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Workers' Perceived Algorithmic Exploitation on Online Labor Platforms

Jennifer Jiang
Technical University Dresden, jennifer.jiang@tu-dresden.de

Isabell Lippert
Technische Universität Dresden, isabell.lippert@tu-dresden.de

Armin Alizadeh
Technical University of Darmstadt, alizadeh@ise.tu-darmstadt.de

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Jennifer Jiang
Technical University of Dresden
Helmholtzstraße 10
01069 Dresden
jennifer.jiang@tu-dresden.de

Isabell Lippert
Technical University of Dresden
Helmholtzstraße 10
01069 Dresden
isabell.lippert@tu-dresden.de

Armin Alizadeh
Technical University of Darmstadt
Karolinenplatz 5
64289 Darmstadt
alizadeh@ise.tu-darmstadt.de

Abstract

Online labor platforms (OLPs) like Uber have become increasingly prevalent, attracting numerous workers with the appeal of flexible work arrangements. OLPs present themselves as an innovative alternative to traditional employment structures, but there remains a sense of exploitation among their workers. This perception is impelled by the platforms' heavy reliance on algorithmic management (AM), which often exerts a tighter form of management than traditional human-led oversight. This study examines how AM induces workers' exploitation perceptions (i.e., perceived algorithmic exploitation) by conducting a grounded theory methodology on 22 interviews with Uber drivers. We identified several forms of perceived algorithmic exploitation (i.e., manipulation, falsification, disempowerment, and dependency), which include AM practices that workers perceive as disadvantaging them to the potential benefit of the OLP. Overall, this study contributes to the "dark side" of AM and offers platform providers and policymakers crucial insights to create more sustainable working environments for platform workers.

Keywords: Online labor platform, algorithmic management, perceived exploitation, grounded theory

Introduction

Technological advances have led to new forms of work arrangements. In particular, one work arrangement that has emerged in recent years is online labor platforms (OLPs) such as Uber, Upwork, or Deliveroo, which heavily rely on digital technology and intelligent algorithms to automatically perform coordination and control functions that are traditionally performed by human managers (i.e., algorithmic management) (Möhlmann et al., 2021). Work on OLPs is becoming increasingly popular: Around 36% of the U.S. workforce was part of the gig economy with the trend rising (Kulach, 2023). While more and more people explore platform work, OLPs are concurrently facing challenges with high turnover rates (Mims, 2019). For example, of the 163 million estimated user accounts on OLPs worldwide in 2020, only 8.6% are active, and only 2% completed at least ten projects or earned a minimum of $1,000 (Kässi et al., 2021). Furthermore, OLPs are also struggling with worker protests which massively damage their image and valuation. For example, in 2019, when dissatisfied ride-hailing drivers engaged in a massive public protest in the U.S., the OLP Uber experienced a sharp drop of around 40% in their stocks (DeManuelle-Hall, 2019).

One of the main triggers for those negative reactions (i.e., turnover, protest) is often caused by workers' perception of being exploited by OLPs (Adam et al., 2023; Shapiro, 2018). Indeed, work arrangements like OLPs have a high potential to increase workers' exploitation perceptions: First, the regulation of labor practices on OLPs is reduced due to its status as a technology company where workers are mostly independent contractors and therefore do not benefit from employee rights (e.g., sick pay, pension) (Ashford et al., 2018; Bidwell and Briscoe, 2009; Martin et al., 2014). For example, the ride-hailing firm Uber portrays itself as a technology company instead of a transportation company, whereas the latter classification comes with much stricter regulations and higher labor standards for its workers (Rosenblat, 2018). Such a reduction in labor rights leads to perceptions of exploitation when workers compare labor standards with their own working conditions (Rosenblat & Stark 2016). Second, the usage of algorithmic management (AM) on OLPs increases power and information asymmetries between OLPs and workers in favor of the former due to the comprehensive, instantaneous, interactive, and opaque characteristics of algorithmic technologies (Curchod et al., 2020; Kellogg et al., 2020). Consequently, OLPs can leverage the advantage of such information and power asymmetries to enforce their interests, often at the expense of their workers (Rosenblat and Stark, 2016). While worker exploitation is an old-age phenomenon, it requires a new understanding and view in the area of technology-driven work arrangements (Livne-Ofer et al., 2019).

Existing literature on workers' perceived exploitation on OLPs has mainly focused on legal aspects (e.g., employee versus independent contractor status) (e.g., Berg, 2015; De Stefano, 2016) and market power perspectives (e.g., easy replacement of workers due to the low entry barrier of such work) (e.g., Anwar and Graham, 2021). Nevertheless, we still have a limited understanding of AM's role in triggering or facilitating such exploitation perceptions. Therefore, this study draws on Livne-Ofer et al.'s (2019) conceptualization of perceived exploitation to investigate workers' perceived algorithmic exploitation referring to worker's perception that they have been intentionally taken advantage of in their relationship with the organization through AM, to the benefit of the organization itself. From a scholarly viewpoint, studying perceived algorithmic exploitation can enhance our understanding of how workers negatively experience AM at work, shedding more light on AM's "dark sides" (Benlian et al., 2022). From a practical perspective, a better understanding of algorithmic exploitation perceptions can help OLPs reduce negative worker reactions if they can make AM practices more transparent in cases where workers' perceptions do not reflect their actual logic of the AM practices. Additionally, we encourage policymakers to protect fundamental worker rights on OLPs. Against this backdrop, we intend to answer the following research question:

RQ: What forms of algorithmic exploitation do workers perceive on OLPs?

To answer our research question, we conducted a qualitative study in the context of Uber. More specifically, we applied a grounded theory methodology (Corbin and Strauss, 2015) to 22 interviews with Uber drivers to derive categories of perceived algorithmic exploitation. To show how some AM practices are perceived as exploitative, we identified for each of these AM practices what disadvantages drivers experience to the potential benefit for Uber. Our analysis revealed four categories of perceived algorithmic exploitation, namely algorithmic manipulation, algorithmic falsification, algorithmic disempowerment, and algorithmic dependency. Additionally, we classified these categories of perceived algorithmic exploitation into constant and progressive forms. While constant algorithmic exploitation involves AM practices that occur regularly and similarly to all workers, progressive algorithmic exploitation involves AM practices that vary over time to change workers' habits in ways that intensify the effects of constant algorithmic exploitation on workers.

This study makes three contributions to the literature on platform workers' perceived exploitation (e.g., Ashford et al., 2018; Bidwell and Briscoe, 2009). First, we propose a new construct called perceived algorithmic exploitation to examine how workers perceive exploitation through AM. Thereby, we derived different forms of perceived algorithmic exploitation that reveal how OLPs can potentially leverage their advantage from the increased information and power asymmetries through AM to benefit at the expense of workers. Second, this study provides a more systematic understanding of perceived algorithmic exploitation by classifying them into constant versus progressive forms. In this context, the findings enhance our understanding of how AM may lead to new and more subtle forms of exploitation. Third, we contribute with a more nuanced understanding of the different relationships between perceived algorithmic exploitation and their impact on workers' disadvantages and OLP's potential benefits by outlining what forms of perceived algorithmic exploitation are linked to which type of workers' disadvantage and OLP's benefits.

Theoretical Background

Perceived Exploitation on OLPs

The exploitation of workers is a long-standing research stream rooted primarily in the work of Marx (1932) and Weber (1922). While much research in this area is based on a rather objective view of worker exploitation, for example, by analyzing the social structures that systematically reinforce worker exploitation (Parsons, 1967), recent research in the organization and management literature complements such an objective view by proposing the construct of workers' perceived exploitation (Livne-Ofer et al., 2019). Perceived exploitation is referred to as workers' "perception that they have been purposefully taken advantage of in their relationship with the organization, to the benefit of the organization itself" (Livne-Ofer et al., 2019, p. 9). The focus here is on workers' subjective perceptions and their actual feelings about the extent to which they feel exploited by their organization (Moore, 1972). Studying exploitation from the perspective of workers' perception can better explain workers' emotional, attitudinal, and behavioral responses (compared to other constructs such as psychological contract breach (Robinson et al., 1994)): It has a positive impact on anger, hostility, shame, and guilt; is also positively related to revenge, turnover intentions, psychological withdrawal, burnout as well as silence; and negatively related to engagement and organizational commitment (Livne-Ofer et al., 2019).

In addition to studying perceived exploitation in "traditional" organizations (i.e., for employees with contracts), the emergence and growing popularity of work on OLPs let scholars also examine the dynamics of exploitation in the platform context. Thereby, existing research has focused on the precarious circumstances of OLP workers under two aspects: First, current studies intensively discussed the legal classification issues of platform workers as independent contractors (e.g., Berg, 2016; De Stefano, 2015). While such independent contractor status removes the employee rights and transfers the risk and social costs of employment (e.g., sick pay, pension) to the worker, OLPs promise workers, in return, a high degree of flexibility and autonomy in deciding when and where to work (e.g., Ashford et al., 2018; Bidwell and Briscoe, 2009; Martin et al., 2014). However, current research reveals that workers perceive their work as constrained by the platform and that they have less control over the work process (Shapiro, 2018; Vallas and Schor, 2020). For example, Rahman (2021) describes how OLPs establish rules determining which workers can see which customer requests. Consequently, workers on OLPs have neither the protections of employee rights nor the actual freedoms of an independent contractor (Kuhn and Maleki, 2017). Second, existing studies also emphasize the low market power of platform workers due to the low barrier to entry for this type of work (Anwar & Graham, 2021). For example, anyone over the age of 21 with a valid driver's license and a well-maintained vehicle can apply to be an Uber driver (Lee et al., 2015). On this basis, platforms can easily absorb the loss of workers who do not accept the terms of the system, as workers are interchangeable for them (Cram et al., 2022). As a result, OLPs have less interest in caring about the problems of workers, for example, by not providing low-performing workers the chance to justify and correct themselves (Curchod et al., 2020). Overall, the consequences of such precarious circumstances for OLP workers (i.e., fewer rights, less control over their work, and low market power) let them perceive exploitation by OLPs such as facing precarity (Anwar and Graham, 2021; Deng et al., 2016), having no job security (Shapiro, 2018), or no bargaining power (Martin et al., 2014). In particular, workers who work full-time and are highly dependent on the income from OLPs are especially vulnerable to exploitative practices (Fieseler et al., 2019). Besides the valuable insights about workers' perceived exploitation on OLPs, one key aspect in this context is still under-researched: The role of digital technology, especially AM, in triggering or accelerating such exploitation perceptions.

Algorithmic Management

A key ingredient to the success and scalability of OLPs' business models is the use of algorithms for managing the platforms' distributed workforce, referred to as algorithmic management (AM) (Lee et al., 2015). Consistent with previous research, we define AM as "the large-scale collection and use of data on an OLP to develop and improve learning algorithms that carry out coordination and control functions traditionally performed by managers" (Möhlmann et al., 2021, p. 2001). Overall, AM comprises algorithmic matching and algorithmic control (Möhlmann et al., 2021). While algorithmic matching enables scalable and highly efficient coordination of supply and demand (e.g., through dynamic pricing or job assignments) (Jarrahi and Sutherland, 2019), algorithmic control aligns platform worker behavior with the goals of the

OLP (e.g., through behavioral nudging) (Kellogg et al., 2020; Wiener et al., 2021). Due to the heavy adoption of algorithms on OLPs, workers often experience algorithms as their “boss” (Curchod et al., 2020), for example, by receiving automated emails threatening deactivation if they cancel too many rides (Rosenblat and Stark, 2016). With the widespread implementation of AM, algorithms introduce unprecedented ways of managing workers (Lee et al., 2015; Möhlmann and Zalmanson, 2017). In particular, AM can be a stricter form of management (especially compared to human-based management approaches) due to algorithmic systems’ comprehensive, instantaneous, interactive, and opaque nature (Kellogg et al., 2020). For example, the comprehensiveness of such systems, and in particular the wide range of underlying devices and sensors, enables the collection of detailed information about workers and their activities (including biometrics and telematics), thereby taking organizations’ surveillance capabilities to a whole new level (Faraj et al., 2018). These characteristics of algorithms reinforce information and power asymmetries in favor of OLPs, which platform providers can leverage by extending their influence over workers to enhance platforms’ interests (Curchod et al., 2020; Rosenblat and Stark, 2016).

Perceived Algorithmic Exploitation

The extended influence of OLPs on workers through AM let many scholars investigate the “dark side” of AM for workers (Benlian et al., 2022; Möhlmann and Zalmanson, 2017). For example, Vallas & Schor (2020) described AM for workers as a “digital cage” and an “accelerant of precarity.” While existing literature has already examined some negative worker-level implications of AM, we still have little knowledge about workers’ *perceived algorithmic exploitation*: Drawing on the definition of perceived exploitation from Livne-Ofer et al. (2019), we refer to perceived algorithmic exploitation as workers’ perception that they have been intentionally taken advantage of in their relationship with the organization through AM, to the benefit of the organization itself. With perceived algorithmic exploitation, we specifically focus on the role of AM in triggering or facilitating workers’ perceptions of exploitation by OLPs.

Existing information systems (IS) literature has already developed diverse constructs that examine how algorithms can lead to decisions that harm individuals or a specific group of people. For example, research on algorithmic injustice investigates how automated algorithmic decision-making that produces unintended harmful social consequences can be seen as a social injustice issue and proposes frameworks to identify and address algorithmic injustice (Marjanovic et al., 2022). Moreover, in the context of algorithmic bias, several studies show how algorithms can produce biased outputs that can be highly undesirable when those biases are, for example, based on specific demographics such as gender or race (Kordzadeh and Ghasemaghaei, 2022). In contrast to algorithmic bias, which is conceptualized as an objectively measurable construct, algorithmic unfairness is often used as a subjective construct where people judge whether the algorithmic bias is fair (Kordzadeh and Ghasemaghaei, 2022; Schulze et al., 2022). While these existing constructs about harmful algorithmic decision-making provide valuable insights into potential negative consequences of algorithmic decision-making, we still have a limited understanding of perceived algorithmic exploitation, which focuses on the perceptions of the intentional usage of algorithms to organizations’ benefit at workers’ expense. Examining workers perceived algorithmic exploitation is particularly important: First, since AM is used in organizations to manage workers, a specific focus on the relationship between workers and the organization is necessary to investigate the harmful effects of algorithmic decision-making in this context. Second, the emphasis on workers’ subjective perceptions reveals their actual feelings and, therefore, can better explain worker reactions than an objective determination of worker exploitation (Moore, 1972). Third, while unintended harmful effects through AM can be rather excused, intended harmful effects can trigger more intense emotional and behavioral reactions in workers (Malle and Knobe, 1997). Table 1 provides an overview of how existing constructs in the IS literature on harmful algorithmic decision-making differ from perceived algorithmic exploitation, based on the key characteristics often used in the literature to define the respective constructs (e.g., Kordzadeh and Ghasemaghaei, 2022; Livne-Ofer et al., 2019; Marjanovic et al., 2022).

The extant literature on perceived algorithmic exploitation provides initial evidence of how workers feel that AM can be purposefully used or designed to harm them to benefit the OLPs (Möhlmann and Zalmanson, 2017; Rosenblat, 2018). For example, Rosenblat & Stark (2016) describe how Uber uses AM to benefit itself by, for example, threatening to deactivate driver accounts if they cancel unprofitable ride requests, resulting in drivers being forced to accept these unprofitable rides. Besides these descriptions of single cases of perceived algorithmic exploitation, we still lack a systematic overview of those algorithmic exploitation perceptions. Such a systematic overview can reveal crucial insights into the consequences of AM for workers and explain why they engage in resistance against OLPs (Jiang et al., 2021).

Construct	Construct Definition	Worker-organization relationship?	Subjective or objective?	Intended or un-intended?
Perceived algorithmic exploitation	Workers' perception that they have been intentionally taken advantage of in their relationship with the organization through AM, to the benefit of the organization itself (based on Livne-Ofer et al., 2019).	Yes	Subjective	Intended
Algorithmic injustice	"Unintended harmful societal effects of automated algorithmic decision-making" (Marjanovic et al., 2022, p. 269).	No	Not specified	Unintended
Algorithmic bias	"[S]ystematic deviation from equality that emerges in the outputs of an algorithm" (Kordzadeh and Ghasemaghaei, 2022, p. 395).	No	Objective	Not specified
Algorithmic unfairness	Human judgments associated with biases in algorithms (Kordzadeh and Ghasemaghaei, 2022).	No	Subjective	Not specified

Table 1. Comparison between Constructs of Harmful Algorithmic Decision-Making

Methodology

Due to the nature of the research question, which examines the different forms of perceived algorithmic exploitation of workers, we adopted a qualitative research design. On this basis, we conducted the Straussian grounded theory methodology, suitable for offering new insights and creating theoretical explanations beyond the already known based on empirical evidence (Corbin and Strauss, 2015; Glaser and Strauss, 1967). The Straussian grounded theory methodology is applied in the setting of the ride-hailing OLP Uber, which is frequently referred to in the literature as an "extreme case" of AM (Benlian et al., 2022; Bernal, 2020; Möhlmann et al., 2021). The units of our analysis were individual drivers' perceptions of how AM is used to exploit them, which consist of an AM practice, the resulting disadvantage from the AM practice, and perceptions of how Uber may benefit from the AM practice.

Data Collection

We decided to conduct semi-structured interviews with Uber drivers to discover how they perceive exploitation through AM in their daily work. In contrast to other data sources such as observations or newspapers, interviews offer researchers comprehensive insight into the perceptions of individual Uber drivers and are thus well suited for our study's objective. Initially, we started recruiting Uber drivers from online forums such as Uberpeople.net. However, after several interviews, we recognized a big variation between drivers' exploitation perceptions through AM. Some drivers do not perceive exploitation at all, while others highly perceive exploitation through AM during their work. Based on these insights, we tried to reach out to more drivers who feel exploited. Therefore, we contacted ride-hailing unions, where Uber drivers organize themselves to collectively protest undesirable practices from Uber because we assumed that most drivers who joined a union have perceptions of being exploited. Indeed, all drivers from the ride-hailing union we have spoken with feel that they are treated unfairly by Uber and that Uber uses digital technologies and algorithms to exploit them. To interview more Uber drivers from ride-hailing unions, we used the snowballing technique by asking those already interviewed drivers to contact drivers in their personal network to see if we could also talk to them.

At the beginning of each interview, we asked our interviewees where, when, and why they started driving for Uber. Afterward, we continued with questions about how they experience the algorithms that Uber uses to influence their daily work and if they think these algorithms are designed fairly. Subsequently, we asked them if they thought that Uber uses the algorithms to exploit them. Although all interviews followed this fundamental structure, we engaged in theoretical sampling according to the guidelines from the Straussian grounded theory and continuously iterated between data collection and data analysis (Glaser and Strauss, 1967). As a result, we have continually adjusted our interview guide based on the findings from the data analysis to better align our questions with the study's focus. We stopped collecting data when we achieved conceptual saturation, which was when we kept hearing the same things from the interviewees (Corbin and Strauss, 2015). Overall, we conducted 22 interviews with 18 Uber drivers from the U.S. between October 2021 and December 2022, where 14 are members of a driver union, and four are not. Most drivers have over five years of driving experience with Uber, are based in California, and work full-time for the OLP. An interview typically lasts for approximately 47 minutes. Every interview was recorded and transcribed.

Data Analysis

We coded the interview transcripts according to the Straussian grounded theory methodology guidelines. Therefore, we started with open coding by analyzing the interview transcripts incident-by-incident (Corbin and Strauss, 2015). Whenever we identified a meaningful concept from an incident in an interview transcript, we attached a label that summarizes our interpretation of that concept. In this regard, we derived first-order concepts describing how drivers feel exploited through AM, the resulting disadvantage for drivers, and their perception of how Uber potentially benefits from it. For example, interviewee 15 stated, "*They have so-called surge areas, which should indicate high demand. You move to those areas, so you can fulfill that demand and potentially make more money. But the truth is that the moment you enter those areas, they disappear. So, it is a tease to get you to move to a certain area, and then once you were there, you didn't have access to that bonus.*" The first two sentences refer to an exploitative AM practice and are coded as "algorithms let surge disappear when drivers arrive surge area" (see row one of Table 2). The last sentence reveals a driver's disadvantage resulting from that AM practice and is coded as "lured to relocation without deserved pay." Furthermore, the last sentence also indicates how Uber may benefit from that AM practice which is coded as "relocate drivers to ensure broad supply coverage." Moreover, we excluded those AM practices where it was not identifiable if an AM practice leads to a driver's disadvantage to the benefit of Uber. For example, interviewee 9 stated, *"I don't think they're that accurate with the algorithms. Sometimes at the airport, there could be many drivers waiting for a ride, and the app tells me to go pick up people at the airport when I'm 20 minutes away from it. So, I think their system sometimes has errors."* In this quote, the driver did not indicate that the usage of such inaccurate algorithms is intentional by Uber, and it is also unclear how Uber can benefit from it. Thus, this AM practice is excluded from further analysis. By doing so, we ensured consistency between the derived algorithmic exploitation concepts from our data and our definition of perceived algorithmic exploitation.

Next, we applied axial coding by integrating the first-order concepts identified in the open coding into second-order themes. Thereby, we separately analyzed the first-order concepts about perceived algorithmic exploitation, driver's disadvantages, and perceptions of Uber's benefits. For example, the first-order concepts of perceived algorithmic exploitation in Table 2 are separated from the other first-order concepts and analyzed independently from them. In this example, the first-order concept called "algorithms let surge disappear when drivers arrive surge area" (see row one of Table 2) and "algorithms punish drivers by sending them fewer rides after too many declines of money-losing ride requests" (see row two of Table 2) are aggregated into "sanctioning or incentivizing drivers to behave to their disadvantage." Following the same logic, the first-order concepts about drivers' disadvantages and Uber's potential benefits from perceived algorithmic exploitation are also aggregated into second-order themes. The first-order concept examples about drivers' disadvantages in Table 2 are aggregated into the second-order theme named "lured to take money-losing rides," and the examples of Uber's potential benefits are aggregated into the second-order theme called "broad supply coverage."

In the selective coding phase, we reflected on the second-order themes that emerged from the previous axial coding and synthesized similar themes into a core category. For example, we aggregated "sanctioning or incentivizing drivers to behave to their own disadvantage" and "withholding crucial information from drivers for business decisions into the core category "algorithmic manipulation." Similarly, the second-order themes of drivers' disadvantages and Uber's benefits are also synthesized into core categories. For example, regarding drivers' disadvantages, "lured to take money-losing rides" is synthesized with three other second-order themes called "made to work longer hours," "not receiving deserved pay," and "forced to take the loss from extra work" into the core category "low compensation." In terms of Uber's benefits, for example, the second-order themes "broad supply coverage" and "passenger satisfaction" are synthesized into the core category labeled "high service reliability."

ID	Quotes	First-order concepts
1	*"They have so-called surge areas, which should indicate high demand. You move to those areas, so you can fulfill that demand and potentially make more money. But the truth is that the moment you enter those areas, they disappear. So, it is a tease to get you to move to a certain area, and then once you were there, you didn't have access to that bonus."* (Interviewee 15)	• Perceived algorithmic exploitation: Algorithms let surge disappear when drivers arrive surge area • Driver's disadvantage: Lured to relocation without deserved pay • Uber's benefit: Relocate drivers to ensure broad supply coverage
2	*"I definitely feel that when I drive and if I decline several rides, because say, they are too far away to pick up to be financially worth it, I feel like I get punished, that sometimes the requests will stop coming."* (Interviewee 11)	• Perceived algorithmic exploitation: Algorithms punish drivers by sending them fewer rides after too many declines of money-losing ride requests • Driver's disadvantage: Being punished for not taking money-losing rides • Uber's benefit: Increase driver's acceptance rate for broad supply coverage
3	*"They manipulate you to get you to accept every ride by not telling you how far the ride goes; because you would only see the destination once you got to the customer's pick-up address and had the customer in the car and pressed to start the ride, only then would you see the destination."* (Interviewee 7)	• Perceived algorithmic exploitation: Algorithms display ride destination to the drivers after they arrive at pick-up location • Driver's disadvantage: Not knowing if a ride request is profitable or not • Uber's benefit: Increase driver's acceptance rate for broad supply coverage

Table 2. Examples of the Open Coding

Finally, we derived the main relationships between the core categories of perceived algorithmic exploitation, drivers' disadvantages, and Uber's benefits by analyzing how different core categories of perceived algorithmic exploitation lead to drivers' disadvantages or Uber's benefits. Throughout the coding process, the first author regularly wrote down her ideas in memos and utilized diagrams to visualize the outcomes of brainstorming sessions. Further, the whole author team assessed the developed core categories regarding internal consistency and logic during several discussion rounds. Based on these discussions, the first author refined the core categories several times until it reached a consensus among all authors.

Findings

Based on our data analysis, we derived four core categories of perceived algorithmic exploitation, namely algorithmic manipulation, algorithmic falsification, algorithmic disempowerment, and algorithmic dependency (see Figure 1). To structure these four core categories, we classified them into constant versus progressive forms: While constant algorithmic exploitation involves exploitative AM practices that always happen to all drivers similarly, progressive algorithmic exploitation involves exploitative AM practices that subtly change driver habits (e.g., incentivize part-time drivers to become full-time drivers), thereby intensifying the negative effect of constant algorithmic exploitation. Accordingly, constant algorithmic exploitation consists of algorithmic manipulation, algorithmic falsification, and algorithmic disempowerment since all drivers regularly face these AM practices during their work. Contrary, algorithmic dependency is classified as progressive algorithmic exploitation because the effect of the AM practices only unfolds after a longer period of time (e.g., when drivers are already highly dependent and addicted to the job) and makes them more vulnerable to constant algorithmic exploitation.

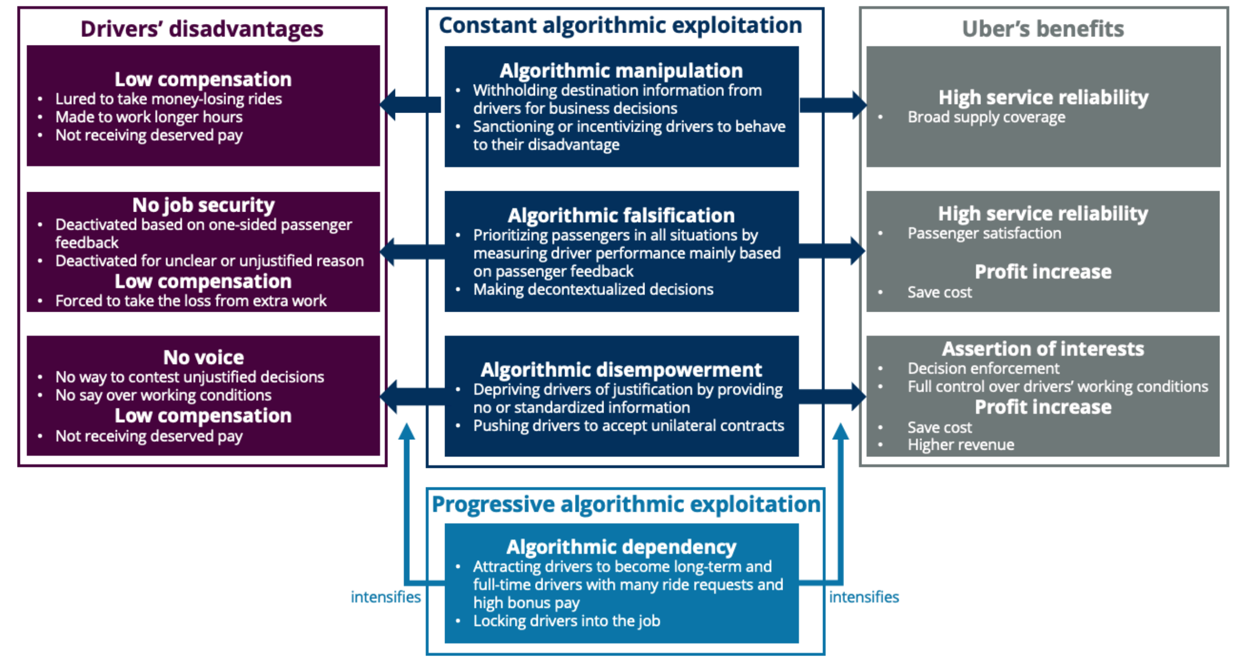

Figure 1. Forms of Perceived Algorithmic Exploitation

Furthermore, we systematically uncovered core categories of drivers' disadvantages (i.e., low compensation, no job security, no voice) and core categories of the potential benefits for Uber (i.e., high service reliability, profit increase, assertion of interests) resulting from exploitative AM practices. Thereby, we recognized that a perceived algorithmic exploitation category could be linked to multiple core categories of drivers' disadvantages or Uber's potential benefits. In Figure 1, all core categories are highlighted in bold, and the respective second-order theme(s) are listed below each core category. The following subsections explain the four core categories of perceived algorithmic exploitation and their relationships to the resulting disadvantage of drivers as well as the potential benefits for Uber.

Algorithmic manipulation

Drivers feel that Uber uses algorithms to manipulate their work behavior. Accordingly, we define algorithmic manipulation as AM practices that subtly influence drivers to behave in ways that benefit Uber at drivers' expense. In particular, drivers reported that AM is used to withhold destination information from drivers for business decisions and sanction or incentivize drivers to behave to their disadvantage.

Withholding destination information from drivers for business decisions. Uber implements AM practices that match drivers with passengers, seeking to create profits for both the OLP and the drivers (Möhlmann et al., 2021). Yet, drivers perceive that the algorithms often tend to assign them a considerable number of money-losing rides—meaning that a driver's costs to pick up the assigned passenger exceed the driver's potential earnings. For example, interviewee 11 explained when the algorithm *"send[s] you a request that's, say, eight miles away,"* but the passenger is only *"going maybe one or two miles,"* Uber is sending the driver a ride request where *"they know you're going to lose money."* Usually, drivers would not accept such money-losing rides, but Uber uses algorithms to make it difficult for drivers to assess the profitability of a ride by withholding crucial information from drivers. While drivers can see the pick-up location of a passenger, they typically cannot see the ride's final destination (at first). Only after accepting the ride request and arriving at the pick-up location the algorithm displays the destination to the drivers. Therefore, it is not possible for drivers to assess the profitability of a ride request before accepting it. Accordingly, Uber can provide broad supply coverage (i.e., high service reliability), as interviewee 10 commented, *"That's how they manipulate drivers to make sure that we're going to be taking every ride."* Several drivers perceive this practice as exploitation since it leaves them without control over their income and into accepting money-losing rides (i.e., low compensation), as interviewee 11 complained, *"It's a terrible practice of making money. The only reason Uber has any money is because of us. It's very unfair that we* *are not able to set our own pricing that we are not able to choose certain metrics for ourselves, and they still get to call us an independent contractor. I have absolutely no control over my own income."*

Further, by withholding the destination information of a ride request, some drivers feel they have also no control over their working time. In this regard, some drivers think that the algorithms can let drivers expand their working hours by sending them rides that unknowingly take them far from their homes. To avoid dead miles on the way back home (i.e., driving miles with no passenger/without pay), drivers must accept additional ride requests in the hope that subsequent rides will bring the driver back close to home. Therefore, drivers must work longer hours and take the risk of dead miles (i.e., low compensation). Drivers perceive how Uber systematically uses this practice to increase the overall supply (i.e., high service reliability), as interviewee 7 told us, *"I'm sure the algorithm played a part, that it was sending in the opposite direction to keep me on the road so that I'm working longer than I actually would like."*

Sanctioning or incentivizing drivers to behave to their disadvantage. Uber also uses algorithms to control drivers by sanctioning or incentivizing them for desired or undesired behavior (Kellogg et al., 2020). However, drivers perceive that algorithmic sanctioning or incentivizing practices are often used to let drivers behave to the benefit of Uber to their own disadvantage. For example, on the one hand, drivers feel penalized for declining money-losing ride requests by restricting their access to the app or threatening with deactivation because of a low acceptance rate or high cancellation rate. In this regard, interviewee 3 described, *"If the driver declines or ignores the [ride request], they are penalized by getting logged off from the app."* On the other hand, drivers feel that Uber incentivizes them to accept money-losing rides by providing a bonus program where the driver can achieve extra pay when they accept a certain number of rides in a row, which also includes accepting money-losing rides. Several drivers who tried to achieve the bonus pay explained that the first rides usually have a close pick-up location, but the subsequent rides are far away from the driver. Therefore, drivers accuse Uber that it knows that drivers do not accept such rides or that if drivers accepted, they would engage in money-losing rides (i.e., low compensation), as interviewee 9 reflected, *"I can see that they could program it, that it makes it harder to achieve those bonuses."*

Another algorithmic incentivizing practice from Uber is surge pricing—a dynamic pricing mechanism to match supply and demand (Guda and Subramanian 2019). Surge pricing is used to ensure a broad supply coverage and avoid shortages in immediate driver supplies. Therefore, the surge pricing algorithm highlights areas with high demand in the driver app. However, drivers noticed that after relocating to a so-called surge zone, the algorithm often does not assign them a single ride within that zone. Sometimes, drivers even receive a ride request where the pick-up location is far away from that surge zone. For example, interviewee 17 told us, *"I'm sitting in the middle of a surge area, and the algorithm would grab somebody from 20 minutes away out of the surge area and say, go get this person. And I'm thinking to myself, like, why?"* Similarly, drivers reported that when they follow the app and drive to so-called surge areas, the surge suddenly disappears as soon as they arrive. For example, interviewee 15 commented on his experience, *"The truth is that the moment you enter those [surge] areas, they disappear. It is a tease to get you to move to a certain area. And then once you are there, you don't have access to that bonus."* In this regard, drivers often claim that this sudden drop in surges is unlikely to be explained by a sudden increase in driver supplies or a decrease in passenger demand in this area. Hence, drivers feel manipulated by the surge pricing algorithm as they bear costs (e.g., fuel) to arrive at the surge zone but do not receive a (the deserved) higher-paying ride request from that zone (i.e., low compensation). At the same time, drivers perceive that Uber can ensure with such algorithmic manipulation a broad supply coverage (i.e., high service reliability).

Algorithmic falsification

Drivers reported that they think the AM decisions by Uber are falsified. In this context, we refer to algorithmic falsification as algorithmic decision-making based on biased data or distorted decision rules to Uber's benefit and drivers' disadvantage. This is manifested in Uber's algorithms prioritizing passengers in all situations by measuring driver performance mainly based on passenger feedback as well as making decontextualized decisions.

Prioritizing passengers in all situations by measuring driver performance mainly based on passenger feedback. AM decisions are based on various data inputs fed into the Uber platform. One key input is passenger feedback in the form of ratings or accusations, collected continuously (e.g., after every ride) and arguably relies on purely subjective performance evaluations from passengers (Cameron and Rahman, 2022). Drivers claim that passengers often give them low ratings when drivers do not meet all passenger requests, including those not part of a driver's actual service (e.g., safe driving). For example, interviewee 6 told us, *"A lot of times it's just the attitude of the passenger, where they just got out of a nightclub, and they want you to drive through a fast-food drive-through to get food. And you tell him no because you don't get paid for that stop. They get mad and give you one or two stars."* These passenger ratings fundamentally impact drivers since a low passenger rating, on average, will lead to account deactivation (i.e., no job security). Similarly, regarding the passenger accusations about a driver, the algorithms follow the "three strikes, you're out"-policy. Accordingly, drivers got their accounts deactivated if they received three accusations from passengers, regardless of whether the accusation was justified. Few drivers have experienced that passengers sometimes make false accusations against the driver just to get a free ride from Uber. For example, interviewee 14 stated*, "I think passengers complain random things about the trip so they can get a refund, and then that counts against the driver too."* For Uber, measuring driver performance based on customer feedback can lead to higher passenger satisfaction (i.e., high service reliability) and saves costs because no deeper investigation of the problem is carried out (i.e., profit increase). In addition, due to the replaceability of drivers, Uber can continue to do so, as interviewee 7 remarked, *"The metrics are designed to minimize workers. Uber knows that this is not fair, but they also don't give a shit because drivers are expendable and replaceable."*

While such one-sided passenger feedback can lead to account deactivation for drivers, they also have significant financial impacts. Since drivers try to avoid receiving low ratings or accusations from passengers, they often provide extra services to the passengers, such as buying snacks and charging cables for them. For example, interviewee 6 told us, *"I would have snacks, candies, water, and all that stuff. I also provide cables for different cellular phones. Even though I only have Android, I still have cables for iPhones. I would also have the connector so that passengers needed to connect their laptops while they were on a ride. So, I invest in all of that stuff to get a better star rating, you know?"* Consequently, measuring driver's performance based on passenger feedback can force drivers to take financial losses from extra work (i.e., low compensation) to satisfy passengers (i.e., high service reliability). In this context, drivers feel that Uber prioritizes passenger satisfaction over drivers' occupational well-being.

Making decontextualized decisions. Uber uses average statistics to detect fraudulent activities of its drivers (Möhlmann et al., 2021). However, they threaten drivers with deactivation who repeat an activity more than the average driver without specifying additional contextual information. For example, interviewee 17 reported, *"I've been accused of fraud. I don't really know what's going on. Sometimes they would actually tell me because I'm statistically done this more than other drivers."* Specifically, one activity that can be determined as fraudulent by the algorithms is reporting a cleaning fee too often. Usually, drivers can request a cleaning fee from the passenger over the Uber platform if the passenger heavily pollutes the car. In some cases, drivers have justified reasons to report cleaning fees more often than the average driver (e.g., drivers often work at night in bar areas where people are more likely to vomit in the car), but they can be deactivated (i.e., no job security), as interviewee 6 stated, "*If you're right on edge, and then you request a cleaning fee, that could be your last day on the job."* Consequently, drivers are afraid to report cleaning fees in cases when they deserve it (i.e., low compensation). Instead, they bear the cost of cleaning the car, as interviewee 15 stated: *"When people make messes in my car, I usually don't charge any fee, just because I don't want it to jeopardize my account. So, you take it as a loss."*

Aside from the additional cost of cleaning, drivers cannot work because of their messy cars (i.e., low compensation). This can be particularly frustrating for drivers during busy periods, as Interviewee 17 explains, for example, *"It's very bad sometimes, like on a busy Friday night, because I lose $200 in fares."* Some drivers try to reduce the loss a little by maintaining two cars, so they can continue driving, as interviewee 2 said, *"I have the second car now, so when somebody vomits in one of my two vehicles, I can still keep driving. I just drive home and switch cars."* Overall, making such decontextualized decisions is a simple way to determine drivers' possible fraudulent activities, which is highly scalable compared to approaches where human involvement may be necessary by considering more contextual information in such decisions (e.g., asking drivers for evidence). Therefore, Uber can save money (i.e., profit increase) at the expense of drivers who are unjustifiably deactivated or forced to take the loss from extra work. In this context, interviewee 7 stated, "*I don't think they care about the people. I think they care about autonomous cars down the line. And we are just seen as a disposable cost; they're trying to minimize the cost. They don't have any empathy.*"

Algorithmic disempowerment

Algorithmic disempowerment refers to AM practices that undermine drivers' ability to co-create their work environment. Hereby, Uber's AM does not reveal its rationale behind a decision to deprive drivers of justification by providing no explanations or standardized information as well as pushing drivers to accept unilateral contracts.

Depriving drivers of justification by providing no or standardized information. When drivers have issues or problems with the platform, they can usually contact Uber support via email. However, they mostly receive replies to their messages from algorithms (Rosenblat and Stark, 2016). This was also confirmed by our interviewees where, for example, interviewee 3 told us, *"I've sent so many messages to Uber support, and I think they're mostly not read by humans. It's just AI, most of the time."* Many drivers experienced that they could not contest (unjustified) decisions from AM via their emails because Uber does not reveal the particular reason for a certain AM decision (i.e., no voice). Instead, drivers often receive standardized information with a list of possible reasons that could lead to this certain AM decision. This standardized information is often not helpful for drivers because it is difficult for them to guess which of these possible reasons were involved in their own situation, as interviewee 2 illustrated, *"When a passenger reported me that I violate the community terms. I'm like, 'What community terms did I violate? What was the trip like? Tell me about the trip, I can prove that I have not.' I have tried that, but [Uber support] won't tell me."* Without knowing the actual reason behind an AM decision, it is not possible for drivers to challenge any unjustified decisions, and this led Uber to enforce its decisions (i.e., assertion of interests), as interviewee 18 revealed, *"I mean, you can definitely protest a lot of this unfairness. But since it's not transparent, you don't know how it's working. And it's hard to argue something you can't see."*

Sometimes it is possible for drivers to escalate their issues to a human employee, but they have to be persistent and keep asking Uber support about their problems. After many messages, drivers can *"pass the AI"* and talk to a human, as interviewee 2 reported. However, since it takes a lot of time to escalate it to a human employee, many drivers do not report their issue anymore and take the financial loss (i.e., low compensation). For example, interviewee 15 said, *"The whole system is designed for you to give up because it's so hard to get a hold of somebody. You cannot spend so much time fighting for those $2 or $3."*

Pushing drivers to accept unilateral contracts. Every few months, Uber sends drivers updated service terms about their working conditions (e.g., change of fare rate). Usually, drivers receive these new terms while working for Uber, and they cannot log into the driver app if they do not accept these terms. For example, interviewee 7 notes, *"You're looking on a mobile device, and there's a lot of pages, and you just can't read them. Especially when you're in your car, and it's a bit dark, and you're trying to work."* Moreover, drivers cannot review the new service terms properly to understand the changes in their working conditions, as interviewee 9 states, *"They don't give you a chance to review it and respond. You have to do it instantly. So invariably, you just say, 'Yes, carry on.'"* Essentially, drivers perceive that they are forced to accept the new terms immediately, which provides Uber full control over drivers' working conditions (i.e., assertion of interests), as interviewee 14 argued, *"So the contract is one-sided. It's [Uber's] way or the highway. I mean, the only thing we decide is when we work or not. Everything else is dictated by them."* Consequently, drivers perceive to have no say over their working conditions (i.e., no voice).

This becomes especially clear to many drivers when a contractual change in the past leads to a new distribution of the fare: On the one hand, Uber increases the fare rate to the passengers, and on the other hand, the percentage of the driver's pay is decreased (i.e., low compensation). While many drivers didn't realize this new distribution of fares at first, they found out over time when they talked to their passengers, as interviewee 9 experienced, *"There'll be times, for example, where the customer will tell me 'Hey, why is this ride $100 when normally is $40?' I'm like, 'I don't know, I am still getting paid the same.'"* This new fare distribution would increase Uber's revenue (i.e., profit increase) and is perceived by many drivers as exploitation. Drivers think that since the actual work is performed by them and all costs associated with this service must also be borne by them, they naturally also deserve most of the fare. In this regard, interviewee 12 stated, *"Uber would not be able to function without drivers. How did they decide what percentage to take of a ride? Something is being used against us, against our own interests. How is that fair? Or right? Even legal? You can't bring back slavery."*

Algorithmic dependency

Algorithmic dependency refers to AM practices that cause drivers to become more dependent and addicted to the job over time, so they are likely to comply with all instructions from the Uber platform, making them more exposed to other forms of algorithmic exploitation. While workers can also highly rely on their jobs in work contexts without AM, we argue that algorithmic dependency allows a much more subtle way to achieve such dependency via personalized and opaque practices. First, this is achieved through AM by sending many ride requests and high bonus pay for new or part-time drivers attracting them to become long-term and full-time drivers. Afterward, drivers get locked into this job which causes a high reliance on the income from Uber's platform.

Attracting drivers to become long-term and full-time drivers with many ride requests and high bonus pay. Drivers feel that the algorithms provide new drivers with high bonuses so that new drivers think they can make good money with this job. After a while, those bonuses are gradually reduced every week, as interviewee 7 described, *"When you're naive and new, you don't know. They gave new drivers an incentive to earn this bigger bonus to hop them in and then gradually reduce it. They start off really happy because they're saying, 'I'm hitting these bonuses, and I'm doing well.' And then gradually, that's removed and reduced."* Relatedly, drivers also recognized that new drivers get more ride requests from the algorithms than veteran drivers. For example, interviewee 10 observed, *"When I first signed up, I was getting ping [i.e., ride request] after ping. It was to the point where I couldn't even stop to go to the restroom."* Over time, the frequency of ride requests received by interviewee 10 declined dramatically. As a result, veteran drivers have to work longer to earn the same amount as new drivers. For example, interviewee 16 explained how he was addicted to holding his earnings on the same level as the beginning, but when the bonuses decreased, he *"just had to work longer hours."*

Furthermore, several drivers mentioned that the algorithm offers part-time drivers a higher bonus than full-time drivers. Therefore, Uber's algorithms seek to *"get part-time drivers on the road,"* but when the algorithm recognizes that *"you're driving every day, they drop bonus week after week"* (interviewee 9). Drivers perceive this favoring of part-time drivers in awarding bonuses as exploitation since full-time drivers are highly dependent on this job compared to part-time drivers, as interviewee 16 told us, *"That's exploitation, that you're going to give money to someone that barely works when I'm out there slaving and grinding my ass away 60-70 hours a week for [Uber]."* Drivers feel that these bonuses are used to get more and more part-time drivers on the road and pretend that they can always earn such bonuses, so they become more dependent on this job. For example, interviewee 6 said, *"You can clearly see what they are doing. They try to get part-time drivers more and more on the road to let them become full-time drivers and, at the same time, treat full-time drivers like crap."*

Locking drivers into the job. The high bonuses and ride request frequency lock many drivers into the job. Under the assumption that they could earn enough as an Uber driver based on their experience of high earnings as a new driver or part-time driver, they quit their previous job to work full-time for Uber. For example, interviewee 10 told us, *"I had one friend who was making really good money when he started with Uber. So, he quit his job, and now he's locked into this job because it's very difficult to get back. You know, if you've been unemployed for a period of time, and you have to explain to an employer that you're driving Uber, they kind of frown upon it."* Other drivers are locked in this job because they took a loan to buy or rent a new car to work for Uber full-time. Therefore, those drivers have to pay back the loan every month. While their earnings as new drivers were enough to cover expenses, the decline in bonuses and ride requests over time left them struggling to make enough money. However, because of the loan, they must continue working for Uber and are tied to that job. For example, interviewee 14 rented a car when he started driving for Uber. Now, he is locked in this job until the car is paid off, as he explained, *"They capture you first to take a credit to buy the car. Then you cannot easily go; you are already imprisoned. That's their way of holding you in this job.*" Interviewee 12 compared this kind of practice with drugs, as she illustrated, *"Uber is like a drug dealer. In the beginning, they will let you have a taste of the drug. They get you addicted. Then, they start pulling back."*

Drivers locked in this job are highly prone to other forms of algorithmic exploitation since they cannot afford to lose this job. For example, interviewee 14 told us, *"They deactivate you, and you are bankrupted. And no one to cover any damage or no one to be to care about what your family earning will be."* Therefore, those drivers are very vulnerable when Uber threatens them with deactivation (i.e., no job security) and are forced to take every ride request from Uber (also money-losing ones) (i.e., low compensation), as interviewee 11 experienced in the past, *"Driver who just has to be on the job to get the most money, don't have the same choices that I do now. When I was in that situation before, I was very angry. I would sit in my car; I would scream and yell at the app."* Furthermore, drivers who are locked in this job also reported that they cannot protest against unfair working conditions due to their high dependency and fear of being deactivated (i.e., no voice), as interviewee 13 explained, *"When you enter, you invested on so much on the car. Until you return that, you have to keep quiet and do nothing. You can't say anything, even if you want to say something."*

Discussion

This study aimed to investigate how workers perceive algorithmic exploitation on OLPs. Overall, we found that algorithmic exploitation perceptions can take the form of algorithmic manipulation, algorithmic falsification, algorithmic disempowerment, and algorithmic dependency. Thereby, we discovered how these categories could be classified into constant and progressive algorithmic exploitation: While constant algorithmic exploitation is perceived by all workers regularly in the same way, progressive algorithmic exploitation is more subtle by changing worker's habits that intensifies the effects of constant algorithmic exploitation on workers' disadvantages and potential OLP's advantages. Furthermore, we specified the nuanced relationships between the different forms of algorithmic exploitation with the resulting worker's disadvantages as well as OLP's potential benefits: While all forms of perceived algorithmic exploitation result in low compensation for workers, algorithmic falsification enhances the missing job security, and algorithmic disempowerment accelerates the missing voice. On the other hand, OLPs may benefit from such algorithmic exploitation via high service reliability, profit increase, and assertion of interests.

Theoretical Contributions

This study provides mainly three theoretical contributions to the literature on the perceived exploitation of workers on OLPs (e.g., Ashford et al., 2018; Bidwell and Briscoe, 2009; Martin et al., 2014). First, while existing studies on workers' perceived exploitation on OLPs mainly studied exploitation from a legal perspective (e.g., Berg, 2015; De Stefano, 2016) or a market power perspective (e.g., Anwar and Graham, 2021), we complement these insights by investigating the role of AM in such exploitation perceptions. We propose a new construct called perceived algorithmic exploitation to examine how workers perceive that AM is intentionally used to benefit OLPs at the expense of workers. Thereby, we reveal what forms of perceived algorithmic exploitation exist on OLPs, namely algorithmic manipulation, algorithmic falsification, algorithmic disempowerment, and algorithmic dependency. These forms show how workers perceive that OLPs can take advantage of them from the increased power and information asymmetries under AM: For example, with algorithmic manipulation, OLPs can use AM to withhold crucial information from workers (i.e., leveraging information asymmetry) or automatically threaten with account deactivation (i.e., leveraging power asymmetry). Relatedly, with algorithmic falsification, workers feel that OLPs deliberately tolerate unjustified decisions by AM based on biased data or data without contextual information to the disadvantage of workers, thereby leveraging the power asymmetry that allows them to continue to do so. Algorithmic disempowerment shows how OLPs can use AM practices to undermine workers' bargaining by using algorithms that do not provide workers with the relevant information (i.e., leveraging information asymmetry) or not allowing them to bargain by using AM practices to push them to accept unilateral contracts (i.e., leveraging power asymmetry). Furthermore, with algorithmic dependency, OLPs can extend their power over workers by luring them with many ride requests and high bonuses to get workers addicted and dependent on the job. Overall, this construct offers researchers a valuable foundation to study the role of AM in facilitating workers' perception of exploitation, which can also serve as an important antecedent to explain workers' negative reactions to OLPs (e.g., high turnover, resistance).

Second, we provide a more systematic understanding of perceived algorithmic exploitation by identifying different types. While previous research describes single occurrences of perceived algorithmic exploitation on OLPs (Cameron and Rahman, 2022; Rosenblat and Stark, 2016), our study goes beyond such descriptions by distinguishing between constant and progressive algorithmic exploitation. Especially progressive algorithmic exploitation represents a more subtle form of exploitation that is only possible due to algorithmic systems' interactive and instantaneous characteristics (Kellogg et al., 2020). Thereby, workers can be managed individually with AM, allowing for (nearly) real-time adaptation of AM practices to individual worker behaviors leading to changing worker habits that are negative for workers but beneficial for OLPs. For example, whenever the AM of the Uber platform recognizes that a driver is working longer hours and becomes a full-time driver, the algorithms immediately reduce bonus pay for this driver. Accordingly, when a driver is driving less time for Uber, the algorithms increase the bonus pay for this driver to lure him or her to increase their working time. Such personalization allows for more intense exploitation with precarious consequences for workers.

Third, this study provides a more nuanced understanding of the different relationships between perceived algorithmic exploitation and their impact on workers' disadvantages as well as OLPs' potential benefits. In line with previous literature, we confirm with our empirical study that platform workers suffer from low compensation, no job security, and no voice (Deng et al., 2016; Rahman, 2021). However, this study additionally outlines what forms of perceived algorithmic exploitation are linked to which type of workers' disadvantage. While algorithmic manipulation, algorithmic falsification, and algorithmic disempowerment all lead to negative financial consequences for workers (i.e., low compensation), algorithmic falsification mainly results in workers having no job security, and algorithmic disempowerment is mainly responsible for workers having no voice in their relationship with OLPs. On the other hand, this study also specified the potential benefits for OLPs from perceived algorithmic exploitation, which consists of high service reliability, the assertion of their interests, and profit increase. Furthermore, we discovered how algorithmic dependency can intensify the impact of the other forms of perceived algorithmic exploitation because workers who highly depend on the work provided by OLPs are forced to comply with all exploitative AM practices (otherwise, they may lose their job). In summary, the nuanced understanding of how perceived algorithmic exploitation relates to workers' disadvantage and OLPs' potential benefits helps researchers to better evaluate potential negative consequences for platform workers under AM.

Practical Implications

This study provides practical implications for platform providers as well as for policymakers. First, this study shows how workers perceive algorithmic exploitation on OLPs. Hence, there might be a gap between workers' perceptions and the actual logic of how the platform provider implemented the AM practices. In cases where the workers' perception does not meet the actual intentionality of OLPs, we suggest OLPs provide more transparency by introducing, for example, the job role of an "algorithmic broker" (Kellogg et al., 2020, p. 389) who communicates the value and logic of algorithmic systems to workers. This might help reduce workers' negative feelings and increase their job satisfaction, thus decreasing their turnover intention and resistance activities.

Second, our study also provides policymakers with crucial insights into how workers on OLPs can be exploited. Several jurisdictions and policymakers worldwide are currently confronted with platform workers fighting back with legal claims against perceived exploitation, such as drivers suing Uber over algorithmic deactivations allegedly based on false passenger accusations (Bernal, 2020). Given that OLPs nowadays hire a large share of the working-age population, these claims are highly consequential for society and must be addressed. Here, our inductively derived forms of perceived algorithmic exploitation can provide policymakers with valuable input for their ongoing discussions on whether certain designs of algorithms contribute to the exploitation of platform workers and thus require stricter regulations. Accordingly, we encourage policymakers to properly investigate the exploitation potential of workers on OLPs to promote "full and productive employment and decent work for all" (United Nations, 2021, p. 42).

Limitations and Future Research

This study also has some limitations. First, the community of Uber drivers is heterogeneous. While some drivers perceive much algorithmic exploitation on Uber, others do not. Since we primarily interviewed Uber drivers who are participating in ride-hailing unions, our data is biased towards drivers who experience exploitation from Uber and actively campaign for more participation. Consequently, our findings might not be representative of the average platform worker. Nonetheless, this extreme case of interviewing mostly drivers from ride-hailing unions helps us recognize many forms of perceived algorithmic exploitation and also speaks to drivers who likely engage in resistance activities against OLPs, representing our study's focus. Second, our study's result is solely based on the single case of the OLP Uber. While we argue that Uber provides an extreme case of AM (Möhlmann et al., 2021) and thereby is suitable to discover many workers' perceptions of algorithmic exploitation, these exploitation perceptions depend on the particular way of

Uber's usage of AM. Therefore, the results may not be directly transferable to all other OLPs and work contexts that employ AM (Lippert et al., 2023), which can be validated and tested in future research.

Besides the limitations, our study adds to a growing body of studies on worker-level implications of AM on OLPs (e.g., Alizadeh et al., 2023; Schulze et al., 2022) and sets the conceptual basis of perceived algorithmic exploitation that opens up promising directions for future research. For instance, while previous research from the organizational and management literature shows how exploitation perceptions can more accurately explain negative worker reactions compared to other related constructs (Livne-Ofer et al., 2019), we might examine whether this also applies to perceived algorithmic exploitation (e.g., compared to algorithmic unfairness). Therefore, future research might quantitatively examine the effect of perceived algorithmic exploitation and how it negatively impacts job satisfaction or positively influences resistance behavior. Moreover, this study focused on workers' perception of being exploited through AM. Future studies could examine the gap between perceived and actual algorithmic exploitation. In the context of AM, such a gap between workers' perception and actual AM practices might be bigger than under human-based management due to the high opaqueness of algorithmic systems (Möhlmann and Zalmanson, 2017).

Conclusion

AM has been recognized as a major enabler of OLPs; however, the long-term success of OLP business models largely depends on platform workers' willingness to comply with AM and, thus, on workers' perceptions of AM. Our study sheds light on how workers perceive that AM facilitates exploitation by OLPs. In this vein, we also highlight the complexity underlying the largely unaddressed role of digital technologies in contributing to workers' exploitation perceptions. We hope our study inspires further research and discussions in this important arena, paving the way for a more sustainable future for online labor markets.

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