

Algorithmic Management Reimagined For Workers and By Workers: Centering Worker Well-Being in Gig Work

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ABSTRACT

Prior research has studied the detrimental impact of algorithmic management on gig workers and strategies that workers devise in response. However, little work has investigated alternative platform designs to promote worker well-being, particularly from workers' own perspectives. We use a participatory design approach wherein workers explore their algorithmic imaginaries to co-design interventions that center their lived experiences, preferences, and well-being in algorithmic management. Our interview and participatory design sessions highlight how various design dimensions of algorithmic management, including information asymmetries and unfair, manipulative incentives, hurt worker well-being. Workers generate designs to address these issues while considering competing interests of the platforms, customers, and themselves, such as information translucency, incentives co-configured by workers and platforms, worker-centered data-driven insights for well-being, and collective driver data sharing. Our work offers a case study that responds to a call for designing worker-centered digital work and contributes to emerging literature on algorithmic work.

CCS CONCEPTS

• **Human-centered computing** → **Human computer interaction (HCI)**.

KEYWORDS

Algorithmic management, gig work, worker well-being, participatory design, worker-centered work design

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1 INTRODUCTION

As work has shifted onto online platforms, the use of algorithmic management has grown within companies to automatically manage, organize, coordinate, and even evaluate workers [48, 49, 55, 56]. The gig economy—characterized by temporary, short-term, and on-demand work—is one domain that has continued to increase its integration of algorithmic management to maintain worker efficiency, set prices, and match at a previously impossible success rate [98]. This increased efficiency and productivity for a company's bottom line, however, has resulted in deleterious effects on workers and their well-being. Under algorithmic management, workers are subject to heavy data collection, opaque automated processes, and asymmetric power dynamics [80]. Additionally, the freedom and flexibility for workers as touted by gig economy platforms is often misleading and at odds with the unyielding control of algorithmic management [62, 80]. In reality, workers can become locked into precarious work situations of overwork and irregular hours, sleep deprivation, and social isolation [96].

Past work on algorithmic management and gig workers has investigated the design elements of algorithmic work and how workers engage with it. From their study of Uber driver posts on online forums and driver interviews, Rosenblat and Stark [80] characterized an information and power asymmetry between drivers and rideshare platforms favoring the platforms. Möhlmann and Zalmanson [65] studied Uber drivers and observed a similar power dichotomy on platforms between supposedly autonomous drivers and unyielding tech platforms, describing various strategies employed by drivers to regain autonomy including guessing, or trying to reason why platforms act in a certain way. Others have similarly denoted worker strategies against algorithmic management [15, 56]. However, these works do not necessarily investigate the impact on worker well-being by algorithmic management, or how platform designs or interventions may be created to support worker well-being.

Additionally, increasingly the human-computer interaction (HCI) community has been pursuing centering worker well-being and needs within algorithmic management platforms or intervention designs [18, 57, 70]. Recently, there have been calls specifically for expanding designs of technological systems by collaborating with and centering the ideas of low-powered workers who are mediated or managed by algorithmic systems [16, 34]. Prior work designing interventions has often sought the feedback of workers to inform

the initial design of tools or evaluate ones already created [10]. However, this limited engagement means that gig workers are rarely engaged in the crucial and meaningful step of directly designing solutions.

As a step in this direction, we use participatory design to center gig workers in the processes of both informing and designing solutions. We conduct focus groups and interviews so that the rideshare drivers we work with may voice their concerns and preferences as informed by their lived experiences. We follow these with participatory design sessions to explore gig workers' ideas and solutions that address the issues that emerged during the focus groups. Through this, we surface themes of platform shortcomings as identified by participants such as exacerbating information and power asymmetries by restricting gig worker information access and eschewing worker well-being through platform designs such as manipulative incentive structures. We share the solutions workers came up with to address these including information translucency in response to information asymmetries and the use of worker analytics to support well-being centered work recommendations.

Our work makes two primary contributions. First, we expand the research body around gig workers and algorithmic management by exploring how their expectations of and experiences on these platforms affect their well-being and the fairness perceptions workers have about algorithmic control the control that employers are able to exert through algorithmic management. Second, we present the types of solutions imagined by gig workers during participatory design sessions, shedding light on the characteristics workers desire to see in their gig work platforms. These solutions not only give a glimpse into what gig workers envision for themselves, they also provide direction for future research around understanding gig workers and technology intended to advance platform fairness and worker well-being. Our findings provide emerging support for how to assist drivers in their work and well-being through the development of specific driver ideas such as data-driven methodologies or collective driver data sharing interventions.

2 PARTICIPATORY DESIGN FOR WORKER WELL-BEING IN ALGORITHMIC MANAGEMENT

In this section, we first describe our research focus and review related work that motivates our problem setting and research method. We summarize past work around the prevalence of algorithmic management particularly in gig work how it is exerted over gig workers/its impact on gig workers, the ways workers respond to it, how it affects gig worker well-being, and how gig workers' psychological contracts with platforms may be impacted by it. We then provide an overview of how gig work has been studied previously with and without the use of participatory methods in order to situate our research methodology. We follow with a description of the lens we incorporate in our study algorithmic imaginaries and why this is appropriate for our work and research method.

2.1 Focus of Our Research

The focus of our research is to investigate the impact of algorithmic management and gig work platforms on worker well-being, and

to work with the workers to learn their ideas on how algorithmic work can better support their well-being. Building on prior work that investigates the relationship between gig work and worker well-being, our research examines how specific design of algorithmic management and its "materiality" [6] are important contributors of worker well-being, such as working conditions that accommodate worker preferences [5, 7, 9].¹ Thus, the primary research questions we seek to explore are: how do gig work's algorithmic management and platform design affect worker well-being? and What do gig workers desire to see in technology designs that support their well-being and work preferences?

2.2 Impact of Algorithmic Management on Worker Well-Being and Psychological Contracts

2.2.1 Worker Control in Algorithmic Management Algorithms are used to manage a variety of workers including UPS delivery-people [81], hotel maids [39], retail employees [60], journalists [77], and doctors [4]. With the work-from-home boom, even white-collar and managerial workers are susceptible to automated monitoring and management [25]. Due to the scale and logistic complexity of gig work, algorithmic management has been a necessity since its inception [96]. Uber has about 26,900 employees and manages at least 3.9 million drivers worldwide as of 2018 [1] with other platforms such as HackerRank achieving even more uneven ratios of 200 direct employees mediating 11 million workers [8]. To manage at that scale, Uber's primary service and asset is its ability to match customers with drivers. Algorithmic management outside of the realm of gig work has been met with a mixed reception but has generally been accepted to produce previously untapped synergy and streamline work processes [4]. Most gig workers express some level of displeasure with algorithmic management but feel powerless to stand up to the technology giants that are their employers [65]. Several issues algorithmic and managerial opacity, constant behavior and performance tracking, and isolation from support result in frustration and burnout, and could possibly explain the high rate of turnover among gig workers [5]. The very autonomy that gig work companies pride themselves in providing their drivers is quintessentially at odds with a system of tracking and management that some drivers find oppressive and confusing.

According to the International Labor Organization, as many as 55 million Americans participated in the gig economy in some form during 2017, either full-time or to earn supplemental income [10]. Because gig work is informal and the barrier for entry is low, many Americans under financial pressure choose to work a gig in addition to regular formal income. Studies have found a majority of gig workers hold traditional jobs of some kind, as well as work gigs across multiple different apps [30]. Previous studies have proposed an organization of gig work into three categories app work (e.g., Uber, Instacart, Lyft), crowd work (e.g., MTurk, Fiverr, Upwork), and capital platform work (e.g., Airbnb, Etsy) to identify and classify

¹It has been found that a worker's well-being is greatly affected by their perceived fairness of their supervisors and workplaces [90]. The fairer workers perceive of their supervisors, the higher their trust and commitment to the organization [66] and the more positively affected their well-being [93].

gig work's diverse companies [29]. In this study, we focus on app workers, specifically rideshare drivers, as research participants.

In theory, independent contractors should be able to accept tasks as they please; however, because of heavy-handed management, gig workers are often directed and manipulated into accepting jobs they would not have otherwise [75]. There can also be harsh, punitive measures levied on drivers for rejecting gigs, such as exclusion and expulsion from driver rewards programs for having an acceptance rate below a threshold (e.g., 85% on Uber). The legal distinction between being an employee and a contractor is at the very center of the current conversation surrounding legislating gig work in the United States. Independent contractors are not entitled to the same legal privileges as employees such as unemployment benefits, paid time off, fair labor standards, or even minimum wage [6]. Detractors have even described gig drivers as 'dependent contractors', due to the misuse of the classification having resulted in mistreatment and a lack of protections and rights that workers should be lawfully entitled to as well as the inappropriately high reliance workers have on the platforms [21].

2.2.2 Worker Resistance to Algorithmic Control Restricting worker autonomy is a pervasive feature of algorithmic management, and workers naturally resist these methods [46, 74], inventing techniques for manipulating the algorithms to their advantage both collectively and independently [49]. The learning process of making sense of black box algorithms for which Uber's is an example gives workers the tools to potentially circumvent or manipulate the algorithm in the future. The process of familiarizing one's self with their management algorithm can be viewed as an extension of "infrastructural competency" the process of building relationships with the infrastructures around one's self to develop sociotechnical practices to complete tasks [34]. For gig workers, this process is analogous to learning a new trade, a new boss, and a new workplace all in one. Building infrastructural competency is essential in gig work, as it leads to opportunities to resist and potentially manipulate the management algorithm [49].

Möhlmann and Zalmanso [65] classified regaining control under algorithmic management in three types: resisting the system (e.g., cancelling or refusing ride requests), switching the system (e.g., operating multiple apps), and gaming the system (e.g., manipulating and exploiting the system). Lee et al [56] explored strategies drivers used to cope with Uber's algorithmic management, including several that could be classified under Möhlmann's system. Lee described drivers rejecting rides from low-rated riders (i.e., resisting), working the Uber and Lyft apps simultaneously (i.e., switching), and collective sensemaking on online forums (i.e., gaming). Cameron [15] classified gig worker behavior in dealing with algorithm as compliance, engagement, and deviance. Behaviors documented in Lee et al [56] can also be classified using Cameron's classifications such as surge chasing (i.e., compliance), strategically turning on and off the driver app (i.e., engagement), and continuously rejecting certain gigs (i.e., deviance).

2.2.3 Gig Worker Well-Being Even when gig workers resist and find autonomy under algorithmic management, emerging research suggests that gig work platforms in general have negative impacts on worker well-being. Well-being refers to one's ability to function as a healthy person across multiple disciplines [76]. In this study,

we primarily considered three aspects of well-being [70] as it pertains to gig workers as Lee et al [57] did in studying shift worker well-being under algorithmic management: psychological, financial and physical. Psychological well-being concerns "the combination of feeling good and functioning effectively" [13]. Physical well-being concerns "the ability to perform physical activities and carry out social roles that are not hindered by physical limitations and experiences of bodily pain, and biological health indicators" [7]. Finally, financial well-being concerns "the perception of being able to sustain current and anticipated desired living standards and financial freedom" [12].

Previous literature explored the psychological well-being of gig workers. Amazon mTurk crowdworkers were studied to understand whether they feel that they "matter" or count [13] and their hope and ability to instigate change [3]. Berger et al [9] surveyed London Uber drivers and found Uber drivers exhibited significantly higher levels of anxiety than the general London workforce likely a result of self-employment and instability but higher levels of subjective well-being because of a genuine affinity for gig work. Drivers often also have to transform their self and space (i.e., their cars) for financial incentives, at the detriment of their psychological well-being because of stress and performed emotional labor [79].

Fairwork [32] explored the effect of precarity on financial well-being, finding a negative relationship due to unpaid working time such as time between gigs, externalization of costs such as fuel and vehicle insurance onto workers, and a lack of a minimum wage or safety net. Gig work is highly precarious, due to the lack of long-term security and transferable skills and experience, meaning it can be difficult for drivers to transition out of gig work [66]. A focus on the effect on physical well-being of workers has also been studied, with gig work being found to cause overwork, sleep deprivation, and exhaustion [96]. The lack of traditional job benefits such as health insurance, paid time off, and the ability to avoid COVID-19 related hazards also has a detrimental effect on worker physical well-being [3, 5].

2.2.4 Psychological Contracts Due to the sporadic, inconsistent, and generally hands-off approach of platform work, the relationships formed between workers and employers develop quite differently in gig work when compared to traditional work. Gig workers are considered independent contractors and in ads by platforms recruiting them, are described as being "Your Own Boss" [1]. Rouseau [82] defined the psychological contract as "an individual's beliefs, shaped by the organization, regarding terms of an exchange agreement between individuals and their organizations". Prior studies [26] found that part-time employees had a similar contract as full-time employees, exhibiting similar fulfillment and outcomes at work. However, other studies focusing on gig workers discovered that heavy use of AI management has a pernicious effect on worker psychological contracts and engagement [192]. Gigs are advertised as low commitment and hyper-flexible, leading observers to believe that the psychological contracts will be similarly low-level and flexible. However, as "harder" algorithmic controls create more demanding expectations for the worker, this may create similarly

²www.lyft.com/driving-jobs

³www.uber.com/au/en/drive/how-it-works

high expectations in the reverse direction, back onto the platform, resulting in the potential breakdown in the relationship [29]. Because of the lack of reciprocal "high level" engagement from the employer that one may expect, such as training, protection, and security, workers can become disillusioned with the platform.

2.3 Algorithmic Imaginaries as a Lens for Participatory Design

In order to get a realistic sense of how gig workers wish to see technology designed that supports them, we incorporate participatory design methods to engage with workers directly in co-design and generate ideas that center their needs. Additionally, to support workers during these sessions in generating tech platform designs that positively impact their well-being, we use algorithmic imaginaries as a lens for gig workers to explore how they believe algorithms should be or imagine algorithms could be designed to support their needs.

2.3.1 Participatory Design Participatory design, also referred to as co-design, first emerged as a way of involving workers in the design of work environments and technologies [9]. In computing and HCI fields, participatory design has evolved as a method for researchers to include stakeholders and end-users in designing digital technologies, from domains such as robots with local neighborhoods [27] to assistive health devices for older people [69], in order to ensure that the technology addresses the needs and concerns of the populations using them. It has also been used for imagining the re-design of existing applications: Alvarado and Wade [2] employed participatory workshops with Facebook users to reimagine the social media platform's interface to improve their algorithmic experiences.

In recent years, calls have been made to examine more critically how participatory design and related design methods are applied with considerations of who gets to participate and is therefore represented in the technological output [48, 73]. Similarly, researchers have also highlighted the need for increased participatory forms of involving workers in the design of algorithmic systems or tools that affect them [95]. Gig workers are a crucial community to include in the design of algorithmic systems or tools intended to assist them, especially as they are almost entirely managed digitally but not necessarily included in the design of the algorithmic systems that manage them. Particularly since the COVID-19 pandemic, it has become clear that gig workers are at a unique risk as essential workers, for in many cases they do not have the luxury of working from home to continue making an income [22].

Much of research around the impact of algorithmic management on gig workers has taken the form of individual interviews, archival analyses of forum posts, and surveys (e.g., [37, 56, 80]). These studies importantly surface tactics that workers use to navigate algorithmic systems such as resistance of algorithmically assigned tasks (e.g., rejecting low-rated riders [56, 65] or compliance of algorithmically mediated functions (e.g., adhering to nudges encouraging increased driving to complete incentives) [5]). However, they do not necessarily work with workers to further develop solutions or designs that would benefit their work or well-being. Some studies though have incorporated varying degrees of worker participation

or input in order to create solutions for gig workers. Irani and Silberman [47] created a solution for mTurk workers, Turkopticon, that allows workers to review tasks and employers. Though not explicitly created using participatory design, this forum was informed by ethnographic data collection and informal surveys with crowd workers to ensure it embodied the values and features they wanted to see. Similarly, You et al. [100] created a social sensing probe for workers to use, informed by initial driver interviews, and conducted a four week experimental study to understand how this probe affected drivers' awareness of their well-being and potential behavioral changes. The subsequent assessment of the tool's efficacy and future design changes, however, was based on passive quantitative and qualitative data gathered from participants' data tracking logs, diary entries, and questionnaires. Notably, Bates et al [7] did use participatory design, holding two in-person co-design workshops to surface together with gig food couriers (cyclists) what they desired in solutions, such as tools to gather their own data, share worker knowledge with one another, and make more reliable the navigation services for cyclists.

We extend this use of participatory design for designing solutions with workers so that they may directly advise of the features and characteristics that will most impact their well-being. Thus, the designs will come from the direct input of workers and reflect their priorities and concerns. Additionally, taking note from the critical reflections of HCI researchers of intentionally considering the representation of our participants and how our activities may hinder participation, we focused on recruiting a diverse driver population and using design activities rooted in rideshare contexts they shared with us rather than methods like blue-sky thinking which Harrington et al [43] observed can enhance privileged ways of thinking.

2.3.2 Algorithmic Imaginaries Algorithmic imaginaries refer to "ways of thinking about what algorithms are, what they should be and how they function" in order to imagine, perceive, experience, and eventually design algorithms [4]. Because the functions and processes of algorithms are unknown to many laypeople, exploring the platonic ideal of algorithms can allow for a more expansive and imaginative discussion, imagining a world radically different than our own [52]. For example, Christin [24] explored the algorithmic imaginaries of legal professionals in the criminal justice system and web journalists, resulting in startling insights in the similarity of the hopes and concerns surrounding algorithms in diverse fields. Probing the algorithmic imaginaries of platform workers can reveal patterns around how they conceptualize algorithmic management, as well as how they would imagine it under their ideal circumstances.

At a glance, a participant's mental model of how a platform functions or how an algorithm operates may seem equally appropriate or comparable to their algorithmic imaginaries. Mental models have typically been used as a lens for understanding how users employ deductive reasoning to determine how systems or devices work [53]. They have been explored with the intent of studying how understanding and supporting mental models can be used to improve user experience with a system [54]. Norman [68] describes how mental models of things are formed by way of an item's perceived

structure in particular from signifiers, affordances, constraints, and mappings.

By this description then, exploring perspectives solely through the mental model lens could potentially lead to participants being constrained by such device or system boundaries. Conversely, algorithmic imaginaries may be more supportive of participants' design thinking during co-design sessions as imaginaries are associated with futures that users envision might be possible and desirable [6]. Lustig [61] describes the possibilities of sociotechnical imaginaries broadly, not limited to algorithmic imaginaries, and advocates for incorporating the use of imaginaries in participatory design as a way for designing more equitable futures. Thus, we choose to explore the perspectives of participants through algorithmic imaginaries to 1) avoid limiting participants' design thinking to how they currently understand platform algorithms to work and 2) encourage participants to generate ideas rooted in how they want or believe algorithms should actually support them. In this way, investigating their algorithmic imaginaries can help participants unearth and place at the forefront their most pressing or preferable attributes for an algorithmic management that works for them.

3 METHODS

We conducted focus groups and participatory design sessions with rideshare drivers in order to understand how algorithmic management affects their well-being and learn their design solutions that reimagine algorithmic management to support their well-being.

3.1 Participants

We had 24 unique driver participants who participated in the focus group and/or participatory design sessions, 11 of which participated in both. Drivers were recruited through a network of members of a major driver advocacy organization (N=10) and two gig-driver subreddits on Reddit (N=14) (Table 1). The driver advocacy organization posted our study flyer in their social media groups. We also posted the same flyer in the driver subreddits which included a link to our pre-screen survey. The pre-screen survey collected drivers' driving and demographic data. Drivers were asked how long they have worked on gig platforms, to self-classify how permanent their gig work career is [30], whether they have another traditional job (either part- or full-time), and how much they rely on their gig working income. For the last question, drivers were given two choices: "Nice to have, but not essential to my budget" and "Essential for meeting basic needs" [87]. Drivers were also asked to identify all of the gig platforms they have ever worked on as drivers, which platforms they actively work on, and which current platforms they work the most on. We used the pre-screen survey to select a diverse pool of participants in terms of their tenure working as a gig platform driver, whether they work another traditional job or not, dependency on the income from gig work, the number of hours spent on gig work a week, and their ethnoracial backgrounds. We intentionally oversampled female or non-binary drivers in order to learn their experience that we would not have otherwise. We verified participants' active driver status with participant-submitted

screenshots of their driver profiles. We recruited 19 participants for our focus groups. For the participatory design sessions, we invited the focus group participants and recruited 5 additional participants who did not participate in the focus groups. A \$50 Amazon gift card was offered for each session, which lasted approximately 90 minutes.

The mean age of participants was 38.1 years (SD = 10.1 years), with ages ranging from 27 to 64. 16 (66.7%) of our participants self-identified as male, 7 (29.2%) identified as female, and 1 (4.2%) identified as non-binary. Among our participants: 12 (50%) were White, 5 (20.8%) were Black, 4 (16.6%) were Asian, and 3 (12.5%) were Latinx. 13 (54.2%) held a traditional job of some kind, and 20 (83.3%) reported that they classified their gig work income as "essential for meeting basic needs". 21 (87.5%) of the participants drove for Uber, 9 (37.5%) drove for Lyft, and 9 (37.5%) drove for some type of gig delivery platform (e.g., UberEats, GrubHub, DoorDash etc.). 17 (70.8%) drivers actively drove for multiple platforms. Additional geographic and demographic information is included in our supplemental materials.

3.2 Procedure

We first conducted focus groups and interviews to investigate how algorithmic management affects driver well-being. In the focus groups and interviews, some driver participants shared their design ideas for services or features that they thought would support their well-being. Inspired by these ideas, we then conducted participatory design sessions to further explore drivers' ideas on how they reimaged the platform to better support their well-being.

3.2.1 Focus Groups and Individual Interviews We conducted six focus groups with two to four participants in each, and two individual interviews due to participant no-shows in two additionally planned focus groups. All sessions were conducted remotely via Zoom videoconferencing and lasted 90 minutes. Each session was facilitated by two researchers. Focus groups were an appropriate method for our research question as they have been shown to be great at "facilitating the grounding of the research in participants' own understandings of the issue(s) under question" [91]. In particular, focus groups have been commonly used for participatory action research, as they "enable the development of collective understandings of shared problems and (often) solutions to the problems" [94].

We structured our focus groups and interviews to investigate the impact of the platform on worker well-being, with a focus on workers' work preferences and perceived fairness of the platform. The focus groups and interviews began with the introduction of the study's focus on worker well-being and a quick overview of physical, psychological, and financial well-being. Then, we presented two sets of two different ride requests, the main "gig" or work of drivers, in order to present concrete contexts to ground discussion (we provide the ride requests that we used in our supplementary materials). The ride requests had two types of information that were revealed to participants in two phases: information the Uber driver app currently shows to drivers at the time of request such as the time to pick up and rider's rating, and hypothetical information that Uber could provide such as rider cancellation rate or feedback

⁴An Uber-contracted demographic study from 2014 indicated that 13.8% of drivers were female. The same study revealed 40.3% of drivers identified as non-Hispanic white, 19.5% as non-Hispanic black, 16.5% as non-Hispanic Asian, and 17.7% as Hispanic [

P	Focus Group	Design Session	Age	Race	Gender	Gig-work Tenure	Hours per Week	Other Job?	Platforms Worked (primary as rst)
1	X		52	Asian	Male	2-5 years	15 - 30	Yes	Uber
2	X		64	White	Female	2-5 years	45 - 60	No	Uber, Lyft
3	X		46	Black	Male	5 years+	30 - 45	Yes	Lyft, Doordash
4	X		31	Hispanic	Male	5 years+	0 - 15	Yes	Doordash, GrubHub, Roadie
5	X		49	Asian	Male	2-5 years	0 - 15	No	Uber, Lyft
6	X	X	50	White	Female	2-5 years	15 - 30	Yes	Uber, Lyft
7	X	X	46	White	Male	1-2 years	30 - 45	Yes	Uber, Lyft
8	X	X	35	White	Male	1-2 years	15 - 30	Yes	Uber, Lyft
9	X		44	Hispanic	Female	2-5 years	15 - 30	Yes	Uber, UberEats, DoorDash
10	X		32	Asian	Male	2-5 years	45 - 60	No	Uber, Lyft, Flash, DoorDash, GrubHub, Amazon Flex
11	X	X	33	Asian	Male	3-6 months	45 - 60	No	Uber, UberEats
12	X	X	27	White	Male	1-3 months	30 - 45	Yes	Uber
13	X		30	Black	Male	2-5 years	45 - 60	No	Uber, Lyft
14	X	X	27	Black	Female	5 years+	15 - 30	No	Uber
15	X	X	27	White	Male	1-3 months	15 - 30	Yes	Uber
16	X		32	White	Male	1-3 months	0 - 15	Yes	Uber
17	X	X	28	White	Non-binary	1-2 years	30 - 45	No	Uber, DoorDash
18	X	X	29	Hispanic	Female	2-5 years	30 - 45	Yes	Lyft, Uber
19	X	X	50	White	Male	1-2 years	60 +	No	Uber, Grubhub, Instacart
20		X	40	White	Male	5 years+	15 - 30	Yes	Uber, Roadie
21		X	34	White	Female	2-5 years	30 - 45	No	Uber, GrubHub, Doordash
22		X	43	White	Female	6-12 months	15 - 30	No	Lyft
23		X	35	Black	Male	2-5 years	30 - 45	No	Lyft, Uber
24		X	30	Black	Male	2-5 years	30 - 45	Yes	Uber

Table 1: Participant demographic and background information

tendency. After each phase, we asked drivers about their preferences regarding ride requests, reasons for their preferences, and kinds of information that they desired to know in order to choose requests that are more aligned with their work preferences. After drivers went through the sets, they were asked to evaluate the different kinds of ride request information and its impact on their physical, psychological, and financial well-being. We also asked whether drivers developed work strategies and if so how, and how those strategies helped them achieve their goals. Then, we asked a question about drivers' perceptions of the managerial fairness of platforms, which led to drivers detailing their experiences with gig platforms and how they potentially fall short in the area of fairness.

3.2.2 Participatory Design Sessions. We followed up our focus groups and interviews with 4 participatory design sessions to co-design solutions with participants. Each session had 3 to 5 participants and took approximately 90 minutes, with 1 session of 5 participants taking 2 hours. The workshops were facilitated by

three researchers. Our format was inspired by past participatory design research that focused on co-design to generate new solutions through prompts [99] and design workbooks [42, 97].

Our participatory design session was structured to co-explore solutions to improve worker well-being in algorithmic management. We generated five prompts that described situations that focus group participants frequently mentioned negatively affect their well-being, and that cover five principles for fair labor platform design such as pay, working conditions, and representation. [37]. The prompts included: 1) ride request matching, 2) Quest invitation, 3) incident between a rider and a driver, 4) platform support for defending a rider's accusation, and 5) driver's self-assessment of work performance and well-being. We also provided three example intervention types gig work platform features, third-party applications, and collective information sharing which reflect types of apps and social media forums that drivers currently use for their work. The use of prompts with intervention types was intended to help drivers generate solutions; however, the final outcome was not to design the three interventions in depth but to analyze the types of solutions drivers came up with and how these met their needs and concerns.

In the session, drivers considered each of the five prompts through the lens of an intervention type, and imagined how the solution could be designed to fulfill driver needs. After each prompt, we asked drivers 1-2 questions that explored their "algorithmic imaginaries" [14], for example, asking "how do you think the platform assigns rides?" after the ride request matching prompt. We included these questions in order to help drivers begin to generate ideas before the follow-up break-out sessions. We were inspired to specifically explore drivers' algorithmic imaginaries by calls for work centering the needs and algorithmic imaginaries of low-powered workers managed by algorithmic systems [64]. After the discussion, we divided drivers into three break-out groups with one facilitator assigned to each. The facilitator asked questions such as "how could this intervention improve ride matches that respect your well-being needs (psychological, physical, financial)?" As drivers brainstormed, the facilitator shared their screen and recorded each idea onto a Google Jamboard which was used to simulate Post-It notes on a whiteboard. This allowed drivers to quickly visualize and keep track of their ideas, and facilitators to organize driver ideas in real-time and refer back to previous ideas. At the end of the 10 minutes, drivers returned to the main room and each facilitator shared one idea from their session (sharing limited due to time constraints) to help drivers gain a sense of what other breakout groups had discussed and potentially consider these during subsequent prompts. The design session continued in this manner until all five prompts had been explored. Please see the Supplementary Materials for the full list of prompts.

3.3 Research Team and Stance

Our research team included people with backgrounds in human-computer interaction, sociology, and design. One researcher worked as an Uber driver for one year, which helped us access specific platform features as well as devise our initial focus group questions. We had a constructive design stance, aiming to effect positive change through creations or redesigns of technological systems. We note

that we first began our research with a focus on understanding workers' well-being related experiences in current algorithmic management. In the focus groups, some participants naturally shared their ideas on how to ameliorate issues that they experienced. These findings inspired us to conduct participatory design sessions in order to work with workers to learn their design ideas.

3.4 Analysis

All focus groups, interviews, and participatory design sessions were screen-recorded using the Zoom recording feature. The recordings were transcribed on Otter.ai, a web tool used to automate speech-to-text transcription. Participants' ideas recorded on Google Jamboards were documented in a spreadsheet. Following the qualitative research thematic analysis method [71], two researchers read transcripts and ideas, then generated initial codes applied at a sentence or paragraph level through the lens of our research questions on worker well-being, work preferences and perceived fairness, and participants' ideas on solutions. The emerging themes were debriefed and discussed in team meetings. In the discussion, we brought in the knowledge from prior literature, particularly different design features of algorithmic management such as information asymmetry and isolated nature of the work, to examine their impacts on worker well-being. We categorized the emerging themes into four groups, which we describe in our findings section.

4 FINDINGS

Through focus groups, interviews, and participatory design sessions, we identified 4 sets of problems drivers experienced as they engaged with platforms: 1) lack of well-being support, 2) problematic gamification and differential incentives, 3) information asymmetry and opacity, and 4) individualized work. We describe the problem as characterized by drivers, followed by the solutions drivers offered and solution impacts on well-being. First though, we provide background on some existing platform features frequently referenced by our driver participants. As the rideshare platform most of our participants worked on was Uber, we describe these features primarily using terms coined by Uber; the other rideshare platform that drivers engaged with was Lyft.

4.1 Background on Rideshare Platform Features

4.1.1 Ride Matching Uber & Lyft use a dynamic matching and pricing algorithm to connect drivers with riders [98]. Uber's use of dynamic pricing creates temporary "surges" in areas of high demand localized increase in fare to stabilize both supply and demand. Uber also utilizes a system named "dynamic waiting" which assigns rides to drivers, even if the driver is still completing a ride to reduce waiting periods and distance travelled.

4.1.2 Gamified Bonus Structure Quest promotions are Uber's primary incentive for encouraging drivers to drive more. They appear unevenly, with Uber not revealing how and why they target specific drivers with specific Quests [28, 72] and with variances across drivers in the criteria for completion: some Quests require just a few rides while others may require a figure in the hundreds. A driver may receive a single Quest or multiple Quests to select from with differing variations in required number of trips and earnings. Once a Quest is selected, however, the driver is unable to opt out

or switch to a different one. Lyft has a similar incentive system called 'ride challenges'⁵. Platforms also use streak (also known as consecutive ride) bonuses to reward drivers for accepting and working multiple rides in high-activity times and areas in a row. These structures are gamified because they use common game elements such as points, levels, leaderboards, competition with others, ratings, and measurable evidence of completion for the purpose of encouraging drivers to work more [63].

4.1.3 Rewards Structure. Uber Pro is Uber's driving rewards program⁷ with 4 tiers drivers can reach. A driver's tier status is based on points (earned by completing trips), driver rating, and cancellation rate. Lyft has a similar rewards program named Lyft Rewards, where drivers earn points based on each dollar earned, instead of the per-ride basis used by Uber Pro. Uber Pro provides high-tiered drivers external platform rewards such as roadside assistance, discounted gas and car maintenance, and qualifying tuition coverage, as well as additional platform features such as each trip's duration and direction, extra earnings on time and distance rates, and superior platform support⁴⁴. Points and tiers reset every 3 months, meaning that drivers must work consistently to maintain their status.

4.2 Lack of Well-Being Support

4.2.1 Problem: Unaddressed Well-Being Support on Platforms. In the focus groups, we asked drivers to share their concerns regarding their physical, psychological, and financial well-being while driving. Reflecting on how platform features supported or hindered their financial well-being, some drivers felt that platforms intentionally obscured the statistics surrounding their work, forcing drivers to focus on short term goals rather than taking on a long term view of their role and prospects as a platform driver. As P7 explained, "They [Uber] really don't want you to know what you're making month-to-month." In a later group, P11 reiterated these sentiments after explaining that platforms lack any yearly or other long form overview for drivers to review their earnings, "Uber discourages you from taking that long view of the past month or the past few previous months. It does remain very weekly focused."

When considering their physical and psychological well-being, drivers often felt they had to forgo these well-being measures due to algorithmic management features, such as Uber's tier system pressuring them to accept a high volume of rides. P3 mused over the irony of driver tier systems that provided more information about rides while simultaneously penalizing drivers if they acted on it by ensuring that this information would be removed if they acted on their preferences. P1 added "it's how they [the platform] force you into driving so much for them", referring to how this method exerts power over workers to get them to work more. Perhaps one of the more extreme of cases we heard, P11 shared the lengths that he goes to continue working as much as possible, literally working himself to the state where he has to catch a sleep in his car: "So I actually keep a pillow in the back of my car, in case I do get tired. So

I'll find a well lit place and I'll pull over for an hour or two to catch a nap if it's really bad." The majority of drivers shared concerns over their physical safety and possible carjackings, including 8 of the 11 non-white drivers we spoke to. P19, a white male, expressed some worry over unsafe neighborhoods, but he added, "I think if I were a woman, I would be more concerned about going into certain neighborhoods late at night." In fact, most female drivers we spoke to brought up this concern about physical safety (5 out of 7) and feeling that they needed to avoid driving at night or that they held a heightened awareness when driving at night. P18 shared, "I'm by myself with this grown man in the backseat. And like, it's like 11pm...if we're not talking, I'm just thinking about all these things that could possibly happen. But it's just like me being a woman, like making sure that I know. And I'm aware of my surroundings".

Notably, in design sessions, drivers pointed out that there is no existing physical or psychological well-being support for them on the platforms, and that the financial well-being support or evaluation tools provided by platforms were rudimentary at best. These concerns were not limited to a sub-group and spanned drivers of all genders, ethnicities, ages (27-64), and experience levels (1-3 months to 5+ years).

To pick up the slack left by the platforms' paltry tools, many drivers told us that they mentally calculate their own driving metrics. Many drivers had specific hourly wage baselines that they calculated in order to determine whether a ride was "worth it". P15 explained, "I definitely have a threshold. So when I'm driving...in terms of gross amount that I'm taking in, I try to aim for like \$30 per hour [before expenses]." Because existing platforms do not have expense tracking features, it is difficult for drivers to calculate net income. P8 similarly calculates his income independently, "I figure out average price of trip. My metrics that I care about are average earnings per ride, average earnings per hour, and average earnings per mile. Those are typically the three variables that I track most closely and that I care most about and that I want to be the highest as possible." However, calculating the sum of several different trips over a long period of time while driving is no easy task and imposes a heavy burden on drivers' minds. P12 revealed what crosses his mind when he realizes his earnings are declining, "Mentally, if I see that dollars per hour going way down? That's pretty disheartening. I mean, I'm doing this as a second job for extra income. If it's not profitable, why am I wasting my time?"

4.2.2 Solution: Data-Driven Insights in Support of Worker Well-Being. Multiple apps exist today to assist drivers with data analytics, and some of our drivers indicated that they use or tried to use these in their work after realizing rideshare platforms fall short in providing any useful data or analytic insights. For example, drivers identified that platforms lack mileage tracking, so instead they turn to tracking with hand ledgers, third party apps, or not at all. In some cases, drivers tried out multiple third party apps with different functions; P10 told us that at one point "I had like four or five apps that I would use" including ones for tracking regional events for potential surge pricing and converting distance to dollars to estimate what fares should be. Others like P1, P2, and P9 attempted this but abandoned these apps once Uber and Lyft integrated the features of the apps or once they became frustrated with the inconvenience of using multiple apps for driving. P8 expressed his disappointment

⁵help.lyft.com/hc/e/articles/360001943867-Ride-Challenges

⁶help.lyft.com/hc/e/articles/115015748908-Streak-Bonus, help.uber.com/driving-and-delivering/article/how-does-the-consecutive-trips-promotion-work?nodeId=de983305-076a-40cf-aaf4-7b23f50a0007

⁷www.uber.com/us/en/drive/uber-pro/

⁸www.lyft.com/driver/rewards

Problem	Solution Themes	Involved Entities
Unaddressed Well-Being Support on Platforms	Data-Driven Insights in Support of Worker Well-Being, Well-Being Centered Nudges	Workers, Platform
Unfair Differentials Imposed By Gamification	Flexible Incentive Configuration, Rewarding Driver Loyalty	Workers, Platform
Uneven Information Access	Transparency in Task Assignment, Improving Information Visibility Between Drivers and Riders	Workers, Customers, Platform
Working and Learning in Isolation	Collective Information Sharing for Investigation & Advocacy, and for Driver Support & Knowledge Building	Workers, Customers, Platform

Table 2: Addressing algorithmic management shortcomings with workers: this table summarizes the four areas of platform limitations and solution themes intended to address them as conceived by workers themselves.

with the basic analytics of platform apps, particularly given that in his view, "Uber is a data company, I mean they're tracking everything that you do...so they're monetizing that data in some form or fashion."

When data and data privacy issues were brought up by one participant, other participants nearly universally agreed with frustration that platforms collect an abundance of data on them. As P12 put it, "it's [driver data] probably already being tracked and monitored and sold to somebody else, so there's not much else we can do about it", reflecting the resigned sentiments of other drivers. Drivers were also pessimistic in the uses of their data, assuming it is used to exploit and manipulate them. P19 asserted, "They [the platforms] withhold a lot of information. Information is really their biggest tool to use in their favor. And it's often used against us, unfortunately." However, when asked how resistant they thought drivers might be to providing their data on a collective platform, P17 didn't believe there would be driver pushback and suggested that since platforms already spy on them with their data, "you [drivers] might as well use that app or use that data to work towards a more fair and equitable and moderated understanding."

During design sessions, participants indeed found inspiration in the possibilities of their driver data being used to help themselves better understand their work patterns and make data-driven recommendations to them. P15 thought data-driven insights could assist him in balancing financial and psychological well-being. He envisioned being prompted with psychological well-being checks throughout his shifts to later combine with driving data and display insights on not only earning trends but also on psychological well-being. This could then help him balance his driving strategy around frequenting areas that boosted his financial vs. mental well-being. Participants like P6 and P12 desired similar data-driven solutions to help them harness their driving data in order to understand their financial performance and tune their strategies to achieve their goals.

P21 and P23 also suggested solution designs that could support their well-being goals. P23 elaborated that data analytics could support drivers by guiding them in creating more balanced schedules that allow them to maintain their financial, physical, and psychological well-being, "if there is like a plan, something should be given to the drivers... you will be able to know when to work, when to

take your break, and when to rest," adding that the information could be handed over to drivers to "do the mathematics yourself" and set up their own individualized plan. P21 considered how P23's idea could reduce her stress while working, "if you've got all of the information that you need, you can reduce the anxiety that you feel as a driver sometimes, because you're trying to be safe and drive at the same time. But then in your own head you're trying to...keep your bottom line in mind. And it's easier to do that, like [P23] was saying, if you've got all of your P's and Q's and everything, like crossed and good to go. You definitely don't have as much mental stress, which reduces the accidents that can happen while you're on the road." This concept for data analytics supporting schedule planning was shared by 5 other drivers, 3 of them female, who all expressed that being able to plan would place them in a less precarious earning position due to unforeseen circumstances. While we did not ask whether rideshare drivers had dependents to ascertain whether precarious wages affected more than themselves, all drivers who suggested a component of data-driven planning reported their rideshare earnings as being essential for meeting their basic needs. Drivers also ranged from experience levels of 1-3 months to over 5 years.

Drivers also imagined how data-driven insights could be applied to improve their experiences with driving incentives like Quests. P15 suggested an intervention that would combine personal driving data and real-time driving information to give drivers an estimate on the attainability of each Quest option (i.e., predicted time to complete each Quest). This would help drivers select the bonus or they could most reasonably achieve in the upcoming period.

These data-driven insights around incentives could improve not only driver financial well-being but also psychological and physical well-being. P15 believed that information detailing Quest attainability would help drivers avoid selecting Quest promotions that could lead to driving while exhausted or sleep-deprived. Both P15 and P18 talked about how knowing Quest attainability would improve driver psychological well-being by encouraging drivers to prioritize work-life balance, socialization, and mental health. P15 elaborated that drivers wouldn't be otherwise chasing driving bonuses "when you would maybe prefer not to...forcing people to miss out on certain things with people who are important in their lives because they want to hit a Quest".

4.2.3 Solution: Well-Being Centric Nudges The physical well-being preferences drivers exhibited during focus groups were centered around their physical safety as well as the exhaustion that accompanied long hours of driving. When they compared different ride requests, some of the most referenced ride request features were "rider identification" (e.g., rider rating and name) as well as the rider's destination. Long tenured drivers (i.e., over 1 year of experience) most strongly held this preference for higher thresholds of rider ratings, explaining that they consistently used rider information to deduce how risky a passenger may be. Locations of pick-up and drop-off were also expressed as variables that hinted about safety due to concerns over "bad neighborhoods" during late hours of the night. Not all drivers felt this way though; some did not perceive a risk with low rider ratings and did not consider the feature in determining their preferred rides.

Driver's preferences over their psychological well-being focused around features they believed caused their mood and stress levels to fluctuate. Rider rating was the feature many drivers believed most affected their psychological well-being. As P2 put it, "A 20 minute ride with somebody that is going to be a problem, it just ruins your entire day. Not only are you nervous on the drive, you are completely exhausted by the time you finally get them out of your car." Rider feedback tendency was also frequently singled out for its potential to affect the drivers' mental health: "When I get a much lower rating...asking myself, what went wrong?...That will be affecting my psychological well-being" (P13). Drivers also called out the connection between financial well-being and psychological well-being, explaining that however successful they felt they were during a shift with their earnings correlated with how their mood was.

In each participatory design session, drivers suggested the use of notifications, or nudges, by platforms to improve their driving conditions and consequently their physical and psychological well-being. Some drivers explained that reminders throughout the day about taking a break, drinking water, and eating something may sound silly but are effective at signaling to drivers that, "I should have a water and snack maybe" instead of just focusing on "I have to earn money all the time" (P12). P18 emphasized the importance of even the smallest efforts for mental and physical health support through tips or resources to help with addressing driver burnout, adding that drivers could set "well-being goals" to ensure specific intervals where these tip notifications would come through. To encourage drivers to actually take breaks, P20 suggested that nudges be accompanied by guarantees of a priority ride after taking a break. P8, P14, and P15 also expanded on well-being solutions by recommending they come with actionable suggestions of locations for food, restrooms, or rest stops. As P15 explained, providing intermittent reminders of taking breaks alongside recommendations of specific crowdsourced spots would reduce the stress of finding an accessible stop in an unfamiliar location. P11 supported the need for such recommendations by raising an often overlooked point that as gig workers particularly if working a full shift of 8 hours or more their car becomes their workplace but lacks common workplace essentials such as break areas, bathrooms, or kitchens, driving the necessity of easy access to services. A handful of drivers also suggested methods for improving physical safety around viewing more context around pick-up and drop-off spots. 4 of 5 of

the drivers making these suggestions were female or non-binary, corresponding with a pattern of safety concerns exhibited earlier by most female and non-binary drivers we spoke to.

4.3 Gamification and Differential Incentives

4.3.1 Problem: Unfair Differentials Imposed By Gamification Rideshare platforms have adopted gamification methods to incentivize drivers (see Section 4.1.2), resulting in systems such as Uber's Quests [45]. Quests require drivers to finish a designated number of rides in a specific time frame to receive an additional bonus amount. However, different Quests are presented to different drivers inconsistently based on a variety of factors outside of drivers' control and vary significantly in terms of the objectives and bonus amounts. P8 explained the unfairness in these differences, "There are variances to Quests though based on driver, which I thought was pretty interesting. And there's also a little caveat at the bottom of each Quest now that says, 'This only applies to drivers that see this notification in their inbox'...inferring that other drivers aren't seeing this notification, or aren't getting this bonus, which I think is not fair or equitable."

From the platforms' perspective, gamified incentives can make drivers more efficient, work harder, and can attract new and former drivers to the platform. In fact, a recent study suggests that gamification increases drivers' extrinsic motivation (but not intrinsic motivation) to work for financial gains [67]. However, the gamification of their profession makes drivers feel like they work in an unequal system, a system with unclear rewards and objectives. P17 echoed many other drivers' dissatisfaction with the Quest system by remarking "They [Uber] gamify this [Quests] in a really unethical way. And they don't have to do that." Drivers repeatedly suggested that Quests unequally benefited new and lapsed drivers, ignoring drivers who have been working for Uber consistently over a long period of time. P11 elaborated, "From what I understand on Reddit, it kind of sounds like the newer drivers get the nice Quests. Then after a week or two, they're back down to the regular level that the regular drivers get."

Exploring algorithmic imaginaries with drivers about the platforms' incentives assignment algorithm further highlighted the unfair treatment they felt from platforms. Drivers unanimously agreed that Quest offers were determined by frequency of driving, drawing from personal and other driver experiences: the more a driver worked, the worse the bonus offers they would receive (i.e., requirements of higher volume of rides for less pay). They believed that platforms tried to attract new or less frequent drivers with enticing initial bonuses but that these would reduce after a few bonuses. P6 added that she had tried experimenting on her own by not using one rideshare app for a week and returning to it to view her bonus offers, finding that sometimes it did indeed give her better Quests while other times "it's like, no, we're not falling for that". While a few drivers also mentioned market factors they believed drove the differences between offers that drivers saw, citing differences in bonus amounts due to a driver's city size or city events, sentiments of all drivers invariably returned to their concerns over unfair driver treatment by algorithms that prioritized luring in new drivers or recently dormant ones instead of rewarding high-performing, loyal drivers.

Figure 1: Thematic analysis map of findings. For a full version of this thematic analysis map with driver gender breakdown, please see the appendix.

Finally, the concern about the platforms' lack of loyalty rewards frequently came up, particularly when drivers discussed current platform driving incentive structures. We note that 19 of our 24 participants had over a year of experience and therefore had a bias for being rewarded based on tenure. Still, it's been found in previous work that 75% of drivers that have completed at least one trip exit before they have driven for a year, so it is curious that platforms still do not have adequate structures in place to encourage and reward their long-term drivers [31]. And while systems such as Uber's "Uber Pro" can be construed as a loyalty reward program, it is based on metrics that are reset and recalculated every 3 months. Thus, the number of years a driver has been consistently working on a platform doesn't amount to much in the long run. P18 explained her feelings about platforms incentivizing new drivers as well as how she views the relationship between drivers and platforms, "I'm not saying don't offer incentives for new drivers. But I think...you're better off keeping drivers that have been driving for years, that are experienced, that have good ratings, that are consistent over a new driver who may be terrible...they only work the incentive and then stop or only work the incentive and then don't care about the platform, don't care about representing any of the platforms. At the end of the day, yes we're contractors, but we're still kind of, like, representing these companies."

4.3.2 Solution: Flexible Incentive Configuration
 Discussions around how incentive differentials could be improved to center worker well-being, one theme of solutions that was discussed revolved around allowing drivers to play a role in configuring their incentive offers. P8 re-imagined driver bonuses: recalling the concerns of past focus groups around troublesome gamification of bonus systems such as Uber's Quests, this driver suggested configuration of incentive offers as an alternative structure to what P6 likened to as a "stupid video game where it's trying to keep you from winning". He juxtaposed his version of a bonus structure to building a personal pizza, comparing pizza toppings to rewards criteria that drivers can combine and change depending on their circumstances that day: "Do you want more rides? Do you want longer rides? Do you want shorter rides? Do you want airport rides? Do you want...late night or [specific] time of day rides? If you can have almost a 'select your menu' or 'build your own Quest!'" He elaborated that these configurations of rewards could then be weighted and ranked by Uber based on its demand forecasting to determine commensurate compensation. In this framing, the gamification's manipulative effects on well-being are subdued and can become co-created, synergistic, and fairer incentives as drivers can make selections for incentives that are attainable to them, but platforms still command the value of incentives being offered and continue to benefit from drivers being motivated to work.

Other ways drivers imagined configuration was through the ability to switch between Quest orders instead of being locked into one or having Quest payouts be based on incremental levels. P17 explained that the current system "makes your drivers stressed out" when they select a higher volume Quest due to a higher payout, but wind up overworking to meet it instead of being able to fall back on an alternative Quest order. They felt the ability to switch between orders could benefit well-being because locking drivers into Quests they're struggling to finish "increases the health hazards of having people that are working for 12 hours or more". P15 and P20 both mentioned their frustration over how currently Quests are "all or nothing" and suggested incremental bonuses instead. The drivers shared that they face uncertainty in how achievable a bonus is, given how many passengers there are requesting rides and their own schedule, and may erroneously get themselves into "a situation where I can't complete the Quest. And you know, I may do 98% of the Quest, but don't get any of the bonus." P20 explained that allowing drivers to work through levels and earn incremental bonuses would remove "the possibility of losing out on all of them".

4.3.3 Solution: Rewarding Driver Loyalty. Solutions drivers generated, some sought to reverse the lack of effort by platforms to reward long-term workers. P24, an Uber driver for the past 4 years, suggested that drivers should be rewarded at time-based milestones for remaining active, consistent drivers, separating rewards from short-term driving bonuses that are based on meeting daily or weekly quotas. P11 argued for a more radical reimagining of the system as a way to guarantee driver earnings. Due to the instability drivers face regarding their long-term earnings, Quests could be used to guarantee a certain income given a set number of gigs completed, recalling the recent efforts in New York and California to establish minimum wages for gig workers. P11 preferred this option as it "would make it [gig work] like a regular job" and that it "would take a lot of the gaming out of it". P19 proposed redesigning loyalty programs like Uber Pro to recognize long-term drivers by making Uber Pro statuses permanent. As a driver who viewed his gig work career as permanent, he explained this would make him feel more valued by the platform, as he feels that the emphasis of Uber's current reward structure overlooks drivers like him in favor of recruiting new drivers.

4.4 Information Asymmetry and Opacity

4.4.1 Problem: Uneven Information Access. Information asymmetry has been discussed in past work [20, 80] to highlight how platforms enforce control over their workers by limiting the visible gig information workers can see to make decisions of. We heard from drivers about similar information asymmetry and opacity they experienced on platforms and the uncertainties it produced on their decision-making. P17 gave an example of operating under this information blindness, accepting a ride request without knowing any information about the drop-off destination and hoping it will be a long enough trip to be profitable: "If I'm driving 20 minutes to get to somebody, I really hope that, you know, their ride is, 10 miles or 15 miles or 20 miles. Or even...the real lucky ones are like, 'we're going to go on a three hour ride', because that to me means that I get to go home with, you know, 150-200 dollars and just stop." P3 articulated exasperation that basic ride information is withheld

from drivers until they "earned" it through reward systems like Uber Pro: "They definitely treat it like it's a perk when it's kind of a necessity". Platforms may be hesitant to provide full information about gigs to all drivers for if everyone holds the same preferences, it may cause ride matching issues. However, we observed a heterogeneity in driver preferences around trip duration to support the integration of driver preferences in algorithmic management. Namely, while their preferences converged under specific circumstances (i.e., preference for shorter trips during Quests requiring a minimum number of trips), under normal circumstances, drivers held varying preferences. P17 and P18 mentioned a preference for longer trips, with P17 explaining that they didn't find short ones to be profitable enough without bonuses and P18 preferring to reach his earnings goals in as few rides as possible; while drivers like P24 and P14 preferred shorter trips because P24 strategized based on trip volume and P14 explained "with short trips, you can kind of take a break and you can just get out and stretch your legs and stuff like that."

Additionally, while exploring drivers' algorithmic imaginaries, we came across more instances of information asymmetry and opacity, such as driver uncertainties over the rideshare platform's matching algorithm. When we asked drivers to share with us how they understood the algorithm to work, their conceptualizations were informed primarily by a set of factors: personal research, past observations, and impromptu speculation. A number of them (N=7) believed that ride-matching is done purely based on time to pick-up. P8 told us he had actually conducted his own research into the algorithm and that the calculation of time to pick-up involved details as minute as roundabouts and u-turns. Other drivers though felt it was random, impacted by "favoritism" (i.e., that the platform prioritizes higher rated drivers or higher tier drivers), considered who had not received a ride request recently, or involved other "more complex" factors. Their variation in responses and uncertainties over the "right" answer highlight the pervasive information opacity and resulting uncertainties drivers must navigate on platforms.

4.4.2 Solution: Translucency in Task Assignment. One surprising revelation from the solutions proposed by drivers was a desire for translucency of information as opposed to demands for outright transparency. Platforms currently do not display passenger drop-off destinations to drivers until they have picked up the rider. While a few participants mentioned desires to view specific destinations of rides before accepting a ride request, more frequently drivers such as P24 actually suggested platforms or interventions help them by providing cues about trip destinations such as direction of the ride or expected length or duration of rides: "I don't care about the final destination because knowing the distance will let me know about the final destination." These suggestions for subtle control over their ride preferences as opposed to unanimous desire to see destinations outright may be explained by focus group participants like P6. P6 mentioned concerns about rider discrimination if destinations were disclosed to all drivers: "I don't know if I'm interested in destination per se... If I'm going to take a trip I'd love to know what direction it's going in and about how far... I don't know if I would want Uber to do too much with, like, specific destination, because we already have a lot of issues with neighborhoods being

discriminated against in Chicago. So I don't know that that's helpful to the city as a whole." Most of the drivers that expressed interest in information translucency were those who have been driving over 2 years, as well as two drivers with 1-3 months of experience. It may be that drivers of longer tenure have become accustomed to not viewing all information and found ways to work around limitations, thus becoming less expectant of complete information transparency from platforms.

Drivers shared that having access to this information would be beneficial for their well-being, allowing them to regain a sense of control. P15 mentioned that his psychological well-being would benefit from this additional information to avoid past negative experiences of blindly accepting rides at the end of his shift that took him in the opposite direction of his home. Platforms do have a "destination mode" to allow drivers to input a destination and receive rides towards that direction, but many drivers reported this feature did not work reliably. Without any translucency into this information, drivers also shared they may end up in a location where they feel unsafe. P10 explained, "A lot of times when I have to drop somebody in like the South Side, the first thing I do I go online...and drive back to the downtown, and then go back online. Nowadays, every week you see in the news, like recently there was an Uber driver who was shot in the Chicago area, the carjacking status every day. Every single day, some Uber driver's car is getting stolen...driving right now in today's time, in Chicago, you gotta be careful."

4.4.3 Solution: Improving Information Visibility Between Drivers and Riders Information asymmetry also exists between passengers and drivers as platforms do not make riders aware of the limitations on drivers and likewise do not provide key contextual information about riders to drivers, creating a gap in communication between the two.

In focus groups, drivers identified that passengers lacked context around the constraints and conditions under which drivers worked. For example, P17 explained that passengers do not know that drivers can't see their final destination and are not compensated for time or mileage to pick them up. P3 told us that riders rarely know that they have their own passenger ratings. The former two pieces of information can result in passengers holding indifferent attitudes about giving tips, not realizing that drivers are often financially dependent on them to ensure livable wages. Roughly 16% of Uber rides are tipped, with only 1% of riders tipping on every trip. Regarding passenger ratings, drivers explained that riders had no incentive to treat drivers well or behave appropriately because riders lack consequences and can easily create new rider accounts.

To address these examples of information asymmetry, driver solutions centered around improving mutual visibility between drivers and riders of each other's situational contexts. Drivers talked about methods for educating riders about drivers and platforms. P14 suggested that riders be shown reminders about platform policies such as how seriously reports or complaints against drivers are taken to dissuade false rider reports. P8 explained that sharing more information to educate riders would help ameliorate rider complaints that stemmed from factors outside of driver's controls (e.g., explain how expensive fares are the result of high demand, not the driver's own decision). To hold riders accountable for their

behavior, P14 suggested prompting riders with action items they can work on based on their driver feedback history so that riders can receive feedback if they consistently get negative ratings. P19 wished for passengers to know whether a driver chose not to pair with them in the future to provoke behavior changes. Following up on multiple drivers desiring to have more information around riders, we found that while some drivers suggested adding problematic riders (P15) or punishing them relative to their offense (P24), others simply wanted to view past feedback that drivers left about riders to make judgments themselves. P14 explained her reasoning and approach: she valued past driver feedback of a rider as a way to help her strategize how to handle problematic riders so she could continue to maintain a high acceptance rate for accessing platform rewards. In a similar vein, P8 told us that eliciting additional information about the rider's condition that drivers should be made aware of (e.g., inebriation of rider) would help drivers prepare for potentially problematic rides.

Drivers' desires to view a rider's past feedback history may not require revealing entire reviews, but just snippets or cues to identified problems. In fact, given that drivers only have a few seconds to make a decision, they would need the information to be displayed in a truncated, more translucent fashion. P14 added specific traits she wanted to know such as whether riders were "rude", "professional", or "left things in your car, were late to pickup, and stuff like that" which could be used to create short, structured cues for drivers to read and act on.

4.5 Individualized Work

4.5.1 Problem: Working and Learning in Isolation The nature of rideshare work inherently isolates drivers from their peers and platforms. Their cars become their workplaces and any socialization they receive during shifts is through rider interactions. Through our focus groups and participatory design sessions, drivers indicated a curiosity about the experiences of other drivers; "I'd like to know, for example, what Quests and bonuses and surges other drivers are seeing? You know, I think we sometimes wonder whether I'm being offered the same opportunities that other drivers in my area are being offered" (P19). Some like P12 and P13 told us that in developing their driving strategies, they bolstered their personal experiences by reading blog posts, dedicated Facebook groups, and subreddit threads. Others referenced anecdotes of other drivers during design sessions, describing occurrences like drivers struggling with adequate platform support, the differentials in bonuses being offered to different drivers, and stories about difficult passengers. As P15 put it, "I think it always helps, you know, if you're experiencing an issue to know that you're not the only one who's experienced it." However, currently drivers lack direct platform features to support them in collaborating with one another for knowledge or support. And existing social media that drivers frequent tend to become places for sharing complaints and negative experiences, rather than giving readers an understanding of an average experience. P18 described, "I'm in a Facebook group where people share this all the time, about their long rides to Houston...and things like that. But it's not very helpful because people they are just like bashing each other. It's actually a very toxic place."

Platform support is a unique gig work area where workers have expectations of being able to communicate with humans rather than algorithms or automated processes. Unfortunately, as described above, these expectations often came up short with drivers not receiving prompt responses or adequate resolutions. Drivers are at particular financial risk when support tickets go unanswered if 1) the driver has been deactivated (and therefore unable to work) or 2) the driver has experienced inaccurate fare compensation or driving bonuses. Drivers mentioned the impact on their well-being when platform support failed to resolve their issues. P19 described an interaction where his background check was improperly led, the platform deactivated him, and despite all of his efforts to follow-up, he was unable to return to work for 10 weeks: "They're [Uber] very quick to deactivate, and are not necessarily in a hurry to get back with you. And they don't seem to really fully appreciate the importance of our income." He added that the canned responses of support agents, though polite, failed to resolve his issues and led him to feel helpless and devalued by the platform. P15 told us that "especially if Uber is your main source of income, to be deactivated can be incredibly stressful", mentioning that without platforms communicating concrete timelines, drivers might just repeatedly check the status of their tickets and stress until they heard back. P20 echoed the anxiety that is induced by unresponsive support systems, saying that upon deactivation, "it's sort of like a bit of a panic mode because you may have been working to pay off a bill or something...but when you're just kicked off, you don't know how long you're going to be in that state."

4.5.2 Solution: Collective Information Sharing for Investigation and Advocacy Participants' solutions leveraged collective information sharing as both a vehicle for investigation and advocacy as well as a support network for drivers. Drivers saw collective information sharing as a valuable tool, especially given "our communication network is pretty flimsy and non-existent, and so we don't really have the strength in numbers that you see in a lot of workplaces because we're so isolated" (P19). In regards to investigation and advocacy, collective information sharing emerged as a tool that could assist drivers in investigating perceived inequities by platforms as well as assist them in advocating for themselves by raising awareness over issues and worker findings. Drivers shared a number of issues they were curious about resolving and felt collective information sharing could assist with. P22 suggested using collective driver data to probe whether driver beliefs about inequities of Quest orders between long-term vs. new or inactive drivers were true or not. P14 conceived of how she would use data amassed by collective information sharing to investigate her hunch that Uber programs Quests to become more difficult to complete as a driver nears the required ride quota: "Maybe like a graph of everyone's data from the last hours of their Quest promotion...seeing how the last hours of that plays out for people, like are they getting more longer trips to stop them from getting the bonus?" P17 shared that they would be interested in using collective information sharing to learn whether Uber truly uses Uber Pro tiers to provide priority support.

Drivers felt that through collective information sharing, findings could potentially be used to promote worker rights and put pressure on the platforms to resolve issues. P18 believed findings could be used to bring awareness about bigger issues drivers face to the

platforms to initiate some recourse. P15 felt collective information sharing results could serve as proof by drivers about prevalence of issues and be used to advocate for policy changes at the platforms level, and also at a legislative level to protect the driver. P20 noted that findings from collected information would be more impactful in evoking change than a single personal anecdote "if it's just you vs. the company, your story doesn't have much weight. But if you have a collective group providing some metrics or data?" though he did exhibit uncertainty regarding whether platforms would engage with advocacy or grievance groups that might use this information.

4.5.3 Solution: Collective Information Sharing for Driver Support and Knowledge Building Drivers felt collective information sharing could function as a support network and knowledge building repository as well. P23 believed that a platform for this could help drivers collectively understand how Quests actually work by sharing their driving information. P20 thought that collective information sharing could help drivers share timelines on support issue resolutions and subsequently help others experiencing similar issues to set their expectations or even resolve issues without platform intervention. P17 suggested that on this type of platform, community leaders or teams could be appointed to support and guide less experienced drivers. P21 proposed the function of daily journaling on the platform such that drivers could read back on their own experiences and other drivers could learn from one another's past experiences to aid in their decision-making or planning. P20 also proposed integrating educational material for drivers on the platform about how to approach common issues "this is what you need to be prepared with, these photos, this stuff" furthering the idea of a platform functioning as a shared knowledge repository. A platform for this purpose would require participation of diverse drivers to ensure effectiveness by way of drivers asking questions and sharing experiences. Of those drivers suggesting collective information sharing, there was an even split in drivers who have been working for less than 2 years and drivers working more than 2 years, suggesting that such a forum could reasonably be of interest to both newer and more experienced drivers.

Drivers identified a few challenges they saw in collective information sharing's reach. P8, P11, and P19 wanted to ensure that such a tool would assure anonymity and prevent rideshare platforms from accessing the collective's information and retaliating against participating drivers. Interestingly, in contrast to that point, some drivers suggested incorporating platform support employees. P17 and P18 thought platform employees could provide transparency and support around common issues, and P12 felt platforms and riders needed to be integrated with any collective information sharing about rider incidents to ensure accountability and truthful sharing of information. Many drivers expressed that while they would be willing to share information such as their earnings per mile to establish a community-wide understanding of driver income, they would not share their own strategies, or "special sauce" (P17) that they developed over time, for example, which location to go to at what time for rides and potential surge pricing. P19 also worried some drivers might be selfish and choose to share false information.

5 DISCUSSION

In our findings, we observed that drivers held concerns over four areas of rideshare platforms: 1) uneven information access between platforms and drivers, 2) unaddressed well-being support for drivers, 3) unfair differentials imposed by gamification, and 4) the isolated nature of working alone. The solutions that the drivers came up with to address their concerns were thoughtful, creative, and insightful: they suggested platform translucency and ways to balance information visibility between drivers and riders, proposed nudge designs and data-driven insights to advance well-being, reimagined systems for incentivizing workers and rewarding loyal drivers, and generated ideas around a driver collective for information sharing and collection.

Below, we discuss the novelties and implications of our findings around 1) worker fairness perceptions of algorithmic control and its impact on psychological contracts in gig work and 2) the future of algorithmic work by workers for workers.

5.1 Fairness Perceptions of Algorithmic Control and the Impact on Psychological Contracts

Researchers have previously studied the ways that workers interact with algorithmic control through tactics including resistance [65], compliance, deviance, and engagement [14] and constrained and experimental reactivity (i.e., decreasing or increasing the amount of interaction with gig work platforms) [78]. Yet the notion of how workers perceive the fairness of algorithmic control has been less explored, especially in the context of gig work [59]. In our work, we probe the ways that workers experience and expect fairness through algorithmic control. In our findings, we identify distinct processes that workers classify as unfair treatment by platforms. These processes revolved around incentive and reward programs implemented by platforms to motivate workers. Contrarily though, workers took issue with the inequities they felt platforms knowingly exacerbated through such programs, such as the concealment of basic gig information from workers unless they maintained a certain platform tier; or the unfair treatment of workers through the allocation of the most profitable incentive offers to newer or inactive workers over long-time, active workers. Notably, the unfair treatment that workers discussed was not at the individual, anecdotal level, but rather was a wider, group level concern. We offer this initial look into how exploring worker fairness perceptions of algorithmic control is revealing of platform shortcomings that researchers and/or practitioners can look to remedy.

These gig worker fairness perspectives also offer additional evidence into the effect algorithmic management can have on worker psychological contracts in gig work [92]. Our research indicates that many workers still hold significant psychological contracts with the gig work platform as if the platform is their employer. At a traditional workplace, fairness is an important content of employees' psychological contracts [40]; employees perceive this contract to be breached by platforms when they observe or experience unfair treatment. In our research, workers reported similar perceived breaches and feelings of violations. One such contract breach raised by participants was the platform's failure to reward driver loyalty or tenure. At a traditional workplace, seniority or

continuing tenure is often rewarded through employee recognition events, larger year-end bonuses, increased number of days off, and/or regular opportunities for promotions and raises. Our participants noted that they hoped or expected platforms to reward workers who had been consistently working for them. This expectation is perhaps moderated by the fact that over half of our participants still hold a traditional job (N=13) and that most of the rest (N=11) can reasonably be assumed to have worked a traditional or non-gig work job in the past based on their age and number of years worked on platforms. Unfortunately, participants observed no such loyalty recognition in current incentive structures. Instead, favorable incentive offers were exclusively presented to new or inactive workers to "lure them in". Participants were turned off by what they viewed as unfair treatment to the platforms' most loyal workers as their expectations of platform obligations to loyal workers went unmet. Our work contributes an expanded understanding of how the psychological contract operates in the nontraditional workplace of the gig economy. We highlight the importance for additional research around how psychological contracts emerge under conditions and fairness perceptions of algorithmic management to better understand how it is mediated between gig workers and algorithmic, platform control.

5.2 Future of Algorithmic Work for Workers by Workers

Prior work discusses common design dimensions of current algorithmic, platform work. This includes information asymmetry and associated power asymmetries [80], differential visibility of work often used for algorithmic control and how it impacts workers [65], and how workers resist or create coping strategies through algorithmic capabilities for autonomy [15, 56, 65]. Our work offers workers' ideas and imaginaries on how algorithmic and platformic work features can be redesigned to enable capabilities like information translucency to address information asymmetries, configurable incentive design as an alternative to unfair incentive systems, and worker-centered data analytics in response to the lack of well-being support from platforms.

To our surprise, the design ideas conceived by workers considered all involved stakeholders' interests (i.e., workers, customers, platforms) instead of simply the workers' own interests. They offered ideas that are realistic and can be implemented without the need to fully expose the working mechanisms of the platform. For example, past work has called for greater transparency in algorithmic work [36, 39], but this notion has been challenged by practical issues like proprietary rights around algorithms, the risks of workers' undesirable strategic behaviors in response, and the often inscrutable nature of some algorithms. Workers' design ideas though suggest that information translucency rather than complete divulgence may be satisfactory for workers to meet their needs.

Another call made by past work is one for eliminating power or information asymmetries. These requests inherently require platforms to relinquish control that may not be palatable to their business strategies. Platforms often implement gamified financial incentive mechanisms to encourage workers into working more or lure new or inactive workers to the platform [45]. These mechanisms establish a power asymmetry favoring platforms because

they allow platforms to influence or control how workers behave (e.g., drivers accepting unpreferable ride requests in order to qualify for an incentive bonus). While participants appreciated incentives and acknowledged the platform's business reasons for the financial incentives, they described accompanying harmful impacts on their physical and psychological well-being. As a way to address the issue, workers made design suggestions that mutually align worker interests and platform business needs and interests, such as allowing workers to suggest promotions that supported their preferences and constraints that platforms could then match to their own acceptable incentive structure.

Workers recognized the unique possibilities of their driver data, given how much platforms collect about them, and imagined ways that their data could be leveraged for the worker's benefit. Their ideas were focused around ways to derive personalized data-driven insights and receive recommendations from platforms to further their well-being. From recommendations around the attainability of their financial goals to planning work suggestions that incorporated financial, physical, and psychological well-being considerations, workers conceptualized ways that uninhibited data tracing on them could actually be used in their favor. Workers' ideas on leveraging data on their work patterns and performances for their well-being point to an area for future research that HCI and human-centered data science can contribute to. Prior research on personal informatics [23, 58] has investigated data collection, analysis, and sharing methods to help people make sense of their lifestyle and health data and improve their well-being. The context of work raises additional questions regarding worker privacy, data ownership, and conflicting stakeholder interests. Gig work platforms, workplaces where most of worker data is already digitized, is an opportune research site where these questions can be explored, which will offer implications for other workplaces that are increasingly being tracked and computer-and algorithm-mediated.

While some designs proposed by our participants are specific to the experiences and needs of rideshare drivers (e.g., around redesigning incentive and compensation structures), others may be applicable to additional gig work domains. For example, driver ideas for exploring their own data and receiving personalized data-driven insights or recommendations may apply to other digital gig work platforms such as food delivery (e.g., PostMates, DoorDash) or freelancing (e.g., TaskRabbit, Upwork, Fiverr). Food delivery workers may benefit from tools providing data-driven insights: these tools could identify their work patterns and earnings or suggest when and where to accept food delivery requests that support their well-being. Similarly, data-driven insights can assist freelancers by providing recommendations around the attainability and profitability of future tasks based on personal worker metrics of completed tasks.

6 LIMITATIONS AND FUTURE WORK

Our research sheds light on algorithmic management's impact on worker well-being, and design solutions that workers devised themselves. We also note limitations of current research that the readers should keep in mind and in the future should investigate. First, while design ideas from participatory design sessions resonated with multiple drivers and genuinely surprised our research team,

their effectiveness will need to be evaluated in future studies that implement and deploy them. Second, this qualitative study offers findings of the impact of the platform on worker well-being, which should be further investigated through a survey study with a large number of participants. Third, our participants were all active drivers and worked in the U.S., thus the experiences and ideas documented in this paper do not reflect those who stopped driving for these platforms or work in different regions of the world. Fourth, our participants were either members of a driver advocacy group or driver forums on Reddit, and 83% of them reported that gig work income was "essential for meeting basic needs". These participants may be more aware of and sensitive to issues in platforms and more likely to seek out to understand other drivers' experiences and consider collective action as a solution.

Fifth, we also acknowledge our participatory design session duration as a potential limitation. We wanted to keep the design sessions to a maximum of two hours for engagement, particularly because they were conducted remotely via Zoom and also due to drivers' time constraints and schedules as many of them are full-time drivers. While we were pleased with the ideas that drivers came up with and the quality of the discussion, we cannot say what other ideas drivers might have come up with if given more time. Furthermore, we recognize that with time constraints and the format of our co-design sessions, we were unable to delve deeply into the quantitative design preferences of drivers (e.g., how collective statistics for investigating work conditions can go further than a single driver's experience). Future work should extend the findings of our study by focusing on how to support workers through quantitative methods of analyses, for instance, collaborating with workers to understand how they can make sense of and use their own data or collective data to support themselves in designing data-driven solutions.

As some of our drivers noted, there is a practical limitation to some solutions due to tech platforms' willingness to make changes that go against their businesses, such as increasing ride information transparency. Designs such as mental or physical well-being nudges may fall in line with the changes companies made during the COVID-19 pandemic (e.g., allowing drivers to report customers who do not wear their masks). Others, however, may face more resistance by platforms as revealed by recent regulations and rideshare companies' reactions to them.

In 2020, Uber provided drivers in California control over ride pricing and viewing ride destinations to avoid classifying them as employees under California's AB5 law which outlined what established a worker as an independent contractor, including having full control over their work performance [3]. However, with the subsequent passing of CA's Proposition 22 classifying gig workers as independent contractors [1], Uber reversed course and removed the autonomy previously provided to California drivers [8]. Additionally, national legislation to provide gig workers with more rights has been at a standstill since March 2021, after the proposal failed to gain support amongst Republicans of the United States Senate [9]. In light of this uncertainty around regulations to support gig workers, future work may be limited to solutions outside of tech platform integration, such as third party applications or gig worker-led cooperatives to realize worker-centric solutions.

Finally, our research focused on drivers' experiences driving on the Uber and Lyft platforms. Recent work highlights the importance of investigating different features of different platforms instead of categorizing experience under the umbrella term of gig work platforms [29]. Because our study focused on rideshare gig workers, some of the solutions and implications of our research may not generalize to other gig work domains and should be assessed accordingly. For example, our findings around the expectation of a psychological contract by workers may not generalize to other gig work domains where workers have more control over setting their own rates for contract work. It would be important to understand how this psychological contract forms depending on the characteristics of the gig work domain and the level of control the worker has over the terms of their work. Additionally, it remains necessary to probe how workers of other gig work domains view fair treatment by their employer platforms, and how they maneuver these working relationships, in order to surface ways to improve the design of algorithmic management. Future work should thus examine our findings in the context of different platforms.

7 CONCLUSION

We discover new, more nuanced understandings of the issues workers face in light of algorithmic management, the ways they imagine addressing these, and how their fairness perceptions emerge towards the platforms they work on. Workers shared concerns around platform's lack of well-being support, unfair incentive structures, information asymmetry, and worker isolation. They co-designed interventions in response to these issues by exploring their algorithmic imaginaries how they envision platform algorithms can and should be designed to support their preferences and well-being. The designs and interventions they come up with were varied and are informative as directions of future work supporting gig workers, from reimagining platforms with well-being support through physical or mental health nudges; to considering how designs should take into account not only driver concerns but also platform and customer needs; to envisioning how worker data analytics can support their work goals. Our study also provides a glimpse into how the exploration of worker fairness perceptions of algorithmic management can surface areas for researchers to focus on to improve worker well-being: by inquiring how workers experience fairness through algorithmic control, we identify distinct processes where workers perceive inequities and how gig work may mediate a unique psychological contract worker expectations of employer and workplace treatment. These findings contribute to a growing understanding around the impact of algorithmic management on worker well-being as well as the ways workers imagine technology design that centers their well-being and work preferences.

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