), pp. 2545-2562, 2021.