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Completed Research Paper

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Abstract

On digital labor platforms, interactions between workers and clients are algorithmically managed. Previous research found that algorithmic management can disadvantage workers. In this paper, we empirically examine algorithmic unfairness from a sociotechnical perspective. Specifically, we conduct online focus groups with 23 workers who directly interact with algorithmic management practices on digital labor platforms. In using grounded theory methodology, we pursue to understand how algorithmic management promotes unfairness on digital labor platforms. Our emergent theory understands algorithmic unfairness as algorithmic management practices that give rise to systematic disadvantages for workers. Algorithmic management practices either automate decisions or automate the delegation of decisions. Workers experience systematic disadvantages in the form of devaluation, restriction, and exclusion. Our findings serve as a starting point for mitigating algorithmic unfairness in the future.

Keywords: Algorithmic management, algorithmic unfairness, worker disadvantages, digital labor platforms, decision-making, automation, delegation

Introduction

Digital labor platforms (DLPs) connect workers who offer their services and clients who are in need of those services (Rai et al., 2019). They include both, platforms that mediate location-independent services (e.g., copywriting, answering surveys, logo design), as well as location-dependent services (e.g., driving, delivering, household services). DLPs have been criticized for poor work conditions in legal and public debates (e.g., Prassl, 2018; Taylor, 2017). For instance, surveys among DLP workers found that for every hour spent on paid tasks, they have to invest between 20 and 23 minutes of unpaid work (Rani et al., 2021). While workers may try and circumvent undesirable platform practices, their opportunities for resistance are limited (Cameron & Rahman, 2022). Because workers on DLPs are often dependent on these platforms for income (Rani et al., 2021), they are especially vulnerable to poor work conditions. The lack of a formal and regulated employment relationship with the platform provider leaves them without typical labor protection devices such as the right to collective bargaining or social security (Rani et al., 2021). As such, they are a vulnerable group that deserves the focus of scholarly attention.

Scholars have identified biases and ethical violations as predominant causes of adverse work conditions on DLPs (e.g., Fieseler et al., 2019; Schlagwein et al., 2019). This in turn has promoted calls for fairer work practices to improve workers' welfare on DLPs. For instance, the Fairwork project investigates and rates the work conditions on different DLPs and aims to contribute to fairer work conditions (Oxford Internet Institute & WZB Berlin Social Science Centre, 2022).

DLPs employ algorithms to manage a large number of interactions between workers and clients (Rani et al., 2021). Applying algorithms to manage work has been termed algorithmic management (AM) (Lee et al., 2015). While AM is instrumental in streamlining worker-client interactions, its pervasiveness bears challenges. Ethical concerns in the likes of unfairness become particularly acute once algorithms are deployed extensively to manage workers (Gal et al., 2017). Recent scholarly debates in information systems (IS) research result in consensus about the necessity of managing the dark sides of AM with means of fairness, accountability, transparency, and ethics (Benlian et al., 2022). The involvement of the workers is crucial in identifying existing problems and implementing solutions (Benlian et al., 2022; Lee et al., 2019; Zhang et al., 2022).

Addressing ethical concerns in the employment of algorithms, in general, is a well-established goal. Many governments and organizations have put forward principles for the employment of algorithms (Fjeld et al., 2020) by seeking answers to questions like "Are there particular groups which may be advantaged or disadvantaged, in the context in which you are deploying, by the algorithm/system you are building?" and "What is the potential damaging effect of uncertainty/errors to different groups?". There are, however, no straightforward answers to these questions. Among the issues of achieving fairness in algorithms is the lack of an agreed-upon definition of fairness criteria, the difficulty in measuring all desirable criteria and satisfying multiple criteria simultaneously (Teodorescu et al., 2021).

Instead of approaching algorithmic unfairness as a computational problem, there is growing acknowledgement that algorithmic fairness cannot be detached from its social context. To this end, there are growing calls for a socio-technical approach to comprehending how algorithms promote unfairness (Dolata et al., 2021; Teodorescu et al., 2021). Yet, to date, there is a scarcity of empirical evidence on algorithmic unfairness, which limits our understanding of the AM practices that create systematic disadvantages and what these disadvantages constitute. This study hence endeavors to offer insights into this issue by proposing an answer to the following research question: *How do algorithmic management practices promote unfairness on digital labor platforms?* Identifying specific AM practices that are unfair in the workers' view and identifying the specific disadvantages they face promises to lay the basis for changing those practices, thereby improving work conditions of platform workers in the future.

We subscribe to the workers' perspective on algorithmic unfairness for two reasons. First and foremost, workers are the least protected, but most protection-worthy group of stakeholders involved on DLPs based on the increased power imbalance on DLPs that disadvantages workers (Pastuh & Geppert, 2020; Shanahan & Smith, 2021). Second, workers are interacting with AM in their everyday experiences with DLPs, making them the experts in human-AM interaction.

To answer our research question, we conduct seven online focus groups and accommodate the subjective views of a broad range of workers who directly interact with AM practices on DLPs. We use grounded theory methodology (GTM) to theorize algorithmic unfairness as AM practices that give rise to systematic disadvantages for workers. We discover that AM practices contribute to workers' disadvantages by either automating decisions for which contingencies could exist, or delegating decisions to parties with opposing interests. In turn, these unfair work conditions disadvantage workers through devaluation (lower returns, losing assets), restriction (fewer chances for returns), and exclusion (losing chances for returns on the DLP).

The paper proceeds as follows. We adhere to the typical structure of a paper that presents the research question and the findings in related literature upfront. However, in line with the inductive grounded research methodology of this study, the specific research question and the focus on AM and unfairness only emerged during data analysis. The interpretive nature of the analysis acknowledges the hermeneutic stance in sensemaking from the data (Klein & Myers, 1999). Therefore, the results presented represent one of many possible thematic foci and interpretations of the data which do not preclude other approaches.

Theoretical Foundation

Algorithmic Management on Digital Labor Platforms

AM can be conceived as the deployment of algorithms for making and executing decisions affecting labor (Duggan et al., 2020). Growing scholarly interest in AM on DLPs yields related literature on the topic in multiple disciplines, such as information systems (e.g., Cram et al., 2022; Möhlmann et al., 2021), computer science (e.g., Lee et al., 2015; Yu et al., 2017), human resource management (e.g., Duggan et al., 2020; Meijerink et al., 2021), and organizational theory (e.g., Kellogg et al., 2020; Kinder et al., 2019). AM has also been studied under related terms, such as algorithmic control (e.g., Kellogg et al., 2020), technology-mediated control (e.g., Cram & Wiener, 2020), algorithmic governance (e.g., Bucher et al., 2021), or people analytics (e.g., Gal et al., 2017). While AM is also partially applied in hierarchical organizations (Cram & Wiener, 2020; Kellogg et al., 2020), it is most prevalent on DLPs, because these platforms apply algorithms to manage several aspects throughout the work processes on DLPs (Jarrahi et al., 2021).

Prior studies characterize AM as functions, mechanisms, practices, or features. There seems to be no agreement on specific instantiations of AM, thereby not clearly distinguishing between AM functions, mechanisms, practices, and features. For instance, Möhlmann et al. (2021) specify AM *functions* as coordination (i.e., algorithmic matching), and control (i.e., algorithmic control), whereas Lee et al. (2015) specify AM features, such as work assignment (i.e., driver-passenger assignment algorithms), informational support (i.e., dynamic in-app display of surge-priced areas), and performance evaluation (i.e., rating systems and acceptance rates that track driver performance). Without attempting to preempt the analysis, we note here, that the multiplicity of AM instantiations is in line with our participants' perceptions of AM, which manifest in forms of "the system", "the platform", "mechanisms", "functions", "applications", "processes" and "features". To facilitate reading, we opt for "practices" for instantiating AM. It allows us to separate practices from the platform owners' goals they want to achieve with AM (as compared to functions) and to account for the procedural, non-static nature of AM (as compared to features). Therefore, we define AM practices as work-related decision-making activities that deploy algorithms. It is important to note that AM represents a set of interrelated algorithms in systems and does not exclude human influence in decision-making. Rather, "the actual enactment of relevant management mechanisms and their delivery/communication to workers is fully automated by algorithms and digital technology" (Benlian et al., 2022, p. 2).

Platform owners decide on the distribution of decision-making rights on the platforms (Tiwana, 2013). They might decide to delegate decision-making to workers, and/ or clients, or to retain decision-making rights (Schulze et al., 2021). While the delegation of decision-making between humans and algorithms has been addressed in IS literature (e.g., Baird & Maruping, 2021), how such delegation is executed on multi-agent platforms, and which outcomes are generated, remains unaddressed.

AM is deemed to possess general attributes that tend to contribute to ethical challenges (Gal et al., 2020). AM tends to be opaque, comprehensive, instantaneous, and interactive (Kellogg et al., 2020). However, there remains a gap in knowledge about how specifically AM practices give rise to disadvantages on DLPs.

Unfairness in Algorithms

Unfairness is a broad concept that is defined differently from mathematical, philosophical, legal, anthropologic, neuroscientific, and psychological perspectives (Dolata et al., 2021). Algorithmic unfairness (or bias) consists of systematic disadvantages for individuals or groups that result from automated decision making (Dolata et al., 2021; Kordzadeh & Ghasemaghaei, 2022). Its focus lies on individuals' perceptions of unfairness (Kordzadeh & Ghasemaghaei, 2022).

Computer and data science provide approaches for mitigating biases in algorithms. For instance, criteria such as demographic parity or equalized odds can be used to quantify and assess bias in algorithms (Kordzadeh & Ghasemaghaei, 2022; Teodorescu et al., 2021). However, agreeing on specific metrics, measuring all of them, or attempting to satisfy multiple fairness criteria at the same time is hard or even impossible (Teodorescu et al., 2021). Therefore, information systems literature has established that a pure computational solution is unable to prevent algorithmic unfairness and calls for a socio-technical analysis of unfairness in algorithms (Dolata et al., 2021; Kordzadeh & Ghasemaghaei, 2022; Marjanovic et al., 2022).

Prior literature approached algorithmic unfairness from a conceptual, literature-based perspective (see Table 1 for a summary). Themes include aspects of unfairness, consequences of unfairness, as well as avenues for addressing unfairness, including identifying subjects involved (Kordzadeh & Ghasemaghaei, 2022; Marjanovic et al., 2022; Teodorescu et al., 2021). These insights provide the necessary foundation for understanding algorithmic unfairness and how to study it. In short, it is established that algorithmic unfairness has context-sensitive negative influences on user- and provider-level outcomes, has to be analyzed by investigating a set of interrelated questions, and can be managed by human augmentation. However, for our specific context and research question it remains unclear how the findings relate to and are contextualized to AM practices on DLPs. We aim to further develop knowledge on algorithmic unfairness by a) providing an empirical analysis of algorithmic unfairness in the context of AM on DLPs, and b) deriving a substantive, i.e., lower level, contextualized theory that allows practical implications for handling unfairness resulting from AM on DLPs.

Reference	**Methodology and Context**	**Findings**
Marjanovic et al. (2022)	▪ Conceptual theorizing based on the theory of abnormal justice ▪ Unintended harmful societal effects of automated algorithmic decision-making in the context of transformative services	The theory of algorithmic justice addresses the key questions: ▪ WHAT is the matter of algorithmic justice? ▪ WHO counts as a subject of algorithmic justice? ▪ HOW are algorithmic justices performed? ▪ And, further, how might we address and resolve disputes about the WHAT, WHO, and HOW of algorithmic justice?
Kordzadeh & Ghasemaghaei (2022)	▪ Extracting eight theoretical concepts from a literature review based on stimulus-organism-response theory (Mehrabian & Russell, 1974), the contextual factors framework (Petter et al., 2013), and the organizational justice theory (Colquitt & Rodell, 2015) ▪ Investigating algorithmic bias, including socio-technical, behavioral, and organizational aspects	The theoretical model suggests that ▪ Algorithmic bias negatively influences perceived fairness. ▪ Perceived fairness positively influences recommendation acceptance, algorithm appreciation, and system adoption. ▪ Moderating contextual factors (individual, task, technology, organizational, and environmental characteristics) influence these relationships.
Teodorescu et al. (2021)	▪ Conceptual arguments based on the "incompatibility theorem" ▪ View augmentation as the solution to achieving fairness in the use of machine learning (ML) models in organizations	Typology of four different approaches to managing fairness through augmentation: ▪ Reactive oversight: low fairness difficulty in which the ML model is the final decision-maker. ▪ Proactive oversight: ML model is the final decision-maker in high fairness difficulty situations. ▪ Informed reliance: the human is the final decision-maker, but there is lower fairness difficulty. ▪ Supervised reliance: human is the final decision-maker in situations of high fairness difficulty.

Table 1. Prior Theoretical Findings on Algorithmic Unfairness

To approach our research question, we follow calls for investigating algorithmic unfairness from a socio-technical perspective (e.g., Dolata et al., 2021; Gal et al., 2020). Thus, we acknowledge that decision-making on DLPs involves humans and algorithms and that their interactions enable decision-making. We take the workers' perspective on how they interact with algorithms and perceive these interactions.

Methodology

We used grounded theory methodology (GTM) in this study. It is especially useful for new phenomena that are yet to be theorized (Glaser & Strauss, 1967; Urquhart, 2012) and when investigating pressing social issues and policies (Charmaz, 2014). Both reasons apply to this study. While prior research exists on AM and algorithmic unfairness (see theoretical foundation), no prior theory explains how AM practices contribute to unfairness on DLPs. Unfairness on DLPs and in interactions with algorithms, in general, is a pressing social issue (see introduction and theoretical foundation). We note here that the specific focus only emerged during analysis (see below). In line with the emergence of our findings from the data in GTM, and our interpretivist stance in analyzing the worker's perspective, multiple specific research questions, thematic foci and codes emerged during data analysis. In this paper, we decided to focus on unfairness in AM due to its importance described in the introduction, while we focus on different aspects in other analyses.

Many different types of data can be collected in grounded theory studies (Urquhart, 2012). In line with the typical qualitative nature of data in grounded theory studies, we conducted focus groups during data collection. As there are different streams of GTM analysis in coding (Urquhart et al., 2010; Wiesche et al., 2017), we specify that we generally followed the coding procedures of Glaser (1978), although we adopted Urquhart (2012), and Urquhart et al.'s (2010) advice on a more theoretical coding without existing coding paradigms or coding families. For analysis of qualitative data, including focus groups, it is a well-suited and adopted methodology (e.g., Karwatzki et al., 2017; Onwuegbuzie et al., 2009).

GTM was used not only to code data, but also to collect and analyze data, and generate theory (Urquhart et al., 2010). GTM techniques and principles such as theoretical sampling, constant comparison, coding, memo writing, strategies for revealing preconceptions (see data collection and data analysis), and theoretical integration (see Table 5) were used (Glaser & Strauss, 1967; Urquhart, 2012). In line with GTM, data collection, analysis and theorizing were intertwined (Charmaz, 2014). However, below, we describe them separately to facilitate reading.

Data Collection: Online Focus Groups

We conducted seven focus groups for data collection. Focus groups are orchestrated discussions among participants who are knowledgeable in the topic of interest (Krueger & Casey, 2014). Through the interactions among participants, focus groups add richness to the discussions, as compared to individual interviews (Merton et al., 1990; Parker & Tritter, 2006), because they allow unknown information to emerge (Fern, 2001). Focus groups have been applied as a method for data collection in information systems research for many purposes, among them generating theory (Bélanger, 2012), as in our case.

As we are interested in workers' perspectives, we recruited DLP workers. The goal of recruitment was to identify workers who are highly experienced with DLPs and are as diverse as possible. We reached out to members of specialized groups and forums on social media sites (Reddit, Facebook, LinkedIn, Baidu Tieba). We posted an invitation to the focus groups that entailed a screening survey to ensure that interested participants have enough work experience on DLPs. The screening survey also included questions on demographics and the participants' availabilities, as well as information on non-monetary (e.g., opportunity for exchange with other workers) and monetary (30 US dollars/ 100- 200 Chinese Yuan) incentives. Interested participants agreed to the privacy statements and provided their email or instant messaging (i.e., WeChat and QQ) contact details. To accommodate as many different workers as possible, we conducted the focus groups online via videoconferencing tools.

The first online focus group took place on January 9, 2021. Seven workers participated in the first online focus group that the first author moderated. The moderator's guide included an introduction, as well as questions about workers' interactions with the platforms and clients throughout the various stages of the work process. Those stages include practices prior to the actual work task, while fulfilling the task, and after finishing the task (Cameron & Rahman, 2022; Wagner et al., 2021) and can be further divided in the awareness, negotiation, fulfillment, and follow-up stages (Schulze et al., 2021). Our initial interest in the workers' interactions with the platform throughout the work process represented the starting hunches (Urquhart et al., 2010) for data collection. The questions were rather broad, such that participants were unbiased by any preconceptions we might have held.

Focus Group	Type of Work	Parti-cipant	Platform Experience	Country	Gender	Age
FG1	Diverse (writing, food delivery, microtasks, creative)	P1	Neevo, Clickworker, Upwork, Freelancer, FreeUp	USA	Male	43
		P2	Fiverr, Amazon Mechanical Turk, Clickworker, Upwork, Freelancer	Pakistan	Male	26
		P3	Care, Doordash, UberEats, Grubhub	USA	Female	21
		P4	Fiverr, Mturk, Oneforma, Clickworker, Usertesting, appen	Greece	Male	33
		P5	Neevo, Clickworker	India	Male	21
		P6	Clickworker, Fiverr, Upwork, Neevo, Upwork, 99designs, YouDo	Russia	Female	25
		P7	Neevo, Clickworker, appen	UK	Female	31
FG2	Writing	P8	Upwork, peopleperhour, Fiverr	Kenya	Male	28
		P9	Fiverr, Upwork	Kenya	Male	25
FG3	Food delivery	P10	Doordash	USA	Female	19
		P11	Instacart, Shipt	USA	Female	42
FG4	Micro-tasks	P12	Clickworker, Upwork, Amazon Amazon Mechanical Turk, Prolific, Microworkers, Swagbucks, Usertesting, PlaytestCloud	Canada	Male	38
		P13	Clickworker, Upwork, OneForma, Yandex	Egypt	Male	21
FG5	Ride sharing	P14	Didi express, Zhubajie, Meituan	China	Male	29
		P15	Didi express, Huaxiaozhu	China	Male	25
		P16	Didi express, Meituan	China	Male	22
		P17	Didi hitch ride, Huaxiaozhu, Haluo hitch ride	China	Female	32
FG6	Creative	P18	Zhubajie	China	Male	22
		P19	Zhubajie	China	Male	25
FG7	Food delivery	P20	Ele.me	China	Male	33
		P21	Ele.me	China	Male	22
		P22	Ele.me	China	Male	20
		P23	Ele.me	China	Male	31

Table 2. Online Focus Group Participants

After the first online focus group, we noticed that the different types of platforms and tasks that workers conduct via the platforms impose obstacles to the discussion. It was difficult for participants to find common ground and dive deeper into their interactions with the platforms. In line with the principle of theoretical sampling in GTM, this led us to reconsider the sampling frame for the next online focus groups on analytic grounds. In the following six online focus groups that took place in spring 2021, we sampled participants based on the tasks that they perform on DLPs and based on country and language.

The first author moderated the following three online focus groups with English-speaking participants, whereas the third author moderated the following three online focus groups with Chinese-speaking participants. In total, the seven online focus groups include perspectives from 23 workers from ten different countries (see Table 2). In line with the general population of workers on DLPs (Rani et al., 2021), our participants are mostly young and male. We collected over 630 minutes of audio-visual data that was transcribed verbatim, and, in the case of the Chinese online focus groups, translated to English.

Data Analysis: Coding

The first author engaged in open, selective, and theoretical coding (Glaser, 1992; Urquhart, 2012) to inductively analyze the data. Open coding was conducted at the sentence-by-sentence level, sometimes even at the word-by-word level. Additionally, incident-by-incident level coding was applied, because statements from participants within one group, and across groups were compared. During selective coding, the research question was refined. Starting out with a rather general interest in the interactions that take place on DLPs, we became more interested in the participants' elaborations on unfair treatment. The core category (algorithmic unfairness) emerged and only codes relating to algorithmic unfairness were included in the further analysis. During selective coding, analytical moves (Grodal et al., 2021) were used to further abstract from open codes, such as asking questions (see refinement of research question) and dropping categories (see focus on core category). During theoretical coding, we were inspired by the potential relationships put forward in Urquhart (2012) but did not use any pre-existing theory, coding paradigm (Strauss & Corbin, 1990), or coding families (Glaser, 1992) to relate the constructs of our theory. Rather, the relationships emerged from our interpretation of the data as theoretical codes. Table 3 exemplifies the coding structure for open and selective codes using the example of the category "automated delegation".

Category	Selective Codes	Open Codes
Automated delegation	Delegating setting task conditions to clients	Client set access requirements arbitrary, amount of money advertised too high, difficult to figure out clients' exact needs, clients' task guidelines are wrong/ ambiguous, realizing that it's not own fault that job cannot be done, platform doesn't check feasibility of tasks, platform doesn't standardize client requirement input, platform doesn't ensure minimum pay
	Delegating payment transfers to clients	Fearing fraud/ trying to avoid cheating clients, getting no money from platform when client doesn't pay, depending on client to pay, losing money when client doesn't pay
	Delegating worker evaluation to clients	Negative review has no requirements for clients, false client accusations/ lying/ fraud, workers refunding unsatisfied clients, clients sell good rating for lower price, power abuse of client possible, maliciously negative ratings, no reasons provided for bad rating, arbitrary negative review
	Delegating banning decision to clients	Clients have power to ban worker

Table 3. Exemplary Open and Selective Codes

Throughout the analysis, data was constantly compared with other data and codes. In case of differences between data that were labeled with the same code, codes were split (Grodal et al., 2021). In case of codes with identical meanings, codes were merged (Grodal et al., 2021). A theoretical memo was written as a text file in which ideas and insights on the codes and their relationships, comparisons between the participants, and among the focus groups, and notes on the codes were documented. The emerging selective and theoretical codes were challenged in weekly discussions with the full author team (Urquhart, 2012). This helped the first author in challenging the ideas and wrestling with any preconceptions held unconsciously.

Results: Algorithmic Unfairness

We identify how algorithmic unfairness manifests on DLPs (see Figure 1). On DLPs, workers interact with AM practices. On the one hand, they interact with practices that automate decisions, such as being assigned certain types of tasks (*automated decision-making*). On the other hand, they interact with practices that automatically delegate decisions to clients (*automated delegation of decision-making*). Both types of AM practices share attributes that contribute to workers' perceptions of unfairness. They give rise to systematic disadvantages for workers that consist of devaluation, restriction, and exclusion.

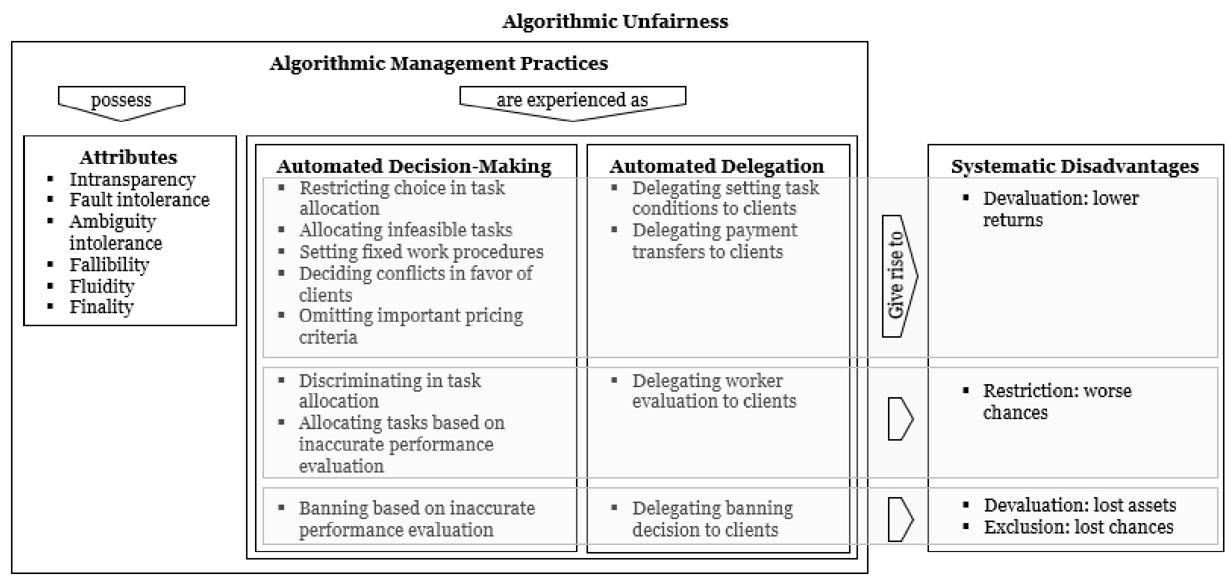

Figure 1. Algorithmic Unfairness on Digital Labor Platforms

Attributes of Unfair Algorithmic Management Practices

All of the AM practices we identified (AM practices automating decisions and delegating decisions) share common *attributes* that contribute to systematic worker disadvantages; intransparency, fault intolerance, ambiguity intolerance, fallibility, fluidity, and finality (see Table 4). For instance, AM practices are fluid, because they may be changed at any time by the platform developers. This gives rise to algorithmic unfairness, because workers have to become aware of changes and cannot rely on stable targets. The attributes might be more or less salient in each of the AM practices.

AM attributes	Exemplary quotes
Intransparency	*"So I am not 100 percent certain how that all works."* (P1)
Fault intolerance	*"And also, if you fail in one attempt, we are not allowed to retake it."* (P12)
Ambiguity intolerance	*"So there is this question, what is good and what is bad, you know? I mean, of course, if you have grammatical mistakes, that's wrong, that that's bad. Of course, if you stray off-topic that's bad, but could a client just cancel because they didn't like it?"* (P13)
Fallibility	*"Sometimes you can't sign in or some payments."* (P14)
Fluidity	*"Later, because they have real less workers in UHRS, so they reduced their threshold and bring it to 80. But I scored 82. But still they don't allow me."* (P12)
Finality	*"So you can't do anything at all, in my opinion."* (P4)

Table 4. Attributes of Unfair AM Practices

Automated and Delegated Decision-Making Algorithmic Management Practices

The two types of unfair AM practices we identified can be described as follows: AM practices that *automate decision-making* are such practices in which an algorithm determines a management decision affecting labor. Thus, the algorithms directly affect disadvantageous outcomes for workers. We identified eight AM practices that automate decisions: restricting choice in task allocation, allocating infeasible tasks, discriminating in task allocation, setting fixed work procedures, omitting important pricing criteria, allocating tasks based on inaccurate performance evaluation, deciding conflicts in favor of clients, and banning based on inaccurate performance evaluation. We describe each of them in more detail and in conjunction with the systematic disadvantages they may elicit in the next section.

AM practices that *automate the delegation of decision-making* are such practices in which an algorithm allocates decision rights to clients. As such, it is still an automated management practice, because an algorithm allocates decision rights, e.g., giving clients an option to rate workers. However, the outcomes are determined by the human decision maker, who may decide against workers. We identified four AM practices that automate the delegation of decisions: delegating setting task conditions to clients, delegating payment transfer to clients, delegating worker evaluation to clients, and delegating banning decisions to clients. We describe each of them in more detail and in conjunction with the systematic disadvantages they may elicit in the next section.

Resulting Systematic Disadvantages

Workers can be systematically disadvantaged by the interactions with AM practices. Generally, those disadvantages are economic in nature. We observe three types of systematic worker disadvantages: devaluation, restriction, and exclusion. *Devaluation* implies lower returns that are generated either by having to invest additional labor for a certain amount of payment or by receiving low or no payment for the labor invested. Devaluation also includes losing the assets that workers earned and/ or built on the platform. These assets can consist of money, that is credited to their platform account but has not been transferred to their private accounts, and/ or of immaterial assets, such as the (good) reputation or track record that they built on the platform. *Restriction* means that workers have worse chances of either receiving tasks at all, or of receiving good (i.e., high returning tasks). *Exclusion* refers to being banned from the platform and losing chances to generate income. Lost chances imply that workers have no more chances of generating returns from their labor on the platform. AM is experienced by workers as practices that shape their interactions with the platform. We identified AM practices that give rise to systematic worker disadvantages. We describe them below in more detail and add quotes from the participants to illustrate the meanings in their own words.

We identified several practices that give rise to systematic disadvantages by **devaluing** workers. First, algorithms might assign tasks to workers that they do not want to do without giving them the option to refuse the task (*restricting choice in task allocation*). The consequence would be that they invest time in a task that might be not worthwhile doing. Simultaneously, they bear opportunity costs for missing out on a more lucrative task.

“I cannot refuse and or I cannot fail to pick up after receiving an order. I literally can’t say no to it. There is no button to say ‘no’ to picking up passengers, so I have to pick them up.” (P17)

Furthermore, algorithms might allocate tasks to workers that are infeasible (*allocating infeasible tasks*). For instance, one participant (P10) received a food order for a restaurant that closed down. Depending on when the worker learns about the infeasibility of the task, all labor invested up to that time is lost. Therefore, their returns decrease.

“And then another issue is like one time I get a call for a delivery and it's a restaurant that that closed down. So it kind of rerouted my whole trip. I wasted time for no reason and I wasn't able to fulfill my order.” (P10)

When algorithms determine how work must be done, these procedures might not be well aligned with the task (*setting fixed work procedures*). Workers have to remember and conduct all procedures that the algorithms set. Having to comply with these procedures takes additional time. Therefore, workers spend more unpaid time on the task than would be necessary for fulfilling the task.

“When we're shopping, you'll have produce at the top, but also you'll have it at the bottom of your list and you have a really long list. So you have to scroll through constantly, which is just time waste [...].” (P11)

In case of conflicts between workers and clients, workers try and request the platform as a neutral mediator. However, platforms might be systematically biased towards clients, irrespective of any neutral evidence (*deciding conflicts in favor of clients)*. As such, clients are spared punishment for misbehavior and workers have to accept the disadvantages they received. For instance, platform owners might not answer workers' complaints or ignore any evidence they provide. Workers spend unpaid time trying to resolve the conflict and end up receiving no compensation.

“I mean, there has been some issue with my payment. It's that it's still ongoing. I wrote to them like a couple of days ago, like two or three days. They replied to me the day after, but they haven't replied to me since then, which is kind of frustrating. I really don't know why they did that.” (P13)

Workers might not get paid the amount of money that they anticipated because of omitted criteria in price setting (*omitting important pricing criteria*). One example is that platforms mediating driving tasks might not consider tolls. Therefore, performing the task will require workers to pay for the tolls themselves, thus lowering their returns. Another example is the loss of money due to service and exchange fees by external payment service providers that are mandatory for workers when transferring payments to their accounts.

“I'm really bitter about that, especially because of course it first gets converted. You cannot, in Russia, you can only get paid through PayPal. And PayPal has awful exchange rates, really. [...] But really, the money that I get is it really is quite a bit lower than it actually was to begin with.” (P6)

Platforms can design algorithms that enable unfairness by automatically delegating the right to make decisions to clients. First, they might delegate setting task conditions to clients (*delegating setting task conditions to clients*). The information clients provide on the conditions might be ambiguous or inaccurate as described by P13 below. Thereby, platforms disadvantage workers, because they enable clients to make such decisions. No AM practice reviews the tasks and determines their legitimacy or provides task templates that set the boundaries of the task. Delegating setting task conditions to clients can lower workers' returns because workers waste time trying to figure out the quality of the client, trying to qualify for tasks, figuring out the exact needs clients have, or receiving lower pay than anticipated.

“So, see, for example, some tasks actually are extremely inconsistent. So, say, for example, your task is to do a certain thing. Your task is to search this business on Facebook, for example, or Google and locate and locate where on the website the opening hours are. [...] but for example, if you say no and it is not there, they would say it's on another page, but you didn't really mention that in the guidelines.” (P13)

Last, platforms might design algorithms that enable unfairness by delegating the decision to pay or withhold paying to clients (*delegating payment transfer to clients*). They provide no escrow services that ensure the transfer of rightful payment from the client to the worker. Therefore, this practice gives rise to clients scamming workers, because it enables the payment decisions to be made unfairly. As workers are not paid for the time they invested in performing the task, their returns decrease.

“But I can't get the money if the passenger doesn't pay.” (P17)

The second type of disadvantage refers to **restrictions**. Workers have lower chances of receiving high returns from the platform because they either receive less tasks, or lower-paid tasks. Again, automated decisions and delegated decisions can give rise to such disadvantages. First, the task allocation algorithm might discriminate against certain (groups of) workers (*discriminating in task allocation*). We discovered perceptions of location-based discrimination. Participants from developing countries reported that they received different (less, less paid, less interesting) tasks than workers on the same platform who are from developed countries. As such, this group of workers has fewer and lower-paid task available. Overall, the worse chances can result in systematically lower returns than other workers can achieve.

“So, they know that if they're if it's someone from a developing country so they would assign dumping tasks to that country and then the high being higher paying ones accordingly.” (P2)

Chances of receiving tasks can also be worse for certain workers if they depend on past performance that was measured inaccurately (*allocating tasks based on inaccurate performance evaluation*). Performance evaluations are inaccurate if the criteria used to evaluate workers are illegitimate, or if meeting performance standards is not feasible for workers. For instance, setting the performance standard as a fixed amount of time for a delivery fails to consider the diverging length of tasks, e.g., when having to climb stairs. Thus, it is not always possible for workers to reach those performance standards. Additionally, reaching performance standards might not be desirable for workers. For instance, determining worker performance by measuring the number of tasks they decline restricts workers' autonomy in choosing tasks. Thus, workers feel disadvantaged by being restricted in their chances for returns.

"You actually can't refuse because your refusal will affect your credit score." (P17)

"And it's also really annoying because you can really do this job much faster, but you have to slow yourself down manually." (P6)

Last, evaluating worker evaluation might be algorithmically delegated to clients (*delegating worker evaluation to clients*). If there are no AM practices in place that assess the rightfulness of these evaluations, they can be arbitrary or even malicious. If client feedback is used to determine access to tasks, this logic disadvantages workers by lowering their chances of receiving new tasks. Moreover, as clients realize the power they hold over workers when determining worker performance, they might force workers into lowering their pay. This happened to P9.

"And she rated me a one star, but before that she said how much she appreciated and loved how I gave her above and beyond service." (P11)

"[…] there was a client who I was working with, and what she did is that I had to maybe give lower the price and all that, because if I… they are going to give they are going to give me a bad review. So, they were kind of holding me in blackmail and all that." (P9)

The last type of systematic disadvantages consists of **exclusion**. Again, AM practices that automate decisions, and those that delegate decisions give rise to these disadvantages. Determining platform access might be based on performance evaluations. If those evaluations are inaccurate, workers are systematically disadvantaged losing access to income opportunities (*banning based on inaccurate performance evaluation*). Again, performance evaluations are inaccurate if the criteria used to evaluate workers are illegitimate, or if meeting performance standards is infeasible for workers. For instance, very high performance metrics cannot always be achieved. Additionally, banning means workers can lose the assets they built on the platform (*devaluation*).

"They keep track of everything and you can be deactivated if you say the slightest wrong thing." (P3)

Furthermore, banning decisions can be delegated to clients (*delegating banning decisions to clients*). If there are no AM practices in place that assess the rightfulness of these decisions, they can be arbitrary or even malicious. Thus, workers are excluded from generating income from the platform due to an unfair decision. Again, they might also lose assets that they built on the platform (*devaluation*).

"The owner of the job, the client can see how you're doing. And if they really want, they can ban you." (P6)

Discussion

Driven by an initial interest in DLPs, we engaged with workers during online focus groups. The analysis of the focus groups gave rise to the specific question of how AM practices promote unfairness. We find that AM practices promote unfairness in terms of systematically disadvantaging workers by devaluing, restricting, and excluding them. Platforms give rise to these disadvantages by employing two types of AM practices. First, AM practices automate decisions that are disadvantageous for workers. Second, AM practices automatically delegate decision-making to clients. Thereby, clients' decision-making power disadvantages workers.

In line with the application of grounded theory methodology (Urquhart, 2012) and the nature of our results, the theoretical contribution of this study lies in the generation of new theory. As we present a theoretical model including relationships among constructs, the degree of conceptualization (Urquhart et al., 2010) is rather high. Therefore, the results of this study represent a theory for explaining (Gregor, 2006).

The theoretical model was developed in the context of DLPs, which gives rise to its boundaries. Specifically, we studied the perspectives of a diverse set of workers who perform work via DLPs, where no uniform definition of fairness exists. Additionally, the intransparency of AM practices gives leeway to sensemaking (Möhlmann & Zalmanson, 2017). As such, actual practices (in terms of how they are programmed) cannot be observed independent of the workers' subjective perceptions and our interpretation thereof. Thus, we do not imply any kind of ground truth, especially as some AM practices might be necessary in managing work on DLPs in the first place and might work as intended for the majority of cases. For instance, as multiple workers prefer the same task, there might only be need for one worker. Necessarily, the others will miss out. Another example is delegating payment transfers to clients. If all clients pay all workers their owed amount, there is no unfairness in delegation per se. Further, platform developers might not be aware of the perceived unfairness AM practices can hold for workers and we do not imply purposeful behavior on the platforms' part. We also note here that the relationships presented in the model are not deterministic. Rather, AM practices give rise to disadvantages for workers. For instance, some practices give rise to disadvantages for certain groups of workers (e.g., from developing countries), while others concern workers in general (e.g., deciding conflicts in favor of clients).

Within these boundaries, we extend the scope of our analysis to a substantive focus (Urquhart et al., 2010), because our theoretical model has implications for algorithmic unfairness in general, beyond AM on DLPs. Our findings imply that algorithms can give rise to disadvantages in two ways. First, they may automate a decision. In this case, unfairness is promoted by the algorithmic system per se. Second, they may automate the delegation of decision-making. In this case, unfairness is promoted by the decision to award decision rights to one party. As this party is algorithmically enabled to make autonomous decisions, unfairness is created deliberately, because of a lack of AM practices that provide evidence or accountability for such decisions. Additionally, the disadvantages workers experience (devaluation, restriction, exclusion) can be generalized to other contexts.

We relate the findings to prior theories in the realms of algorithmic unfairness and delegation to delineate our contribution from prior knowledge and extend prior knowledge (see Table 5). We argue that the findings can be integrated into the theory of algorithmic justice (Marjanovic et al., 2022). Thereby, we extend the theory of algorithmic justice by providing empirical evidence for its applicability, and by contextualizing it to AM on DLPs, rather than transformative services. Our findings deviate from the theoretical model of algorithmic bias (Kordzadeh & Ghasemaghaei, 2022), as we study experienced disadvantages rather than perceived fairness. Here, our findings suggest that the separation of AM practices from the disadvantages they give rise to might not be conceived by measuring perceived fairness. Regarding approaches to managing fairness (Teodorescu et al., 2021), we argue that the case of AM presents a system of interrelated algorithmic decisions that fit neither of the approaches presented (high vs. low fairness complexity, and human vs. algorithmic decision-maker). As we surfaced existing algorithmic unfairness, we suggest that despite high fairness complexity, reactive oversight might be a useful approach to identifying algorithmic unfairness. Last, we relate our findings to the IS delegation theoretical framework (Baird & Maruping, 2021). We extend their framework to a multi-agent perspective including the platform developers, workers, and clients. AM, developed by platform developers (human agents) can be conceptualized as an agentic IS system that may delegate decision-making to clients (human agents). The outcome of such a delegation can consist of disadvantages for workers (human agents).

Reference	**Findings**	**Theoretical Integration**
Marjanovic et al. (2022)	The theory of algorithmic justice addresses the key questions: ▪ WHAT is the matter of algorithmic justice? ▪ WHO counts as a subject of algorithmic justice? ▪ HOW are algorithmic justices performed? ▪ And, further, how might we address and resolve disputes about the WHAT, WHO, and HOW of algorithmic justice?	We integrate our findings into the theory of algorithmic justice as follows: ▪ WHAT: maldistribution (economic dimension). We find economic disadvantages for workers. We do not identify cultural or political dimensions. A reason might be that our focus was on DLPs, rather than social welfare systems. ▪ WHO: workers. We do not observe misframing. This might be explained by our explicit focus on the workers' perspective. ▪ HOW: AM practices set by platform developers give rise to disadvantages. We detailed specific AM practices.

		▪ Resolution: The AM practices we identified might be changed by platform developers or policymakers.
Kordzadeh & Ghasemaghaei (2022)	The theoretical model suggests that ▪ Algorithmic bias negatively influences perceived fairness. ▪ Perceived fairness positively influences recommendation acceptance, algorithm appreciation, and system adoption. ▪ Moderating contextual factors (individual, task, technology, organizational, and environmental characteristics) influence these relationships.	We delineate our findings from the theoretical model of algorithmic bias, because our findings imply, that ▪ Algorithmic bias may be implemented in AM practices (see automated decision-making and delegated decision-making). However, it is not separable from the disadvantages that it creates. ▪ Perceptions of algorithmic unfairness depend on the disadvantages workers actually receive. Should there be no disadvantages, AM practices might not be perceived as unfair.
Teodorescu et al. (2021)	Typology of four different approaches to managing fairness through augmentation: ▪ Reactive oversight: low fairness difficulty in which the ML model is the final decision-maker. ▪ Proactive oversight: ML model is the final decision-maker in high fairness difficulty situations. ▪ Informed reliance: the human is the final decision-maker, but there is lower fairness difficulty. ▪ Supervised reliance: human is the final decision-maker in situations of high fairness difficulty.	We extend the typology of approaches to managing fairness through augmentation as follows: ▪ On DLPs, there exist many AM practices that are interrelated. Therefore, the typology might be expanded to address systems of algorithms, in which the final decision-maker can vary between different types of actors (i.e. humans, algorithms). ▪ Although we perceive fairness complexity to be high in the case of AM on DLPs, we studied algorithmic unfairness from the workers' perspective. This implies that as a starting point, reactive oversight might be a useful approach to raising algorithmic unfairness issues in the first place.
Baird & Maruping (2021)	The IS delegation theoretical framework ▪ Differentiates between human agents and agentic IS - defined as software agents that perceive and act. ▪ States that tasks can be delegated back and forth between humans and IS agents to achieve outcomes.	We follow the authors' suggestion to extend the framework from dyadic to a multi-agent perspective on DLPs as follows: ▪ Platform owners (human agents) develop algorithms that carry out management (tasks) at scale. ▪ These algorithms manifest in the shape of AM (agentic IS) as they coordinate and control workers and clients (human actors). ▪ The AM system delegates some of the management tasks to clients. ▪ Delegated algorithmic decisions can result in worker disadvantages, and may be an instantiation of algorithmic unfairness.

Table 5. Theoretical Integration

Improving fairness is an objective that is desirable for workers, society at large, and the sustainable success of DLP business models (Rani et al., 2021). Workers might become aware of the practices that are used on the platforms they work with. They might try and avoid platforms with multiple AM practices that give rise to unfair outcomes. Platform owners might become aware of how the practices they employ create unfairness in the workers' view. As a response, platform developers might attempt to mitigate algorithmic unfairness by changing AM practices or how they transparently counter-argue unsupported perceptions of unfairness. For instance, they might implement additional AM practices that add accountability to clients' decisions, such as collecting and reviewing evidence. Another potential remedy to algorithmic unfairness might be to lower performance metrics and account for unexpected problems that might arise in any work process. Policymakers might be better able to regulate DLPs if they understand AM practices as automating decisions and automating delegation of decisions. They, as well, have a starting point for tackling algorithmic unfairness on DLPs by regulating AM that gives rise to devaluation, restriction, and exclusion of workers.

Next, we acknowledge the limitations in our work. While theoretical sampling is a central aspect of grounded theory methodology (Urquhart, 2012; Urquhart et al., 2010), practical limitations can interfere with overlapping data collection and analysis (Urquhart et al., 2010). We sampled theoretically after our first focus group by sampling the following groups according to the tasks they do and by culture/ language. While these decisions were based on analytic grounds, further data analysis proceeded only once data collection was finished. One reason was that transcribing all focus groups and translating the Chinese focus group transcripts took longer than collecting new data. The reason is that sampling for online focus groups has to be quite quick (Schulze et al., 2022). Therefore, our chance to conduct online focus groups with additional participants could not be delayed by finishing data analysis first.

Like many others, our theoretical insights represent interim struggles (Weick, 1995) and hold the potential for further theorization (also compare "scaling up the theory" (Urquhart, 2012; Urquhart et al., 2010)). Settling on a core theme and specific research question during selective coding naturally excludes other interesting avenues for investigation. For instance, while our cross-sectional data helped expand the scope of the theory beyond a single platform, the overall configuration of AM practices on every single platform might be more or less disadvantageous for workers. Additionally, we explore what constitutes and characterizes AM practices that give rise to fairness by providing advantages for workers in a different conference paper. With theoretical sampling, we might expand the scope of our findings and add to their generalizability. Additional data could be collected that extends the boundaries to other complex algorithmic systems to derive strategies for achieving fairness in such systems. Apart from covering more of the specifics of AM attributes that contribute to fairness or unfairness perceptions, other interesting research questions would also be why DLPs employ algorithms that are unfair to workers, and how algorithmic unfairness can be addressed by DLPs.

Conclusion

We followed calls for research and empirically examined how algorithms affect unfairness and what consequences unfairness has for workers (Dolata et al., 2021; Gal et al., 2020; Padmanabhan et al., 2022). We find that AM practices that automate decisions that give rise to economic disadvantages. Alternatively, AM practices give rise to workers' disadvantages by automatically delegating decision-making to clients. Our findings confirm that algorithmic unfairness is a sociotechnical issue that can be investigated based on the perceptions of those affected. Building on our findings, future research can identify remedies for algorithmic unfairness.

References

Baird, A., & Maruping, L. M. (2021). The Next Generation of Research on IS Use: A Theoretical Framework of Delegation to and from Agentic Is Artifacts. *MIS Quarterly*, *45*(1), 315–341. https://doi.org/10.25300/MISQ/2021/15882

Bélanger, F. (2012). Theorizing in Information Systems Research Using Focus Groups. *Australasian Journal of Information Systems*, *17*(2), 109–135. https://doi.org/10.3127/ajis.v17i2.695

Benlian, A., Wiener, M., Cram, W. A., Krasnova, H., Maedche, A., Möhlmann, M., Recker, J., & Remus, U. (2022). Algorithmic Management: Bright and Dark Sides, Practical Implications, and Research Opportunities. *Business & Information Systems Engineering*. https://doi.org/10.1007/s12599-022-00764-w

Bucher, E. L., Schou, P. K., & Waldkirch, M. (2021). Pacifying the Algorithm – Anticipatory Compliance in the Face of Algorithmic Management in the Gig Economy. *Organization*, *28*(1), 44–67. https://doi.org/10.1177/1350508420961531

Cameron, L. D., & Rahman, H. (2022). Expanding the Locus of Resistance: Understanding the Co-constitution of Control and Resistance in the Gig Economy. *Organization Science*, *33*(1), 38–58. https://doi.org/10.1287/orsc.2021.1557

Charmaz, K. (2014). *Constructing Grounded Theory* (Second edition). Sage Publications.
Cram, W. A., & Wiener, M. (2020). Technology-Mediated Control: Case Examples and Research Directions for the Future of Organizational Control. *Communications of the Association for Information Systems*, *46*, 70–91. https://doi.org/10.17705/1CAIS.04604
Cram, W. A., Wiener, M., Tarafdar, M., & Benlian, A. (2022). Examining the Impact of Algorithmic Control on Uber Drivers' Technostress. *Journal of Management Information Systems*, *39*(2), 426–453. https://doi.org/10.1080/07421222.2022.2063556
Dolata, M., Feuerriegel, S., & Schwabe, G. (2021). A Sociotechnical View of Algorithmic Fairness. *Information Systems Journal*, 1–65. https://doi.org/10.1111/isj.12370
Duggan, J., Sherman, U., Carbery, R., & McDonnell, A. (2020). Algorithmic Management and App-Work in the Gig Economy: A Research Agenda for Employment Relations and HRM. *Human Resource Management Journal*, *30*(1), 114–132. https://doi.org/10.1111/1748-8583.12258
Fern, E. F. (2001). *Advanced Focus Group Research*. Sage.
Fieseler, C., Bucher, E., & Hoffmann, C. P. (2019). Unfairness by Design? The Perceived Fairness of Digital Labor on Crowdworking Platforms. *Journal of Business Ethics*, *156*(4), 987–1005. https://doi.org/10.1007/s10551-017-3607-2
Fjeld, J., Achten, N., Hilligoss, H., Nagy, A., & Srikumar, M. (2020). *Principled Artificial Intelligence: Mapping Consensus in Ethical and Rights-Based Approaches to Principles for AI*. Berkman Klein Center for Internet & Society.
Gal, U., Jensen, T. B., & Stein, M.-K. (2017). People Analytics in the Age of Big Data: An Agenda for IS Research. *ICIS 2017 Proceedings*.
Gal, U., Jensen, T. B., & Stein, M.-K. (2020). Breaking the Vicious Cycle of Algorithmic Management: A Virtue Ethics Approach to People Analytics. *Information and Organization*, *30*(2), 100301. https://doi.org/10.1016/j.infoandorg.2020.100301
Glaser, B. G. (1978). *Theoretical Sensitivity: Advances in the Methodology of Grounded Theory* (1st edition). The Sociology Press.
Glaser, B. G. (1992). *Basics of Grounded Theory Analysis: Emergence Vs. Forcing*. The Sociology Press.
Glaser, B. G., & Strauss, A. L. (1967). *The Discovery of Grounded Theory: Strategies for Qualitative Research*. Transaction Publishers.
Gregor, S. (2006). The Nature of Theory in Information Systems. *MIS Quarterly*, *30*(3), 611–642.
Grodal, S., Anteby, M., & Holm, A. L. (2021). Achieving Rigor in Qualitative Analysis: The Role of Active Categorization in Theory Building. *Academy of Management Review*, *46*(3), 591–612. https://doi.org/10.5465/amr.2018.0482
Jarrahi, M. H., Newlands, G., Lee, M. K., Wolf, C. T., Kinder, E., & Sutherland, W. (2021). Algorithmic Management in a Work Context. *Big Data & Society*, *8*(2), 20539517211020332. https://doi.org/10.1177/20539517211020332
Karwatzki, S., Trenz, M., Tuunainen, V. K., & Veit, D. (2017). Adverse Consequences of Access to Individuals' Information: An Analysis of Perceptions and the Scope of Organisational Influence. *European Journal of Information Systems*, *26*(6), 688–715. https://doi.org/10.1057/s41303-017-0064-z
Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at Work: The New Contested Terrain of Control. *Academy of Management Annals*, *14*(1), 366–410. https://doi.org/10.5465/annals.2018.0174
Kinder, E. K., Jarrahi, E. K. M. H. J., & Sutherland, W. (2019). Gig Platforms, Tensions, Alliances and Ecosystems: An Actor-Network Perspective. *Proceedings of the ACM on Human-Computer Interaction*, *3*(CSCW), 1–26. https://doi.org/10.1145/3359314
Klein, H. K., & Myers, M. D. (1999). A Set of Principles for Conducting and Evaluating Interpretive Field Studies in Information Systems. *MIS Quarterly*, *23*(1), 67–93. https://doi.org/10.2307/249410
Kordzadeh, N., & Ghasemaghaei, M. (2022). Algorithmic Bias: Review, Synthesis, and Future Research Directions. *European Journal of Information Systems*, *31*(3), 388–409. https://doi.org/10.1080/0960085X.2021.1927212
Krueger, R. A., & Casey, M. A. (2014). *Focus Groups: A Practical Guide for Applied Research* (5th edition). Sage Publications.
Lee, M. K., Kusbit, D., Kahng, A., Kim, J. T., Yuan, X., Chan, A., See, D., Noothigattu, R., Lee, S., Psomas, A., & Procaccia, A. D. (2019). WeBuildAI: Participatory Framework for Algorithmic Governance. *Proceedings of the ACM on Human-Computer Interaction*, *3*, 1–35. https://doi.org/10.1145/3359283

Lee, M. K., Kusbit, D., Metsky, E., & Dabbish, L. (2015). Working with Machines: The Impact of Algorithmic and Data-Driven Management on Human Workers. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 1603–1612. https://doi.org/10.1145/2702123.2702548

Marjanovic, O., Cecez-Kecmanovic, D., & Vidgen, R. (2022). Theorising Algorithmic Justice. *European Journal of Information Systems*, *31*(3), 269–287. https://doi.org/10.1080/0960085X.2021.1934130

Meijerink, J., Keegan, A., & Bondarouk, T. (2021). Having Their Cake and Eating It Too? Online Labor Platforms and Human Resource Management as a Case of Institutional Complexity. *The International Journal of Human Resource Management*, *32*(19), 4016–4052. https://doi.org/10.1080/09585192.2020.1867616

Merton, R. K., Fiske, M., & Kendall, P. L. (1990). *The Focused Interview: A Manual of Problems and Procedures* (2nd edition). Free Press.

Möhlmann, M., & Zalmanson, L. (2017). Hands on the Wheel: Navigating Algorithmic Management and Uber Drivers' Autonomy. *ICIS 2017 Proceedings*.

Möhlmann, M., Zalmanson, L., Henfridsson, O., & Gregory, R. W. (2021). Algorithmic Management of Work on Online Labor Platforms: When Matching Meets Control. *MIS Quarterly*, *45*(4), 1999–2022. https://doi.org/10.25300/MISQ/2021/15333

Onwuegbuzie, A. J., Dickinson, W. B., Leech, N. L., & Zoran, A. G. (2009). A Qualitative Framework for Collecting and Analyzing Data in Focus Group Research. *International Journal of Qualitative Methods*, *8*(3), 1–21. https://doi.org/10.1177/160940690900800301

Oxford Internet Institute, & WZB Berlin Social Science Centre. (2022). *Fairwork Principles*. Fairwork. https://fair.work/en/fw/principles/

Padmanabhan, B., Fang, X., Sahoo, N., & Burton-Jones, A. (2022). Editor's Comments—Machine Learning in Information Systems Research. *MIS Quarterly*, *46*(1), iii–xix.

Parker, A., & Tritter, J. (2006). Focus Group Method and Methodology: Current Practice and Recent Debate. *International Journal of Research & Method in Education*, *29*(1), 23–37. https://doi.org/10.1080/01406720500537304

Pastuh, D., & Geppert, M. (2020). A "Circuits of Power"-based Perspective on Algorithmic Management and Labour in the Gig Economy. *Industrielle Beziehungen*, *27*(2), 179–204. https://doi.org/10.3224/indbez.v27i2.05

Prassl, J. (2018). *Humans as a Service: The Promise and Perils of Work in the Gig Economy*. Oxford University Press.

Rai, A., Constantinides, P., & Sarker, S. (2019). Next Generation Digital Platforms: Toward Human-AI Hybrids. *MIS Quarterly*, *43*(1), iii–ix.

Rani, U., Dhir, R. K., Furrer, M., Gobel, N., Moraiti, A., Cooney, S., & Coddou, A. (2021). *World Employment and Social Outlook 2021: The Role of Digital Labour Platforms in Transforming the World of Work* [ILO Flagship Report]. International Labor Office.

Schlagwein, D., Dubravka Cecez-Kecmanovic, & Hanckel, B. (2019). Ethical Norms and Issues in Crowdsourcing Practices: A Habermasian Analysis. *Information Systems Journal*, *29*(4), 811–837. https://doi.org/10.1111/isj.12227

Schulze, L., Trenz, M., Cai, Z., & Tan, C.-W. (2022). Conducting Online Focus Groups—Practical Advice for Information Systems Researchers. *HICSS 2022 Proceedings*. 55th Hawaii International Conference on System Sciences, Virtual Conference.

Schulze, L., Trenz, M., & Nickerson, R. C. (2021). Fingers in the Pie: Characterizing Decision Rights Partitioning on Digital Labor Platforms. *ICIS 2021 Proceedings*. International Conference on Information Systems (ICIS), Austin, TX.

Shanahan, G., & Smith, M. (2021). Fair's Fair: Psychological Contracts and Power in Platform Work. *International Journal of Human Resource Management*. https://doi.org/10.1080/09585192.2020.1867615

Strauss, A., & Corbin, J. (1990). *Basics of Qualitative Research: Grounded Theory Procedures and Techniques* (2nd Revised edition). Sage Publications.

Taylor, M. (2017). *Good Work: The Taylor Review of Modern Working Practices*.

Teodorescu, M., Morse, L., Awwad, Y., & Kane, G. (2021). Failures of Fairness in Automation Require a Deeper Understanding of Human-ML Augmentation. *MIS Quarterly*, *45*(3), 1483–1500. https://doi.org/10.25300/MISQ/2021/16535

Tiwana, A. (2013). *Platform Ecosystems: Aligning Architecture, Governance, and Strategy*. Morgan Kaufmann.

Urquhart, C. (2012). *Grounded Theory for Qualitative Research: A Practical Guide* (1 edition). Sage Publications.

Urquhart, C., Lehmann, H., & Myers, M. D. (2010). Putting the 'Theory' Back into Grounded Theory: Guidelines for Grounded Theory Studies in Information Systems. *Information Systems Journal*, *20*(4), 357–381. https://doi.org/10.1111/j.1365-2575.2009.00328.x

Wagner, G., Prester, J., & Paré, G. (2021). Exploring the Boundaries and Processes of Digital Platforms for Knowledge Work: A Review of Information Systems Research. *The Journal of Strategic Information Systems*, *30*(4), 101694. https://doi.org/10.1016/j.jsis.2021.101694

Weick, K. E. (1995). What Theory Is Not, Theorizing Is. *Administrative Science Quarterly*, *40*(3), 385–390.

Wiesche, M., Jurisch, M. C., Yetton, P. W., & Krcmar, H. (2017). Grounded Theory Methodology in Information Systems Research. *MIS Quarterly*, *41*(3), 685–701. https://doi.org/10.25300/MISQ/2017/41.3.02

Yu, H., Miao, C., Chen, Y., Fauvel, S., Li, X., & Lesser, V. R. (2017). Algorithmic Management for Improving Collective Productivity in Crowdsourcing. *Scientific Reports*, *7*, 12541.

Zhang, A., Boltz, A., Wang, C. W., & Lee, M. K. (2022). Algorithmic Management Reimagined For Workers and By Workers: Centering Worker Well-Being in Gig Work. *CHI Conference on Human Factors in Computing Systems*, 1–20. https://doi.org/10.1145/3491102.3501866