Fair and Unfair Algorithmic Management Practices – Perspectives of Workers on Digital Labor Platforms

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Introduction

DLPs provide new sources of income for workers globally. Acting as an intermediary between workers and clients in service fulfillment, over 700 DLPs have been documented in 2020 (Rani et al., 2021). 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). This substitution of human management by technology, called algorithmic management (AM), enables the platforms' business model (Benlian et al., 2022; Rani et al., 2021). Employing AM holds great potential, such as efficient management for platform owners, or equal treatment for workers. However, it also comes with ethical challenges (Fieseler et al., 2019; Gal et al., 2020; Schlagwein et al., 2019). 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. As such, they deserve the focus of scholarly attention.

In the literature, AM on DLPs has been investigated from a fairness and unfairness perspective, separately. First, specific DLPs were studied in depth in order to identify whether and which ethical challenges, including unfairness, exist for workers (e.g., Deng et al., 2016; Fieseler et al., 2019; Schlagwein et al., 2019). Thereby, many factors were identified, for instance, remuneration, transparency, dispute settlement, feedback and respect (Fieseler et al., 2019). These studies combined contribute an encompassing list of factors that promote unfairness on DLPs. However, those studies barely consider AM – the central aspect of DLPs (Rani et al., 2021) which is designed and deployed deliberately and thus may be adapted. Therefore, it remains unclear how AM practices, specifically, contribute to unfairness from the workers' perspective.

Second, specific AM practices that workers consider to be fair were identified in prior literature. This has largely been achieved by researchers developing fair AM practices in close collaboration with workers (e.g., Lee et al., 2019; Zhang et al., 2022). While this approach shows that fairness can be incorporated into the design of AM practices, it remains unclear how AM practices existing on DLPs contribute to workers' fairness perceptions.

Therefore, we allege that there is a lack of a comprehensive analysis of both fairness and unfairness in AM practices across a wide range of DLPs. In this research project, we investigate the following research question: *What makes AM practices fair or unfair, from the workers' perspective?*

Theoretical Foundation

Algorithmic Management Practices on Digital Labor Platforms

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 everyday activities of organizing (Feldman & Orlikowski, 2011).

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 can be supported by algorithms fully or partially (Cram & Wiener, 2020). These algorithms may or may not be based on machine learning. 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 platforms use to interact with workers in managing work tasks.

Fairness and Unfairness

Fairness is a broad concept that is defined differently in many IS-related disciplines (Dolata et al., 2021). A body of literature on fairness in the workplace, organizational justice literature, has grown in management (Greenberg, 1990). Today, two sets of justice types define organizational justice. The first set consists of distributive, procedural, and interactional justice (Colquitt et al., 2001). These justice types differ based on whether outcomes, processes, or interpersonal interactions are concerned. The second set consists of restorative and retributive justice that both take place after an unfair event occurred (Darley & Pittman, 2003; Robert et al., 2020). 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). Retributive fairness is directed toward the offender and involves the offender's punishment. Restorative fairness takes a broader perspective and 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).

In this research project, 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 of individual workers, in line with others (e.g., Cropanzano et al., 2015). IS scholars suggest addressing algorithmic fairness from a socio-technical perspective (Dolata et al., 2021; Marjanovic et al., 2022), which we adopt.

Methodology

We take an interpretive perspective in the analysis and engage with principles of interpretive research (Klein & Myers, 1999). We conducted seven online focus groups with 23 workers who shared their experiences about working (online or offline) on different DLPs (such as Upwork, Clickworker, Ele.me, or Didi). Participants were recruited through social media, stem from ten different countries and are, on average, rather young and male. Through the interactions among participants, focus groups add richness to the discussions, as compared to individual interviews (Merton et al., 1990), because they allow unknown information to emerge (Fern, 2001). In the analysis, we adopt established grounded theory methodology (GTM) techniques as specified by Glaser (1978) and Urquhart (2012; 2010).

Preliminary Results

The findings (see Figure 1) reveal that AM practices are considered unfair if they give rise to systematic disadvantages for workers in the form of devaluation (lower returns, losing assets), restriction (fewer chances for returns), and exclusion (losing chances for returns on the DLP). Unfair AM practices arise from automated decision-making or from the delegation of decision-making to clients. However, AM practices can also contribute to fairness. First, AM practices can promote fairness in order to avoid unfairness. For instance, AM practices can inform workers, offer high agency to workers or take over tasks on the workers' behalf. Second, as unfairness may never be completely avoided, following instances of unfairness, AM practices can influence the process of dispute resolution, or the outcome of the dispute to restore fairness.

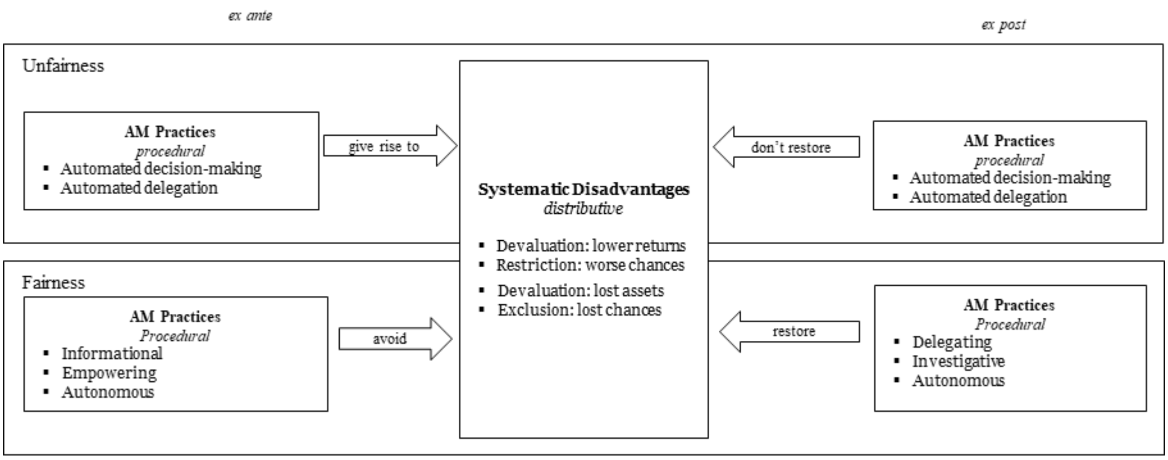

Figure 1. Fair and Unfair AM Practices on DLPs

Expected Contributions and Outlook

Reconciling how AM practices promote fairness and unfairness has the potential for addressing the issues of (un)fairness in the context of AM on DLPs. 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).

This research project has been going on for some time and preliminary analyses were conducted and published. Moving forward, we are mainly working on a) refining the main concepts (fairness, AM), b) choosing the most appropriate theoretical grounds (organizational justice, fairness in algorithms, others), c) collecting additional data (in line with theoretical sampling), and d) advancing our theorizing efforts for instance by applying methods specific for the analysis of focus group data (e.g., Nili et al., 2017). We aim for a theoretical contribution to IS literature (e.g., by explaining how the design of AM practices, as one form of algorithmic decision-making, can cause fairness or unfairness).

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