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Schulze, Laura ; Trenz, Manuel; Cai, Zhao; Tan, Chee-Wee

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# Fairness in Algorithmic Management: How Practices Promote Fairness and Redress Unfairness on Digital Labor Platforms

Laura Schulze
University of Goettingen
laura.schulze@uni-goettingen.de

Manuel Trenz
University of Goettingen
trenz@uni-goettingen.de

Zhao Cai
University of Nottingham Ningbo China
zhao.cai@nottingham.edu.cn

Chee-Wee Tan
Copenhagen Business School
ct.digi@cbs.dk

## Abstract

*Algorithmic management (AM) is employed on digital labor platforms (DLPs) to efficiently manage interactions between workers and clients. However, AM comes with ethical challenges, such as unfairness. Identifying best practices that counter these challenges promises to deliver actionable solutions. Therefore, we identify AM practices that workers deem particularly fair. We conduct seven online focus groups with a diverse set of platform workers and analyze the data through an organizational justice lens. Our findings reveal that AM practices can promote fairness by providing information, empowering workers, or autonomously executing tasks in their interest. Alternatively, in the case unfairness occurred, AM practices can redress unfairness. These practices include delegating dispute resolution to the involved actors, investigating evidence, and autonomously determining restorative consequences. Our findings have theoretical implications for fairness in algorithms, AM, and organizational justice literature. They might also be adopted in practice to improve workers' conditions on DLPs.*

**Keywords:** Algorithmic management, fairness, organizational justice, digital labor platforms

## 1. Introduction

DLPs provide new sources of income for workers globally. Acting as an intermediary between workers and clients in service fulfillment, over 700 DLPs – catering to a broad range of services like driving, food delivery, microtasks, writing, and programming – have been documented in 2020 (Rani et al., 2021). DLPs continue to enjoy exponential growth and high volumes of funding (Mastercard & Kaiser Associates, 2019). Together, the largest DLPs, Appen, Instacart, Meituan, Uber, and Upwork generated a total revenue of about USD31.2 billion in 2019 (Rani et al., 2021).

On DLPs, algorithms rather than humans manage the large number of interactions between workers and clients (Lee et al., 2015). However, deploying algorithms for managing workers comes with ethical challenges (Fieseler et al., 2019; Gal et al., 2020; Schlagwein et al., 2019). Due to their dependency on the income (Rani et al., 2021), workers have limited power in negotiating their work conditions with DLP owners. Additionally, their opportunities for resistance are limited (Cameron & Rahman, 2022). The large discrepancy between supply (workers) and demand (clients), with supply outstripping demand by up to 99% (Rani et al., 2021), further exacerbates the problem.

Aspiring for fairer work environments is beneficial for workers, platform owners, policymakers, and society at large. Workers expect fairness on DLPs (Deng et al., 2016), especially when they are managed by technology that is supposedly more 'objective' than humans (Ryan & Wessel, 2015). Failure to meet workers' expectations of fairness not only adversely affects their job satisfaction and trust (Liu & Liu, 2019), but is also detrimental to platform owners through higher turnovers (Ma et al., 2018; Song et al., 2020). Likewise, for policymakers and society, harmful societal effects generated by the use of technology are to be avoided (Marjanovic et al., 2022). This is especially desirable in the workplace, as human virtue is concerned (Gal et al., 2020).

Fairness has been touted as a guiding principle for developing and deploying algorithms (Barocas et al., 2022). On DLPs, fairness principles entail fairness in pay, conditions, contracts, management, and representation (Oxford Internet Institute & WZB Berlin Social Science Centre, 2022). While these principles can guide algorithm developers on platforms, predicting what will be perceived as 'fair' and how AM practices shape those fairness perceptions remains a challenge.

In the absence of implementable answers to these challenges, past studies have put forth frameworks for investigating fairness in algorithmic decision-making (e.g., Marjanovic et al., 2022; Robert et al., 2020; Teodorescu et al., 2021). They suggest defining fairness, identifying the subjects who are concerned, evaluating if and how fairness is established, and addressing

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disputes (Marjanovic et al., 2022; Robert et al., 2020). In analyzing fairness in algorithms, a socio-technical perspective is necessary (Dolata et al., 2021; Teodorescu et al., 2021). We follow these frameworks and recommendations in our study.

While unfairness on DLPs has been repeatedly documented in the literature (e.g., Fieseler et al., 2019; Schlagwein et al., 2019), solutions to achieve fairness are less prominent, although notable exceptions exist (e.g., Lee et al., 2019; Zhang et al., 2022). We follow the latter approach and focus on best practices. Identifying solutions to fairness holds the potential for deriving actionable recommendations for DLPs, workers, and policymakers. Thus, we focus on identifying AM practices that establish fairness from the workers' point of view. We investigate the following research question: *How can algorithmic management be fair, from the workers' perspective?*

We analyze data we collected during seven online focus groups with 23 workers who share their experiences about working on different DLPs. The findings reveal AM practices that promote fairness and AM practices that redress unfairness. First, AM practices that promote fairness exhibit high transparency (informational AM practices) and may additionally offer high agency to workers (empowering AM practices). AM practices that are low on transparency and agency, are also perceived as fair if they take over tasks on the workers' behalf (autonomous AM practices). Second, following instances of unfairness, AM practices can redress unfairness by influencing the process of dispute resolution (delegating and investigative AM practices), or the outcome of the dispute (autonomous AM practices).

Our findings contribute to literature by empirically contextualizing frameworks for studying fairness in algorithms. Further, we discuss the practical implications of our findings for workers, platform owners, as well as policymakers. We conclude with the limitations of this study and avenues for future research.

## 2. Theoretical foundation

### 2.1. Algorithmic management and fairness

DLPs (also called online labor platforms, crowd work platforms, or gig economy platforms) mediate between workers, who perform services, and clients, who pay workers for their services (Rai et al., 2019).

AM is deployed on DLPs to manage the large number of interactions among workers and clients. We follow Lee et al.'s (2015) foundational definition of AM: "software algorithms that assume managerial functions and surrounding institutional devices that support algorithms in practice" (p. 1603).

AM is characterized by opacity (Gal et al., 2020; Kellogg et al., 2020; Möhlmann et al., forthcoming), as the algorithmic logic underlying how workers are managed remains hidden. Managerial and operational functions (Tarafdar et al., 2022) can be supported by algorithms to a certain degree, i.e., fully or partially (Cram & Wiener, 2020) and may be based on artificial intelligence (AI) technology, such as machine learning or not. However, workers interact with the algorithm through digital interfaces, e.g., apps, receive instructions from the system, and perceive algorithms as co-workers or bosses (Möhlmann et al., 2021; Tarafdar et al., 2022). Therefore, AM in this study encompasses all practices that platforms use to interact with workers in managing work.

A growing body of literature on AM established dimensions (e.g., algorithmic direction, evaluation, and discipline (Kellogg et al., 2020)) and outcomes (e.g., tensions and sensemaking (Möhlmann et al., 2021, forthcoming)). Additionally, AM has been instantiated in many ways such as functions (e.g., Kellogg et al., 2020) or features (Lee et al., 2015). In line with other scholars (e.g., Meijerink et al., 2021), we study AM as practices that represent activities, such as performance appraisals. While it has been recognized, that working on DLPs has advantages and disadvantages for workers (e.g., Deng et al., 2016), it remains unclear, how fairness on DLPs can be promoted by AM practices.

Fairness is a broad concept that is defined differently in many IS-related disciplines, such as computer science and management (Dolata et al., 2021).

In computer science, certain criteria for achieving fairness in algorithms have been established, e.g., establishing demographic parity, equalized odds, or equalized opportunities (Kordzadeh & Ghasemaghaei, 2022; Teodorescu et al., 2021). However, satisfying these fairness criteria algorithmically is hardly feasible considering the complexity of real-world situations (Teodorescu et al., 2021). Additionally, as multiple fairness criteria are oftentimes incompatible, it becomes impossible to achieve them simultaneously (Teodorescu et al., 2021). Accordingly, IS scholars suggest addressing algorithmic fairness from a socio-technical perspective (Dolata et al., 2021; Kordzadeh & Ghasemaghaei, 2022; Marjanovic et al., 2022). In this paper, we define fairness and unfairness in a *relational* manner (i.e., the positive or negative evaluation of a comparison with other workers, clients, or platform owners) and from the *subjective* view from the workers. The relational and subjective views are in line with literature (Adams, 1963; Cropanzano et al., 2015; Dolata et al., 2021).

Summarized, fairness is an issue related to algorithms that requires a socio-technical lens that takes the perspective of those affected (workers, in our case).

However, it remains unclear what characterizes fair algorithms or, in our case more specifically, AM practices. To this end, we introduce our theoretical lens for studying workers' perceptions of fair AM practices next.

## 2.2. Organizational justice lens

In this study, we build on organizational justice literature as a theoretical lens. Literature on organizational justice is concerned with fairness in the workplace (Greenberg, 1990). It is widely adopted by management (Colquitt et al., 2001, 2013) and information systems (Dolata et al., 2021; Robert et al., 2020) scholars. For instance, it has been used as a theoretical lens in studies on related topics, such as identifying cases of unfairness on DLPs (Fieseler et al., 2019), or structuring literature on AI in organizations (Robert et al., 2020). We chose this theoretical lens due to its potential to inform our study of workers in the platform context as described beloy.

Organizational justice research emerged from psychology and social sciences (Dolata et al., 2021; Greenberg, 1990). In early research, fairness was defined as a comparison of the input/ output ratio of an individual with the same ratio of reference individuals (Adams, 1964). This perspective has been further developed and extended in may directions (Colquitt et al., 2001, 2013; Greenberg, 1990). Today, two sets of justice types define the construct.

The first set consists of distributive, procedural, and interactional justice (Colquitt et al., 2001). Distributive justice refers to the distribution of outcomes (Cropanzano et al., 2007). Procedural justice refers to the procedures that are used to determine the outcomes, and interactional justice to the interpersonal treatment that individuals receive (Cropanzano et al., 2007). Interactional justice can be further divided into informational justice and interpersonal justice. Informational justice entails sharing relevant information with employees. Interpersonal justice concerns treatment with dignity, courtesy, and respect (Cropanzano et al., 2007). Thus, these justice types differ based on whether outcomes, processes, or interpersonal interactions are concerned.

Second, restorative and retributive justice are distinguished in literature (e.g., Darley & Pittman, 2003; Mahony & Klaas, 2008; Robert et al., 2020; Wenzel et al., 2008). Based on criminal justice literature, the victim (i.e., a person who experienced unfairness) is distinguished from the offender (i.e., a person who created unfairness) (Kidder, 2007). Consequences are determined for each party. Retributive fairness is directed toward the offender and involves the offender's punishment. Restorative fairness takes a broader perspective and includes all actors involved in the resolution process. It may include compensating the victim, or other victims of similar offenses, as well as meaningful punishments of the offender that benefit the victim or the whole community (Kidder, 2007; Wenzel et al., 2008). Both types of justice share the preceding of unfairness. They take place *after* an unfair event occurred, as compared to preventing an unfair event *before* it occurs (temporal perspective).

As AM replaces human managers (Duggan et al., 2019; Möhlmann & Zalmanson, 2017), and DLPs diverge from hierarchical organizations (Meijerink et al., 2021; Möhlmann et al., 2021) theoretical advancements are necessary for studying how AM practices contribute to fairness on DLPs.

Therefore, we reconcile the insights from prior literature (see Figure 1) and expand on them (see discussion section). We differentiate between AM practices that promote fairness and AM practices that redress unfairness. In the former case (*promoting fairness*), unfairness is less likely to arise because of the way AM practices are designed. However, there might always be unexpected issues or failures of fairness, such that it cannot be ruled out that unfairness arises. In the latter case (*redressing unfairness*), AM practices are designed to restore fairness. Thus, the difference between promoting fairness and redressing unfairness lies in the advent of unfairness (has not happened vs. has happened).

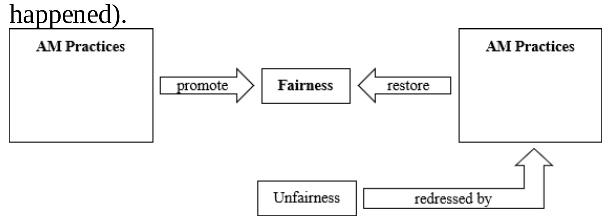


**Figure 1. AM practices promoting fairness and redressing unfairness.**

The terms 'justice' and 'fairness' have been used interchangeably in the literature (Goldman & Cropanzano, 2015). We follow Goldmann & Cropanzano's (2015) and Cropanzano et al.'s (2015) argumentation in differentiating justice from fairness, whereby justice refers to normative standards and fairness to the appraisal of such standards, i.e. the *subjective* assessment of justice. In line with our focus on the workers' perspective, we view all AM practices as fair that workers perceive to be fair.

# 3. Research design

We collect data through focus groups. Focus groups are appropriate for our purpose because they enable exploring new phenomena from participants' perspectives, and creating theory in IS research (Bélanger, 2012).

We recruited participants via specialized groups and forums on social media sites (Reddit, Facebook, LinkedIn, Baidu Tieba). The recruitment post included a short introduction of the topic, non-monetary (e.g., an opportunity for exchange with other workers) and monetary (i.e., USD30 or equivalent in other currencies/ CNY100-200) incentives, and a link to a screening survey. The screening survey's purpose was to allow for an appropriate selection and sampling of participants based on their platform work experience, demographics, and availability. Provided their informed consent, participants were contacted via email or instant messaging (i.e., WeChat and QQ).

The first online focus group was held in January 2021. In accordance with theoretical sampling (Urquhart, 2012; Urquhart et al., 2010), we used the insights from the first focus group to inform the following data collection process. Thus, we decided to include only participants with substantial platform work experience, high willingness to contribute to the group discussion, and fluency in English or Chinese. Our strategy for within-group sampling involved homogeneous attributes among participants regarding the type of work they are doing (ride-sharing, design, writing, food delivery, or microtasks) and the language they spoke (English, or Chinese).

All focus groups took place online via videoconferencing tools and were moderated by one of the authors using a semi-structured moderator's guide. After an introduction, participants were asked to describe their experiences with the platforms and clients in the awareness, negotiation, fulfillment, and follow-up stages of their work on platforms. Due to the open questions participants elaborated on many aspects of their work on DLPs, such that multiple specific topics emerged, one of which was fair AM practices.

In total, we conducted seven online focus groups (7, 2, 2, 2, 4, 2, 4 participants) with 23 platform workers (average age = 27.57 years, 26.1% female) who shared their experiences with a total of 28 DLPs. The bias towards young and male platform workers is in line with the characteristics of platform workers in general (Rani et al., 2021). Participants stem from ten different countries (Canada, China, Egypt, Greece, India, Kenya, Pakistan, Russia, UK, USA). The purpose of this diversity in participants was to capture as many subjective experiences across individuals and platforms as possible. 630 minutes of audio-visual data were collected, transcribed verbatim, and in the case of the Chinese focus groups, translated to English.

The transcripts were then analyzed using grounded theory techniques, as common for focus group data analysis (e.g., Karwatzki et al., 2017; Onwuegbuzie et al., 2009). Specifically, we employed coding based on Urquhart's (2012) evolution of Glaser's (1978, 1992), recommendations. Additionally, we used grounded theory techniques such as theoretical sampling, constant comparison, and memo writing. We take an interpretivist philosophical perspective in the analysis.

The first author engaged in open, selective, and theoretical coding to inductively analyze the focus groups (Urquhart, 2012). An example of the coding structure is provided in Table 1 including open and selective codes on informational AM practices used to promote fairness.

**Table 1. Illustration of open and selective codes.**

| | |
|---|---|
| Core category | AM practices promoting fairness |
| Sub-category | Informational AM practices |

| Open codes | Selective codes |
|---|---|
| knowing exactly how performance is measured, speed metric transparent for worker | Disclosing performance measurement logic |
| comparing evaluations with those of competitors, platform allows workers to compare themselves, client review transparent after 3 hours, client review and complaints are shown to workers, delivery station master knows performance of workers next day, good learning tasks are helpful because they provide explanations, instant feedback helps to improve | Disclosing (relative) performance |
| notification of received pay, transparent payment process, knowing how much money earned, transparency on payment due | Disclosing payment (status) information |
| workers can contact clients directly, platform messaging is ok/ good, daily communication through platform, upfront communication helps to concentrate on job, communicating extensively with client before taking job, clarifying quality metrics before accepting job, chat of co-workers on same project, internal platform forum | Enabling communication |

Open coding included sentence-by-sentence, and where appropriate, word-by-word labeling of the data. In line with the many opportunities generated through the rather open questions and the many open codes, multiple opportunities for more specific analyses emerged, among them a focus on unfairness, which we discuss in a different conference paper.

During selective coding, in this paper, the core categories (AM and fairness) were identified and only codes relating to the core concepts were included in the further analysis. The goal of the theoretical coding stage is to relate the emerging constructs in meaningful ways to generate theory (Urquhart, 2012). At this point, we discovered the natural fit of the emerging codes with organizational justice literature. Therefore, we used our theoretical understanding of the difference between promoting fairness vs. redressing unfairness (see Figure 1) as a theoretical lens that guided our emergent theory.

## 4. Findings

### 4.1. How AM practices can promote fairness

We identify three ways in which AM practices can be considered fair by workers: if they provide workers with information, if they empower them to make informed decisions, or if they autonomously execute work surrounding the actual task on the worker's behalf, thereby reducing their workload. We distinguish these three types of AM practices that promote fairness on two dimensions (see Figure 2): transparency, i.e., to which degree AM practices ensure that workers receive information (low vs. high), and worker agency, i.e., to which degree AM practices ensure that workers have individual choice and control in decision making (low vs. high).

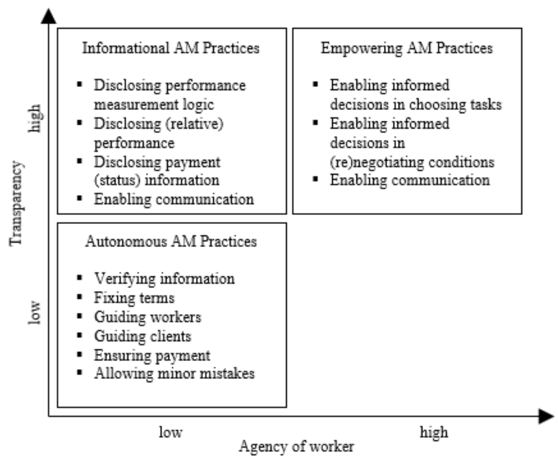


**Figure 2. AM practices promoting fairness.**

*Informational* AM practices make information transparent for workers. Informational AM practices are highly transparent (high transparency), but do not delegate any immediate decision rights to workers (low worker agency). Disclosing information about how performance is measured allows workers to improve based on these metrics. Disclosing information about their own (relative) performance informs them about their competitive position in relation to other workers. Additionally, feedback on task performance allows them to learn and improve in the future (see quote).

*Sometimes they [learning tasks] can be pretty helpful because as you're working, it kind of helps you to keep on track and it kind of helps you to resolve some more difficult cases and just explain what you are doing and how you're supposed to. [P6]*

Disclosing information about their payment (status) allows workers to infer the quality of the platform and client. Moreover, enabling communication between workers and clients, as well as among workers, helps workers receive more information.

*Empowering* AM practices enable workers to make their own decisions (high worker agency) in addition to providing workers with relevant information for making those decisions (high transparency). When choosing (or declining) tasks workers can deliberately make this decision at their discretion without any negative consequences. Additionally, workers are provided with relevant information for making the task acceptance decision (see quote).

*First of all, I do what clients do to the freelancers, I also check their rating. And if there is a freelancer or a number of freelancers who have complained about the clients or the ratings of his authority, I'm not going to apply for a job. […] If the method of payment is not verified, I don't apply. So those are some of the things I actually check before applying for a job. […] So, I think the client has to have the right personality and be a good person generally so that you can do the work together. [P8]*

This includes details on the task (e.g., amount of payment, task expectations) and on the client (e.g., identity, past worker evaluations of the client, payment history). Again, communication between workers and clients as well as among workers is enabled, such that workers can further establish the suitability of the task, and the trustworthiness of the clients.

In negotiating the task conditions, workers are empowered to set their own conditions and renegotiate them, if necessary. Workers can negotiate the scope, price, and logistics (such as monitoring) of the task with clients and the platform helps them to do so (see quote).

*But then the client wants a fourth revision. So, what happens is that we already did the three revisions and this work should be considered done and I delivered. But then if you want more than three revisions, you're going to add that. So, we go back to renegotiating. So, you are going to add me a certain amount of money so that I can do an extra revision again and do this as you want. [P9]*

This also implies that there are no prerequisites from the platform side, such as having to fulfill the task within a certain period of time or having to do the task by oneself, rather than subcontracting certain aspects of the work to others. Again, communication is enabled that allows for information sharing in order to make better-informed decisions.

*Autonomous* AM practices are low on the transparency and the worker agency dimension. Hereby, AM practices execute tasks that protect workers from adverse client behavior and help workers perform their work. Specific AM practices include the verification of information. For instance, platforms ensure the legitimacy of tasks. Moreover, the platform fixes the negotiated task conditions, such that future, unilateral changes from the client side can be prevented. When conducting the work, AM practices guide workers through process, such that they are faster in delivering their services. For instance, platforms provide navigation services for food delivery workers. Additionally, AM practices guide clients to behave in ways that are desirable for workers. For instance, clients receive reminders for being on time in the case of ride-sharing services. Autonomous AM practices also include the monitoring of work hours and the automatic release of payment once the agreed-upon work is done to ensure the rightful payment of workers (see quote).

*So, once you've submitted the tasks, your hours are automatically uploaded based on how many tasks you've done. [P7]*

To this end, platforms provide escrow services. Last, AM practices can also ensure worker payment in case of suboptimal performance. As every human is fallible, allowing workers a few mistakes is considered fair when determining payment or evaluating performance. Showing a certain level of fault tolerance avoids overly strict performance metrics which eliminates disputes before they can emerge. For instance, the platform might automatically remove a worker's lowest rating.

Summarized, AM practices can promote fairness for workers in three different ways (see Figure 2). They provide information, empower workers to make their own decisions or execute decisions autonomously in the workers' interest.

## 4.2. How AM practices can redress unfairness

In contrast to AM practices that promote fairness, AM practices may restore fairness after workers feel like being treated unfairly. Transparent information allows workers to discover unfairness, which is a prerequisite for redressing unfairness (see Figure 3).

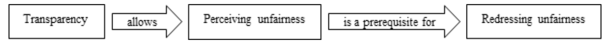


**Figure 3. Conditions for redressing unfairness.**

AM practices are considered fair by workers if they provide workers with agency in the process of dispute resolution, conduct careful investigations in the process of dispute resolution, or if they autonomously make outcome decisions in the workers' interest. We distinguish three types of AM practices that redress unfairness on two dimensions (see Figure 4): worker agency, i.e., to which degree AM practices ensure that workers have individual choice and control in decision making (low vs. high), and the object of agency, i.e., whether the process or the outcome of the dispute is concerned (process vs. outcome focus).

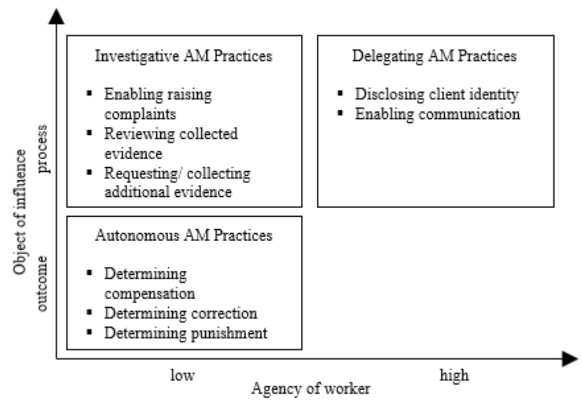


**Figure 4. AM practices redressing unfairness.**

*Delegating* AM practices include disclosing the client's identity and enabling communication with the client. Hereby, the worker can directly interact with the client and try and resolve the conflict. For instance, workers can negotiate the valence of a review with clients directly, as P19 states below.

*After the bad reviews, we go to negotiate and ask people where they are dissatisfied, and so on. [P19]*

The platform is not involved any further despite providing workers with the information they need to solve the conflict directly with the client (high worker autonomy). The outcomes are further determined based on the next steps taken by the worker and client, and therefore, are not influenced by the AM practices (process focus).

*Investigative* AM practices are enacted by the platform to provide evidence for unfairness and to determine culpability (worker agency low; process focus). To bring fairness to the platform owner's attention, AM practices allow the worker to raise complaints, such as reporting a client to the platform. Consequently, the platform will take over the role of a mediator for the conflict. Workers consider it to be fair if the platform collects evidence, such as reviewing the communication logs between workers and clients (see quote below), or verifying if a transaction actually took place in case of an unjustified review. Additionally, the platform might ask the parties involved for additional evidence.

*The platform will verify the background of the chat history between you. [P19]*

Subsequently, it is considered fair if the platform acts upon the evidence collected and reviewed. *Autonomous* AM practices are enacted autonomously by the platform owner. This dimension is in line with the autonomous AM practices that promote fairness (see section 4.1 and Figure 2). Contrarily to the autonomous AM practices presented above, the autonomous AM practices identified here, concern the outcome of the platform's attempt to redress un unfair event after it took place (worker agency low; outcome focus). Outcomes can be manifold. First, the platform might compensate workers, such as reimbursing outstanding client payments. Second, AM practices can ensure to spare workers negative consequences and thereby correct automatic consequences that would affect workers in the case of no intervention. This might even involve human intervention, such as manually reallocating tasks. Alternatively, the platform might implement workaround practices for unexpected situations (see quote), such as extending the time limit for a certain task.

*The order will go back to the system and be allocated to the next delivery person who may on the way, or the system will determine it is the merchant's responsibility and cancel the order. [P20]*

In terms of punishment, fair AM practices include showing benevolence in case the worker was found culpable. For instance, performing a task badly might lead to minor performance metric decreases only. Alternatively, if the client was found guilty, punishing the client is also considered fair by workers.

Summarized, AM practices can redress unfairness for workers in three different ways (see Figure 4). They delegate conflict resolution to workers, investigate complaints, or autonomously determine outcomes in the workers' interest.

# 5. Discussion and implications

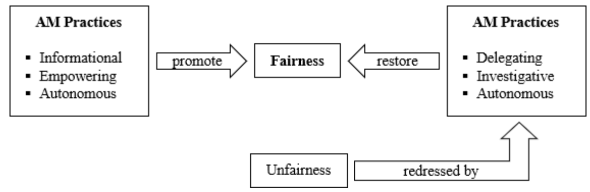


**Figure 5. Summary of AM practices considered fair.**

Our findings imply that while AM practices may try and promote fairness and reduce the likelihood of unfairness, unfairness cannot be fully eliminated. In other words, AM practices do not seem capable of achieving fairness at all times for all workers. This observation is consistent with literature on machine learning algorithms that "optimize outcomes for large samples at the expense of individuals" (Kane et al., 2021, p. 374). This fact highlights the importance of our identified AM practices that redress unfairness for individuals, such that fairness will be restored. Delegating AM practices that enable workers to resolve conflicts directly with clients, investigative AM practices, that ensure the collection and review of evidence, and autonomous AM practices, that handle exceptions by providing workarounds or alternative processes, are especially important means for redressing unfairness.

Another theoretical implication of our findings concerns the nature of AM. Our definition of AM was rather broad. Thereby, we were able to identify practices that include human augmentation. Precisely, in exception handling to redress unfairness, such as determining corrective actions like reassigning tasks, workers talked about human intervention. While not stated explicitly due to the "black-box" characteristic of AM, it seems likely that reviewing evidence might also be a task done by humans. Therefore, AM is a complex system including tasks done by humans and algorithms, as well as human and algorithmic decision-making. Hereby, human augmentation can help improve fairness (Teodorescu et al., 2021). Considering the importance of theoretical integration in grounded theory studies (Urquhart, 2012), we demonstrate how our findings relate to existing literature, next.

As compared to distributive, procedural and interactional fairness (Cropanzano et al., 2007), and restorative and retributive fairness (Darley & Pittman, 2003), we suggest an aggregated, temporal perspective that distinguishes between whether there are AM practices in place that try and prevent unfairness (promoting fairness) and practices that try and restore fairness after unfairness was perceived by a worker (redressing unfairness).

Despite this general difference, there are some commonalities. In organizational justice literature, informational fairness refers to providing employees with relevant information (Cropanzano et al., 2007). On DLPs, transparent information take on an important role as well. First, fairness can be promoted through informational and empowering AM practices. They disclose information to workers that are relevant for immediate or future decision-making. Second, to discover unfairness, it is imperative that workers may discover unfair treatment (see Figure 3). Only then workers can form fairness perceptions. To avoid a broken feedback loop (Tarafdar et al., 2022), AM practices redressing unfairness become important. Third, unfairness can be redressed through delegating AM practices that open the avenue for worker self-defense by providing information in case of a dispute.

While AM practices, in general, are of a procedural nature, some of the identified practices concern the distribution of rewards, as in distributive fairness (Cropanzano et al., 2007). Autonomous AM practices that promote fairness include ensuring payment for workers. Autonomous AM practices that redress unfairness include determining compensation.

AM practices redressing unfairness share the preceding of unfairness with restorative and retributive fairness practices. Overall, AM practices redressing unfairness rather comply with the perspective on fairness from the restorative view. Restorative fairness has the goal of integrating all perspectives in the dispute resolution process and may include compensation of the victim or more affected parties, as well as punishment of the offender in a meaningful way (Kidder, 2007; Wenzel et al., 2008). In line with this goal, delegating AM practices give the responsibility of resolving the conflict to the involved parties. Alternatively, investigative AM practices determine who the victim and who the offender is, based on evidence collected. Following this investigation, autonomous AM practices can include compensation of the worker, correction of actions that would harm workers, and punishment for clients that benefit workers in general, e.g., banning an unfaithful client from the platform.

Our findings can be used by practitioners in the following ways. Workers can identify fair AM practices on the DLPs they currently use or consider using in the future. This might help them deciding on their continuance intention or acceptance decision of offering their services through a certain DLP. They might also try and convince platform owners to implement fair practices based on our description of fair AM practices.

Platform owners and AM developers receive insights into the subjective views of the workers they affect through AM practices. Therefore, they might be better able to grasp the needs and desires of the workers. This can be helpful for improvements of AM to increase worker retention.

For policymakers, our findings provide specific examples of how AM can be used to improve fairness and thereby conditions for workers. This allows them to make specific suggestions for AM practices that are relevant for workers when regulating DLPs. Our findings help propose AM practices that are fair for workers, based on empirical evidence.

## 6. Limitations and future research

Our study was conducted within certain boundaries in scope and depth, which reflect the limitations of our findings. The scope of the study was limited in two ways. First, we studied the subjective perspectives of workers. As digital platforms are multi-actor settings that require the integration of multiple perspectives (de Reuver et al., 2018), the workers' perspective is only one among others. Therefore, future research can integrate the perspectives of fairness in AM from clients' and platform owners' perspectives.

Second, we studied AM on DLPs. While AM is most prevalent on these platforms, traditional organizations are increasingly using technology to manage workers as well (Jarrahi et al., 2021). Our findings are somewhat specific to DLPs, because of the direct interactions of workers with AM instead of human managers, and workers' direct transactional relationship with clients. Therefore, future research might study fairness in AM in traditional organizations.

A potential expansion in depth includes addressing why certain AM practices are considered fair, and when they are considered fair. Hypotheses based on the observation of individual preferences among workers (Hong et al., 2020; Rani et al., 2021) and our findings could be: Workers prefer AM practices that automate tasks and decisions in case workers have homogenous interests (such as receiving payment). Contrarily, they prefer informational and empowering AM practices in case there are heterogeneous individual preferences (such as allocating and negotiating task conditions).

Additionally, workers' characteristics might have an influence on fairness perceptions (Myhill et al., 2021). In the data, we found indications of cultural differences. This might be rooted in the juridical systems because they influence workers' perceptions of fairness (Kidder, 2007). To identify and compare individual differences, a follow-up study could interview more diverse workers confronted with the same AM practices on the same DLP.

Last, our study was rather explorative, providing first and preliminary insights on fair AM practices. Follow-up studies might provide statistical evidence and extend these findings. They can determine a) the extent of fair AM on different platforms, b) the relative influence of each AM practice for an overall assessment of fair AM practices on a platform, and/ or c) the effect of fair AM on outcomes, such as turnover intentions or workers' satisfaction with specific DLPs. The last question is especially promising, as there might be opposing effects on worker satisfaction between investigative AM practices that rely on the collection of evidence, and privacy concerns created by the collection of data, such as screenshots (Liang et al., 2022).

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