Original Research Article

BIG DATA & SOCIETY

Big Data & Society
July–December: 1–13
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DOI: 10.1177/20539517221133779
journals.sagepub.com/home/bds
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Algorithmic precarity and metric power: Managing the affective measures and customers in the gig economy

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Abstract

Drawing on a qualitative, multi-case study of three kinds of geographically tethered gig work—ride-hailing, delivery, and domestic services platforms—in the United States, I examine how workers anticipate the influences of metrics, live with metrics, and cope with algorithmic precarity. Data for this project include in-depth interviews with 50 gig workers about their efforts to interpret and manage metrics as part of their everyday work practices. The analysis reveals that participants were anxious about metrics primarily because of the disciplinary outcomes, that are, the threat of job loss and the valued job features. It also directs attention to how workers felt and experienced customer-sourced ratings and system-generated behavioral metrics variously across platforms. Information asymmetries and the perceived lack of control also intensified a sense of powerlessness among participants. While participants articulated strategies that aimed at managing the uncertainty of customer-sourced ratings—and more precisely, the work-related uncertainty created by "difficult customers"—throughout service interactions, their feelings of anxiety could not be resolved. Furthermore, the (in)visibility of metrics, the settings of platform-mediated worker–customer interactions, and workers' platform dependence contributed to the varying disciplinary power of metrics. The study contributes to understanding how metrics as affective measures mediate the trilateral relationship between platforms, workers, and customers in the gig economy.

Keywords

Platforms, gig economy, metrics, precarity, algorithmic management, service triangle

Introduction

Quantification of work through performance metrics has long been a critical feature of labor control in manufacturing and service workplaces (Braverman, 1974; Moore, 2018a; Ranganathan and Benson, 2020). Scholars have shown that corporations rely upon algorithms and data to quantify and evaluate workers' performance in real-time (Kellogg et al., 2020; Moore, 2018a). The platform-mediated gig economy—which is "characterized by independent contracting that happens through, via, and on digital platforms" (Woodcock and Graham, 2020: 11)—amplifies the trend of quantification through the reliance on algorithmic technologies for managing workers at a distance (Jarrahi et al., 2021; Kellogg et al., 2020). One notable feature of algorithmic management is the integration of metrics, such as customer-sourced ratings and system-generated behavioral measures, into algorithmic evaluation and discipline (Gandini, 2019; Kellogg et al., 2020; Stark and Pais, 2021). An Uber driver quoted in a technology blog article, for example, shared, "We're not just working for money … We're working for ratings, but ratings have no value. Ratings serve only to prevent you from getting fired" (Dzieza, 2015: para 27). A minor change in customer-sourced ratings can hinder workers' job prospects, though workers have limited ability to dispute the influences of ratings (e.g. Chan, 2019b; Rahman, 2021; Rosenblat, 2018). The fragility and opacity of ratings contribute to workers' feelings of anxiety and insecurity (Kellogg et al., 2020; Ravenelle, 2019; Wood and Lehdonvirta, forthcoming), or what Duffy (2020) terms "algorithmic precarity."

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Much scholarship has examined the disciplinary outcomes of metrics on various geographically tethered (e.g. ride-hailing and domestic services) and cloudwork (e.g. online freelancing) platforms (Griesbach et al., 2019; Sutherland et al., 2020; Ticona and Mateescu, 2018; Veen et al., 2020). This comparative research examines how the affective power of metrics and workers' precarious experiences vary across geographically tethered platforms—including ride-hailing, delivery, and domestic services platforms—in the United States. Geographically tethered platforms require workers to perform an on-demand task in a particular location (Woodcock and Graham, 2020). The three cases of gig work involve some forms of service interactions with customers, which situate metrics into the service triangle—a "three-way contest for control and satisfaction" (Leidner, 1993: 22). There are two main types of metrics, namely customer-sourced ratings and system-generated behavioral measures. Customer-sourced ratings entail customers' assessment of service quality and can impact one's employment opportunities on the platform. On ride-hailing and delivery platforms, customer-sourced ratings can determine the continuity of platform-based employment. On TaskRabbit, ratings affect the visibility of workers' online profiles. Additionally, system-generated behavioral measures are often designed to facilitate efficient service transactions. Examples include workers' job acceptance rates, cancelation rates, and speed metrics (e.g. how long a courier takes to deliver, how quickly a TaskRabbit worker responds to a service request, and how fast a ride-hailing driver drives).

I argue that metrics—and more specifically, what metrics make visible, to whom, and for what purposes—serve as a valuable avenue for examining the algorithmic discipline of workers (Kellogg et al., 2020) as they reveal how the measured *ought* to be represented. Building upon Beer's (2016) work on metric power, I conceptualize metrics as "affective measures" that "are aimed at stimulating anticipation and uncertainty—often coupling these with senses of insecurity and precarity" (p. 210). Metrics provoke preemptive and reactive affective responses (Beer, 2016; Espeland and Sauder, 2016). As we consider the (in)visible metrics as affective objects that have the potential to make workers feel anxious and precarious (Beer, 2016), how do gig workers encounter, feel, and manage metrics across labor platforms? In what ways do metrics shape and intensify gig workers' precarious experiences? How do platform-based metrics shape the power dynamics between platforms, workers, and customers in the gig economy?

Drawing on a qualitative, multi-case study of ride-hailing, delivery, and domestic services platforms in the United States, I examine how workers anticipate the influences of metrics, live with metrics, and cope with algorithmic precarity. Data for this project include in-depth interviews with 50 gig workers about their efforts to interpret and manage metrics as part of their everyday work practices. The analysis reveals that these workers were anxious about metrics because of threats of job loss and valued job features (e.g. job flexibility). Information asymmetries and the perceived lack of control over customer-sourced ratings further contributed to workers' precarious experiences. Therefore, interviewees articulated strategies to manage the uncertainty of customer-sourced ratings—and more precisely, the work-related uncertainty created by "difficult customers"—before, during, and after service interactions. Such strategies hoped to safeguard workers' ratings and, therefore, their employability; however, they could not resolve workers' concerns and feelings of anxiety. While anxiety is often considered a psychological state of anticipating an uncertain yet threatening future (Ahmed, 2004), it operates as a technique of governing the self across labor platforms (Beer, 2016; Moore, 2018a). Despite the convergent themes about the affective power of metrics and worker's strategies across the three cases, the (in)visibility of metrics, the settings of platform-mediated worker–customer interactions, and workers' platform dependence contributed to the varying disciplinary power of metrics.

This study makes three contributions. First, following Beer (2016), it contributes to understanding metrics as affective measures by attending to how metrics shape and are shaped by the trilateral relationship between platforms, workers, and customers. It is through the perceived disciplinary outcomes of metrics and unpredictability of customer that metrics can make workers feel and govern themselves. Second, following previous scholarship (Cameron and Rahman, 2022; Pink et al., 2018), the study offers a processual and relational view of how workers strategically manage the power of metrics throughout platform-mediated labor processes. Third, by examining gig workers' practices around metrics across labor platforms, the study contributes to understanding the convergence and divergence of metric power in the gig economy.

The power and reactivity of metrics

Metrics are connected with the process of quantification, which is "the production and communication of numbers" (Espeland and Stevens, 2008: 8). Sociologists of quantification have demonstrated the profound impacts of metrics on the subjects of evaluation—which can be individuals, organizations, or social fields—and their decision-making processes (Christin, 2020; Espeland and Stevens, 2008; Mennicken and Espeland, 2019). Three interrelated points explicate the social power of metrics in the literature. First, quantification defines what counts by "turning qualities into quantities on a shared metric" (Espeland and Sauder, 2016: 41). Second, metrics establish social hierarchies of worth in terms of what count as socially desirable (Mau, 2019). Uber's 5-star ratings, for example, do not present drivers' scores on an ordinal scale, but they can prescribe what counts as "high-quality" service and orient drivers' attention toward such normative standards (Chan, 2019b; Mason, 2019). Third, metrics are reactive, meaning that "people change their behavior in reaction to being evaluated, observed, or measured" (Espeland and Sauder, 2007: 1).

Particularly relevant to this study is the concept of affective measures, which can be understood as a key mechanism of reactivity (Beer, 2016). Metrics, explain Beer, "as deeds, are a part and product of a series of affective practices that have the power to make people feel uncertain, precarious, and anxious" (p. 203). Metrics are affective objects because metrics are used to provoke particular forms of affective responses that favor productivity and market competition through the production of uncertainty. Workers worry about a low customer-source rating primarily because they may fail to realize "the cluster of things that the object promises" (Berlant, 2011: 24), which could be related to competitive advantage and the evasion of deactivated from labor platforms (see Beer, 2016). Metrics generate perpetual pressure (Mau, 2019) for workers *always* strive to perform better to avoid becoming targets of punishment. This draws attention to the practices that make metrics affective—how anxiety becomes attached to metrics and circulates across the social world (Ahmed, 2004; Beer, 2016).

The power dynamics of metrics in the gig economy are distinct from those in other contexts such as public measures (e.g. Espeland and Sauder, 2007, 2016) and social media metrics (e.g. Christin and Lewis, 2021; Duffy et al., 2021). Compared to public measures like university rankings, algorithmic metrics remain largely opaque in the gig economy (Rahman, 2021; Rosenblat, 2018). This provides opportunities for exploring how workers navigate metrics in the absence of clear evaluative criteria. Following Leidner's (1993) work on the service triangle, the presence of customers adds another layer of uncertainty to workers' reactivity to metrics because platforms and workers cannot control customers' service interactions and evaluative practices. Without occupational training, metrics help to script service interactions through evaluation and discipline. An examination of metrics allows us to consider how they mediate conflict and coordination among platforms, workers, and customers.

Different types of metrics come with various disciplinary outcomes in the gig economy. Most of the platforms (i.e. Uber, Lyft, DoorDash, Instacart, and TaskRabbit) I studied deploy a five-star customer rating system. Like social media metrics (Christin and Lewis, 2021; Cotter, 2019), TaskRabbit workers' ratings are markers of visibility. From participants' perspectives, the higher their ratings are, the more likely their online profiles will be seen by prospective clients on TaskRabbit. When ride-hailing drivers and couriers' average customer-sourced ratings fall under a certain location-based threshold, they may receive warnings or even become "deactivated" by the platforms. Meanwhile, ride-hailing, delivery, and domestic services platforms measure workers' job acceptance rates, cancelation rates, and other behavioral metrics. Following Beer (2016: 77), "*not all measures are equal*" since "some become more visible, more telling, or more consequential than others" (italics original). By exploring gig workers' affective encounters and practices with algorithmic metrics at different stages of the labor process (see Cameron and Rahman, 2022), this study helps understand the heterogeneity of metric power and algorithmic management in the gig economy.

Governing the precarious and anxious worker in the gig economy

The gig economy encompasses geographically tethered work and cloudwork that are matched and mediated via digital platforms (Woodcock and Graham, 2020). Despite the promises of flexibility and autonomy in the gig economy, workers are subject to precarious work conditions and algorithmic management (Kellogg et al., 2020; Ravenelle, 2019; Wood et al., 2019). Precarious work, explained by Kalleberg and Vallas (2018: 1), refers to "*work that is uncertain, unstable, and insecure and in which employees bear the risks of work … and receive limited social benefits and statutory protections*" (italics original). Precarity entails not only workers' anxiety about job loss but also the loss of valued job features, such as task discretion in uncertain futures (Gallie et al., 2017). Much research has highlighted the precarious labor conditions in the gig economy (e.g. Sun et al., 2021; Van Doorn, 2017). By classifying gig workers as independent contractors, labor platforms may disown employment obligations and shift work-related risks to workers (Gregory, 2021; Van Doorn, 2017). According to Jarrett (2022), the informal employment status of platform workers indicates "an almost total absence of formal mechanisms for providing work and skill reproduction security" (p. 51) as well as occupational safety and health (OSH) (see Gregory, 2021).

Algorithmic management, together with the uncertain working conditions, contributes to gig workers' precarious experiences (Gregory, 2021; Ravenelle, 2019; Wood and Lehdonvirta, forthcoming; Wood et al., 2019). Metrics represents a key technique of algorithmic management (Gandini, 2019; Kellogg et al., 2020). Workers' metrics may either influence the continuity of platform-mediated employment (Griesbach et al., 2019; Rosenblat, 2018) or affect the accumulation of reputational capital (Fourcade and Healy, 2017; Sutherland et al., 2020; Ticona and Mateescu, 2018). Customer-sourced ratings can be mobilized as the revival of customer control (Cameron and Rahman, 2022; Maffie, 2022; Rosenblat, 2018) and techniques of gamification that attempt to win workers' consent (Mason, 2019; Vasudevan and Chan, 2022). While reputation systems rooted in interpersonal relations have traditionally been utilized to gain trust in freelance markets, Wood and Lehonvirta (forthcoming) contend that labor platforms contribute to reputational insecurities by disrupting reputation, amplifying the power of customers over workers, and facilitating algorithmic opacity.

What is at stake here is how workers feel algorithms in their everyday encounters with metrics (Beer, 2016; Bucher, 2017; Pink et al., 2018). As Bucher (2017) contends, "what people experience is not the mathematical recipe as such but, rather the moods, affects, and sensations that the algorithm helps to generate" (p. 32). While precarity is often cast as a convergent outcome of algorithmic management, Schor et al. (2020) have demonstrated that economic dependence and barriers for platform participation (e.g. asset requirements) result in variations in precarity (see also Ravenelle, 2019). As precarity can be unequally distributed (Jokinen, 2016), so can feelings of anxiety.

Gig workers can reclaim their labor agency in their everyday lives by learning to navigate metrics—and more broadly, algorithmic management—on which they are being tracked, evaluated, and disciplined. Such everyday practices include unpaid labor, emotional labor, gaming algorithmic rules, and collective sensemaking practices (Cameron and Rahman, 2022; Chan, 2019b; Rosenblat, 2018; Sutherland et al., 2020; Vasudevan and Chan, 2022; Wood and Lehdonvirta, forthcoming). Cameron and Rahman (2022) argue that workers engage in preemptive, interactive, and reactive resistance tactics before, during, and after work. They found that workers' agency is not evenly distributed throughout the labor process. For example, freelancers can safeguard their ratings by vetting customers before accepting a task, mainly because customers do not know their actions and cannot rate them. There is a diminishing of workers' latitude to resist the influences of labor control and customers after accepting and performing tasks. Although freelancers might try to gain the favor of customers through interactive tactics during work and submit a complaint about an unfair rating to the platform after work, they have limited control over how customers evaluate their performance and whether the platform would remove the rating. Their processual approach (see also Pink et al., 2018) helps to understand how the affective power of metrics may be circulated at different stages of work.

Accordingly, I examine how gig workers are governed by metrics before, during, and after platform-mediated service interactions. Workers' anticipatory practices, on the one hand, can be characterized as attempts to maintain their routines and cope with feelings of anxiety. On the other hand, data are continuously produced, so are feelings about data (Pink et al., 2018). Pink et al. (2018) draw attention to how individuals continually cope with data anxieties in their mundane routines of everyday life, whereas Jokinen (2016: 85) argues that precarious everyday agency is "a habit of habit-breaking." In league with Berlant's (2011) work, Jokinen considers precarization as a social process through which a society becomes more precarious, disorganized, and discontinuous. While habits help individuals to organize their daily life, the repetition of habit-breaking becomes a norm that *disorganizes* daily routines. To put this simply, Jokinen states, "The sense of the present is intensified in precarious agency. What happened yesterday, or last year, or during half of your life, might not be relevant today" (p. 96). While workers articulate coping strategies to routinize their work practices momentarily, such strategies can be endlessly disrupted by algorithmic management in gig workers' everyday lives.

Cases and methods

This study was undertaken as part of a larger project that investigated how workers encountered, interpreted, and managed algorithmic metrics in the gig economy in the United States. The project began by studying ride-hailing drivers' (i.e. Uber and Lyft drivers) work practices around ratings,[1] and then included the cases of delivery (i.e. DoorDash, Uber Eats, and Instacart) and domestic services (i.e. TaskRabbit) for comparing the affective power and reactivity of metrics across a range of platform-mediated gig work. Central to a multi-case study approach is "the idea that the objects of investigation are similar enough and separate enough to permit treating them as comparable instances of the same general phenomenon" (Ragin, 1992: 1). The three cases are considered geographically tethered gig work (Woodcock and Graham, 2020) and service work. Workers must complete on-demand tasks and interact with customers in a particular location. The emphasis on service workers helps to situate metrics into specific settings of platform-mediated worker–customer interactions. Meanwhile, the cases vary in terms of the visibility of metrics and metrics-related rewards and sanctions.

Ride-hailing platforms enable drivers and customers to rate one another's performance on a 5-star scale. Drivers' ratings remain visible to themselves and customers during service interactions, but customers cannot view the former's ratings since then. Drivers' ratings are not only used for determining the continuity of working on Uber and Lyft but are also one determinant of participating in platform-based rewards programs. Uber Pro rewards program, for instance, requires drivers to maintain at least a 4.85 rating to earn their status in a given period. Additionally, system-generated behavioral measures include acceptance rates, cancelation rates, and speed metrics.

The second case includes workers on Uber Eats, DoorDash, and Instacart. DoorDash and Instacart both use a 5-star rating system, whereas Uber Eats asks customers to give a thumbs up or thumbs down to couriers. Like ride-hailing platforms, couriers' ratings directly affect the continuity of employment. While DoorDash and Uber Eats match a customer to a driver algorithmically, Instacart uses ratings to determine which delivery orders workers can view and select on the platform. Delivery platforms' system-generated behavioral measures are similar to that in the case of ride-hailing platforms, but the former (e.g. DoorDash) also measures couriers' completion rates and on-time/early rates.

In the third case, I examine TaskRabbit, wherein service providers (or "Taskers") can be hired for various domestic tasks such as moving, cleaning, and furniture assembly. Taskers can communicate with customers *before* accepting and completing a task. After completing a task, Taskers will be rated on a 5-star scale. TaskRabbit measures workers' response, acceptance, and reliability rates. A Tasker's profile indicates whether s/he is an "Elite Tasker" and displays individual reviews and a percentage of "positive" ratings (3 to 5 stars). As such, ratings have a high level of visibility for Taskers and their prospective clients, but they are only used for determining the visibility of Taskers' online profiles.

The case studies involved 50 in-depth interviews with workers, including 21 ride-hailing drivers, 11 TaskRabbit workers, and 18 couriers. I drew upon platforms' corporate discourses about ratings to supplement and contextualize the findings. The project was divided into two phases.[2] I began by studying ride-hailing platforms in the first phase of the research in 2017 and 2018. Most of the interviews with ride-hailing drivers (14 of 21) were conducted at that time. I set out, in 2020, to interview more ride-hailing drivers and include the other two cases for comparative analysis. Although I conducted interviews with gig workers during the early period of the COVID-19 pandemic, the primary goal of this study was to understand how algorithmic metrics shaped and intensified workers' precarious experiences across labor platforms. Yet, particularly with delivery platforms, participants' precarious experience and mitigation strategies became intersected with the evolving work environment during the pandemic.

As gig workers lack a shared workplace, I recruited interviewees online (e.g, posting recruitment messages on Twitter and worker-to-worker online communities) and through snowball sampling via interviewees' networks. The interview sample varied in the lengths of platform-mediated work experience (from 2 months to 9 years), working hours (from 3 h to 72 h per week), and geographical locations (over 10 cities throughout the United States). The sample was skewed to male gig workers (40 of 50), partly because driving and delivery work are male-dominated industries and partly because female gig workers might be in a more vulnerable position to accept an interview request in worker-to-worker online communities.

Interviews were conducted over the phone and/or videoconferencing tools (e.g. Skype and Zoom) and were audio-recorded with participants' permission. I used a similar interview guide in both research phases, while I refined the wordings to correspond to specific platform interfaces and features. Topics included participants' background, uses of metrics and platforms, interactions with customers, acquisition of work-related information, and reflections on their work. Most of the interviews lasted between 30 min and 1 h. I followed a process outlined by LaRossa (2005), which is consistent with the grounded theory approach. I began with open coding, which identified the key terms and basic frames used by the participants. Axial coding identified the conditions through which the interviewees felt about metrics. Finally, the themes concerning the affective power of metrics emerged from selective coding. During the analysis, I paid attention to similarities and differences in participants' responses to the affective discipline of platform-based metrics across the three cases.

Findings

Affective power of (in)visible metrics

During their expositions, most interviewees anticipated the disciplinary outcomes of metrics and expressed affective feelings about metrics. Echoing Beer's (2016) observations that not all metrics are equal, I found that the interviewees kept close attention to customer-sourced ratings but less to system-generated behavioral measures. Being rated low by customers could threaten workers' employment opportunities and valued job features. The disciplinary outcomes of the behavioral measures, nonetheless, remained somewhat obscure. For example, Derek, an Instacart driver, noted that cancelation rates and speed metrics "are not important" because they do not "impact how many batches you will see." Roger also learned from Reddit's discussions that "acceptance rate means nothing" for Uber Eats and DoorDash couriers because they would not result in deactivation. He added, "if the acceptance [rate] doesn't ruin it, then I can choose what I want to do." While Derek and Roger considered that system-generated behavioral measures are dispensable to their employability, Sean believed that having a low completion rate might result in deactivation on DoorDash. Importantly, the perceived necessity of maintaining a high completion rate might threaten the flexibility of accepting orders they saw as valuable. Sean offered an example:

> Something I do pretty often is I'll accept an order to see how much money the order was because people who order more money worth of food are usually going to tip more. If I accept an order and because it says it has 12 items and I pull open the order and I accept it and it's 12 water bottles, it's not a big order, it's probably not going to be a big tip. So it probably won't be worth the time. I'll cancel that order. That affects my completion rate.

Sean's experience exemplifies how system-generated behavioral metrics (e.g. completion rates) become intertwined with other parts of the labor process. Although the platform did not provide sufficient information about the orders, he had to accept most of the orders he received to maintain the completion rates. Jeremy raised a similar concern about Uber's acceptance rate, "So in a way, it's kind of like I should be an independent contractor as an Uber driver but if I reject too many ride requests, that could put my standing on the platform in jeopardy." In short, the interviewees had a disagreement over the potential disciplinary outcomes of system-generated behavioral measures. This might explain why many of the participants paid less attention to such metrics. Moreover, as I will illustrate below, customer-sourced ratings are more difficult to maintain due to the unpredictability of customers in service interactions.

It was more common for the interviewees to express their concerns over customer-sourced ratings guided by metrics-related rewards and sanctions. The (in)visibility of metrics contributes to workers' affective responses to ratings. Since TaskRabbit's ratings are *visible* to prospective customers and may increase the visibility of workers' profiles, Taskers were under the impression that their ratings were essential to clients' hiring decisions. An "Elite Tasker," Renee, shared, "I have built up profile with reviews and really high metrics. So it becomes … just an opportunity for me to make money and let clients come to me." Murdock, too, suggested that "With TaskRabbit, the metrics are very important. I have to have really good reviews … And I've had clients choose me because of the kindly written review that was left by a previous job."

Ratings remain relatively *invisible* and have different disciplinary outcomes in ride-hailing and delivery platforms. The majority of the interviewees shared that the rating system was "useless" and did not have any "real benefits" because positive ratings could not be transferred into monetary rewards. What is at stake here is the threats of job loss and other perceived disciplinary outcomes of the evaluation. Shawn, for instance, looked at his customer-sourced ratings on DoorDash "because if [I] get under a certain rating, then that's when they terminate me." Among the interviewees, Jeremy was the only one who had received a warning message about his rating dropping from 4.7 to 4.6 from a platform (Uber). He did not understand why this occurred and told me, "I was extremely confused, and I was panicking because, well, if they deactivate me, it kind of makes me screwed." The interviewees felt affectively attached to ratings because failing to maintain a minimum rating means that they might no longer be able to work on the platform in uncertain futures.

Let us look at Eddy, who worked as an Uber driver for 3 months in 2014 and later worked for Lyft between 2017 and 2018. Recalling his first time driving for Uber, he shared, "I had heard a rumor [from Reddit] that if you drop below four stars, then you could be in danger of getting kicked off the app. Because I was dependent on it at the time, entirely dependent on it for income, I definitely was aware." Despite working for a different platform (Lyft) 3 years later, he continued,

> At the time as a driver, I didn't, to be honest with you, see very much difference … I think I even received an email from Lyft, they would blast out these driver newsletters that said "You want to stay roughly above 4.8 and that anywhere below 4.6 is dangerous." That made me worry about the rating and in very much the same way I did in 2014.

Both Uber and Lyft changed the design of their platforms and rating systems to promote "transparency" in this period; however, these changes did not resolve Eddie's anxiety about job loss associated with metrics in uncertain futures.

Customer-sourced ratings entail anxiety about perceived threats to valued job features. Connected his ratings with the Uber Pro program, Dominic explained that being qualified as a Diamond driver would allow him to "get preferred pickups at the airport" and "get the destination" information. Each Uber Pro program period only lasted for 3 months, and he explained, "If we're closer to the end of the ratings year, which actually one just ended January 31st, I would be more anxious about it. Because you need 4.85 to get it." He was, therefore, under pressure to maintain the rating to keep him qualifying for the ability to accept the most profitable rides.

Making sense of affective measures: The production of work-related uncertainty

For participants to cope with algorithmic precarity, they must interpret what counts the most and how they could manage metrics to avoid punishment. Yet, information asymmetries and perceived lack of control intensified a sense of powerlessness among participants who were anxious about their employability in the gig economy.

First, workers often lack actionable information to "improve" their performance, which is consistent with existing research (Jhaver et al., 2018; Rahman, 2021; Rosenblat, 2018). There was a common refrain among the interviewees that they "don't really know," when asked about their understandings of customer-sourced ratings. Here, the epistemic uncertainty is less about the lack of knowledge about the calculation methods and consequences of metrics and more about the difficulties of interpreting and managing metrics. Kuzma shared his experiences about TaskRabbit's customer ratings, "Particularly the ones [negative ratings] that don't offer an explanation, those are the most frustrating because I'm a person to admit that I don't know everything or I'm not the best of everything." On ride-hailing and delivery platforms, individual ratings for each service transaction remained invisible to drivers and couriers. The interviewees mentioned that when they looked at the "rider feedback" in the driver application, they might only see the "top reported issue" (e.g. "cleanliness") with no further explanations. Carter's reflection on DoorDash's rating illustrates the unpredictability of ratings:

> I understand that they're telling us what is the range between 4.60 is medium, or 4.80 is high. 5.0, it's higher, above average. But what I really would like for them to do one thing, and this is what I requested numerous times. Please, if our customer ratings drop, they should be giving us a list to know, what was going on, why did our rating drop? … So I know how I can do [a] better job next time.

From a design perspective, customer ratings should ideally provide a trustworthy assessment of service quality and hold workers accountable. While interviewees like Carter and Kuzma would agree with the ideal functions of ratings and wanted to improve themselves, they soon realized that ratings worked against their desire to pursue self-improvement due to the lack of actionable feedback.

Second, workers have limited power to control their ratings due to the unpredictability of customers. Interviewees' speculations about their ratings were primarily related to their service interactions with "difficult customers," those who had "unreasonable" expectations about workers and thereby gave them a low rating. As one of my interviewees shared, "the worst customers I get are the customers who don't understand what the job of the driver [worker] is." Examples of unreasonable customer expectations include requesting ride-hailing drivers to pick them up in places where drivers cannot park and stop, squeezing too many people in the backseat of the vehicle, and asking drivers to go over the speed limit. On TaskRabbit, workers encountered customers who might have unreasonable expectations about their rate and the estimated length of tasks.

The case of delivery platforms is illustrative of the perceived lack of control and unreasonable customer expectations. Consider, for example, the timely delivery of orders, which seems a reasonable customer expectation at first glance. Nonetheless, customers might misattribute the responsibility of restaurants to workers through their ratings. Sean and Dylan suggested some restaurants consistently deprioritized platform-mediated orders. Sean told me, "There are restaurants that I definitely avoid because they aren't quite honest with me about when the food will be ready, and I end up waiting there for a long time." Dylan similarly noted, "Uber Eats drivers may receive lower priority at certain restaurants and they will focus on other customers even if they arrive afterwards." Couriers might have a long yet uncompensated waiting time at a restaurant while being rated low by their customers.

The perceived lack of control becomes amplified among couriers during COVID-19 because the pandemic's disruptions have recognized the delivery process. While platforms suggested couriers check whether the items inside the bag were accurate before COVID-19, restaurants have now sealed their delivery bags for safety reasons. Yet, couriers could potentially receive a low rating because of missing items. Clara observed that the instances of reporting missing items and orders, or what she called "scams" on DoorDash seemed to increase during the pandemic. While she complained about these instances to DoorDash, the platform tended to favor customers over workers. She added, "[T]his is going on our rating, that we are not doing the properly delivery … You have no testimony. You have no witness. You have nothing." Inherent in her reflection is a sense of the powerlessness of workers to dispute unfair ratings. Ronnie shared, "So when they're [customers are] asked by DoorDash how they felt about their delivery experience, they will rate us negatively based on what happened at the restaurant, which was beyond our control." His experience is telling of the distinction between evaluation of delivery experience and of restaurants. Although DoorDash and Uber Eats have separate rating systems for couriers and restaurants, they remain ambiguous in practice because it is subject to whether customers follow the evaluative rules.

In sum, workers encounter difficulties in interpreting customer-sourced ratings due to information asymmetries. Customer-sourced ratings place workers in a vulnerable position because ratings reinforce and rationalize power imbalance between platforms, workers, and customers. The unpredictability of customers is built into gig workers' everyday lives through metrics, which facilitate the production of work-related uncertainty.

Managing the affective measures and customers

I now turn to discuss how different types of workers cope with algorithmic precarity, followed by an examination of the varying disciplinary power of metrics across platforms. Building upon Cameron and Rahman (2022), I analyze workers' routine practices for managing customer-sourced ratings and customers at different stages of platform-mediated labor processes. Specifically, participants learned to filter difficult customers *before* service interactions and manage customers' expectations *during* and *after* service interactions. Although participants carried out such practices to routinize their communication with customers and to reduce work-related uncertainty, they could not resolve the feelings of anxiety because the root of the anxiety has to do with the fear of losing employment opportunities and the valued job features.

Managing ratings and customers before service interactions. Dealing with "difficult customers" was a common frustration among the interviewees. Central to workers' agency was how they could anticipate and filter these customers in advance and decide not to accept their requests.

A common strategy for ride-hailing drivers was to refuse taking any shared rides (i.e. UberPool), though Uber's rating protection had included "co-rider" as one of the qualifying options for removing negative ratings automatically. Clayton denounced UberPool as "a bad product":

> I hate UberPool because you consistently get rated lower on UberPool than you do on UberX, because it's a bad product, not because you're a bad driver … If you miss your airplane because you took UberPool, you're going to one-star your driver, even though it's not the driver's fault … Or you'll get in the car with somebody you don't like … Because you're mad about Billy, who's arguing with you about politics or whatever, you had a bad experience on your drive, you're going to rate your driver lower, even though it's not his fault. It's Billy's fault.

Clayton's comment reveals why drivers strategically avoid providing carpooling services, as evident in existing research (e.g. Reid-Musson et al., 2020). As Brandon put this, "It's a lose-lose for the driver." While a few interviewees might use customers' ratings to screen difficult customers, it was more common for participants to dismiss customers' ratings because drivers only had 15 s to respond to ride requests. As such, the temporal visibility of ratings constrained how drivers could use ratings to vet customers.

Like ride-hailing platforms, couriers only had a few seconds to accept an order, and they had even less information about their customers before accepting orders, because DoorDash and Instacart do not allow couriers to rate their customers. This might explain why the interviewees who worked on delivery platforms had limited ability to filter their customers to protect their metrics. Couriers mostly attended to the restaurants and the pay of the orders. As noted earlier, participants realized some restaurants might give platform-mediated delivery orders a low priority; therefore, they preferred to filter out restaurants that tended to have a long waiting time. Shawn only accepted orders above $6 with customer tip because he found that customers who did not tip might give him a low rating.

Compared to the other cases, Taskers had the most latitude to manage metrics at this stage because they could communicate with their prospective clients before accepting a task. All the interviewees told me they would carefully examine the initial task explanations and ask questions about a task before accepting it. In the pre-hiring process, participants wanted to look for "understanding and flexible clients" and to ensure that both of them had the same expectations about the task. For example, Scarlett was 71 years old and mainly performed the tasks of delivery and shopping. She learned to ask prospective clients questions about the delivery and pickup addresses, time expectations, and the delivery items after receiving a negative review when a client had hired her to organize for moving, packing, and unpacking delivery items. As she explained, "More often than not, the clients are not very clear with what they want, and sometimes it's because they're poor communicators and sometimes it's because they're not clear themselves." While Scarlett directed attention to the "fitness" of the task, Murdock attempted to profile "sketchy" customers who provided little information in the initial task explanation. He reasoned, "The client can just use anybody's credit card and debit card and just sign up and hire somebody." In this case, he would tell clients he might not be "a good fit" and asked them to cancel the tasks. As he said, "If the client cancels, there is no risk on my half or my metrics. If I cancel, there's a risk of me losing that acceptance rates."

Participants maintained that the process of communicating expectations must take place via TaskRabbit's chat, even though prospective clients might call them to discuss the tasks. Using the chat function allowed them to document and protect themselves against difficult customers at the later stages. As Neyland explained, "Actually in each step with the client, it's very important to have the expectations set pretty clearly." In doing so, he added, "[I]f anything does go wrong or if they try to ask more or cause a dispute in regard to the job, then it's very clear in writing that nothing's going on." Kooper, too, shared "I've made sure to document everything in the chats … If anyone has tried to or will try in the future to … say there's something wrong, we clearly discussed it in the chat."

Managing ratings and customers during and after service interactions. All interviewees, regardless of the platforms they worked on, considered being a "people person" a required skill for them to navigate their work and manage their customers. This is because customers have a higher degree of control during platform-mediated service interactions (Cameron and Rahman, 2022).

The routine practices of managing customers' expectations occurred *before* the physical encounter between workers and customers. Ride-hailing drivers and couriers might contact customers via phone call or in-app messages to tell them their estimated arrival time, especially when they anticipated they might be late. Although customers could see such information in the apps, participants found this strategy helpful for conveying "friendliness" to customers. Importantly, platforms could have inaccurate estimation due to weather, heavy traffic, and other factors. For instance, couriers might have a long waiting time at a restaurant. Explaining this situation to customers allowed them to clarify the liability for the delay in delivery.

On TaskRabbit, workers needed to discuss the details about the task at various stages of the work process. Reflecting on his strategy for maintaining a positive rating, Kooper shared "over-communication has been my trademark," because he would spend extensive time discussing with his clients. This was a common strategy among the Taskers I interviewed. This process of virtual communication not only demonstrated their commitment to the task, but also set clear service expectations, especially because some customers might not stay in their homes during the task. Kooper explained,

> You never see the client in person. So, you do the job and then you leave and then they come and write a bad review, but then you're not able to communicate what was going on. They didn't communicate to you how you could assist. You couldn't defend yourself.

This narrative exemplifies the importance of communicating with clients in person. Kuzma noted that a client's description of the task might differ from the actual situation, which required instant communication. For instance, he had been hired for an hour for a moving job, but he realized soon after arriving that the task might take 4 h. He needed to immediately communicate with the client to manage expectations about the length of the task. As Taskers might have multiple tasks in one day, participants avoided scheduling back-to-back appointments to safeguard their metrics.

Participants, particularly those working on TaskRabbit and delivery platforms, learned to document their work in service interactions to protect themselves against difficult customers. In addition to communicating with clients via the platform's chat for documentation, Taskers would take photos of their tasks (e.g. furniture assembly and cleaning) and share them with customers in the chat. As Zoey explained, "I try to make sure everything is in the chat, so if something goes wrong, I have proof." This was because TaskRabbit had a relatively better dispute mechanism than the other two types of platforms. Jeffery, Zoey, and Kooper had filed complaints regarding unfair ratings. They perceived that TaskRabbit would remove the ratings as long as they provided detailed documentation about their tasks.

Couriers had relatively limited interactions with customers, in part due to the introduction of contactless delivery during COVID-19. Nonetheless, contactless delivery has created another form of work-related uncertainty. Connor's comment exemplifies this, "Negatively, you have to trust that the customer will take their order off their own doorstep, which sometimes can lead to the order disappearing altogether or them claiming they never received the order." Echoing Clara's previous observations about "scams" on delivery platforms, customers might rate couriers low when they report missing items. As a response, participants learned to protect their ratings. Lorenzo, for example, shared, "I take a lot of pictures of things that I've dropped off just as protection because I've had people report that I haven't delivered things when I have." Sean echoed this and shared, the "picture proof" resulted in "a lot less issues with people claiming that I didn't deliver the food when I actually did." These interviewees, however, never successfully disputed an unfair rating because delivery platforms tended to prioritize the authority of customers. Derek condemned Instacart for enabling "customers do anything" to "hurt the shopper." He explained, "Many times, we take pictures of delivery or the good, and then if a customer claim they have a wrong item, totally fraud, and we can report it in the app, but that doesn't remove the rating … The customer has total privilege to give you any ratings they like."

Workers have limited control over their ratings after service interactions (see Cameron and Rahman, 2022). While they could dispute what they considered "unfair" ratings, participants—except those working on TaskRabbit—found that the dispute rarely changed their ratings. Recalling his experience of contacting Uber and Lyft to dispute ratings, Adrian shared that the help desk would simply read "you a basic script … they don't understand day-to-day" operations. Collin shared similar concerns, "Uber Eats' support, I think, is meant more [for] the customer than for the driver because when I talk to the support, I describe my problem to them, and they have no idea what I'm talking about." Taskers were satisfied with the dispute outcomes, but participants pointed out a successful outcome required unpaid efforts of documentation, and that the dispute process took a long time.

Workers attempted to routinize their interactions with customers to minimize the source of unpredictability. However, every service interaction is a new one and critical in determining their ratings and thereby their future-oriented employability. Participants felt anxious about metrics, because difficult customers could break their work routines and threaten their employability by having unreasonable expectations about service interactions. Indeed, as gig workers strive for a good rating, they are hopeful that the rating could help them to stay on the platform and even increase employment opportunities. What is cruel here is that while workers attempt to gain the favor of customers with hope of maintaining their employment, ratings may fail to deliver on the promise. As one of the interviewees noted, "People can misuse you, and you can't get out of it … because they have the right to rank you."

The varying disciplinary power of metrics

Much of the analysis discussed the similarities across the three cases in terms of workers' affective responses to ratings and the strategies that they articulated to cope with their precarious experiences. I primarily focused on customer-sourced ratings rather than system-generated behavioral measures as most of the participants were more attentive to the former. Being rated by customers was associated with the fear of losing employment opportunities on the platforms and being deactivated, whereas the latter's disciplinary outcomes remained unclear. Additionally, there are three key factors that make up the varying disciplinary power of customer-sourced ratings across platforms, namely the (in)visibility of metrics, the settings of platform-mediated worker–customer interactions, and workers' platform dependence.

As Beer (2016) argues, "metrics can be used to expose or conceal, to highlight or obfuscate, to illuminate or shade" (p. 173). What is at stake here is what and how metrics are visible to workers and customers *before* service interactions. Of the three cases, TaskRabbit workers anticipated that their prospective customers would look at their ratings and profiles before hiring them. Making metrics visible to customers empowers customers to make informed hiring decisions, but it simultaneously makes workers anxious about the outcomes of evaluation. Ride-hailing drivers' and couriers' metrics were visible privately, but they remained largely invisible to customers. Even though ride-hailing drivers could look at customers' ratings, they only had a few seconds to respond to a ride request. Such information then became meaningless to ride-hailing drivers. Ride-hailing drivers and couriers felt anxious about customer-sourced ratings because of the threat of job loss. In this vein, (in)visibility of metrics incited workers to act upon scripted expectations about service interactions.

Additionally, participants were more satisfied with their work on TaskRabbit, compared to those in the other cases. There are two key reasons. First, TaskRabbit had a better dispute mechanism than ride-hailing and delivery platforms. Second, while platforms are the core of algorithmic management (Gandini, 2019; Veen et al., 2020), service interactions are out of sight, leaving room for workers to temporarily claim their labor agency. Although customers are often presumed to be "alienating figures" in service interactions, Korczynski (2009) observes that workers' subjective feelings of alienation depend on the worker–customer relationships. Ride-hailing and delivery work can be characterized as one-off "encounters," whereas Taskers could have repeated online and offline interactions with clients at various stages of work. Customers can request a specific worker on TaskRabbit, which provides incentives for workers to cultivate long-term interpersonal relationships with customers. TaskRabbit's tempo-spatial settings of worker–customer interactions further contribute to workers' relational maintenance practices, as worker–customer interactions may take place in customers' homes and have a longer duration than the other two types of work.[3] Most of the interviewees (8 of 11) had repeat clients on TaskRabbit, and 4 of them tried to ask customers to hire them outside of the platform. Participants would only give customers their business cards when they believed the customers were likely to give them a positive rating. Notably, TaskRabbit prohibits workers from having transactions with customers outside of the platform. Hence, participants would only accept requests from "trustworthy" customers because they would not tell TaskRabbit about this shadow business. Participants also avoided having such conversations within the app. Though the strategy came with risk, it allowed workers to mitigate the influences of ratings and be independent of the platform.

Finally, workers' feelings of platform dependence shape workers' affective responses to metrics (see Schor et al., 2020). Participants who did not consider gig work as a viable future career option were more likely than others to ignore metrics. This is particularly salient in the case of delivery platforms, for which a subset of the interviewees (6 of 18) began working since COVID-19. These "newcomers" were college students who started working on delivery platforms as a side gig when classes went online. They planned to stop working on these platforms after graduation or the transition back to campus. Therefore, they had little motivation to navigate platform-based metrics and algorithms. They cared less about the operation and consequences of metrics, as long as their accounts would not be deactivated.

Conclusion

In this article, I have examined how gig workers anticipated, interpreted, and managed algorithmic metrics across ride-hailing, delivery, and domestic services platforms in the United States. Specifically, most interviewees felt anxious about customer-sourced ratings because they are consequential to workers' platform-based employability, whereas participants might feel ambivalent about system-behavioral measures depending on their varied considerations of the relevant disciplinary outcomes. Such differences illustrate that individuals can feel and experience metrics unevenly (Beer, 2016). The analysis finds the convergent reception of customer-sourced ratings because of the platforms' unequal treatment of customers over workers and the inherent unpredictability of customers in service work. In the three cases, workers anticipated and mitigated the influences of customer-sourced ratings at various stages of the work process. Metrics do not only exercise affective power *after* individuals are being measured (Beer, 2016). Nonetheless, the strategies for managing affective measures and customers only allowed them to momentarily routinize service interactions and regain control of their work. Echoing Cameron and Rahman's (2022) observations, workers have the most autonomy in the pre-hiring process in which they can filter difficult customers and strive to manage customers' expectations. As service interactions proceed, workers have limited ability to influence customers' evaluations and dispute ratings, thus intensifying their precarious experiences. TaskRabbit workers felt more satisfied with their work than ride-hailing drivers and couriers (see Schor et al., 2020) because Taskers were likely to have repeated interactions with customers which allowed them to cultivate a long-term interpersonal relationship. Alongside the settings of platform-mediated worker–customer interactions, the (in)visibility of metrics and platform dependence shape workers' practices toward metrics.

Algorithmic management rests upon a trilateral relationship between platforms, workers, and customers (Stark and Pais, 2021). The evaluation of workers is not just about the management of distributed workforces, but also about building trust with consumers in anonymous marketplaces. Ratings help to enroll workers and customers "in the practices of algorithmic management without managerial authority having been delegated to them" (Stark and Pais, 2021: 47) at a low cost. While platforms discourage workers from filtering customers and declining orders, platforms may anticipate and encourage workers' management of customers. The inducement of anxiety might be better understood as a technique of algorithmic management for cultivating self-improvement and performance management (Beer, 2016; Espeland and Sauder, 2016).

Importantly, gig workers' past ratings and strategies might not always be relevant to themselves because customers represent a key source of work-related uncertainty. Management by and of customers remain focal points of production in the three cases. Rethinking algorithmic management through the lens of the service triangle (Leidner, 1993) allows us to situate gig work into long-standing, unequal power relations between managers, workers, and customers. Using Berlant's (2011) idea of "cruel optimism," Jarrett (2022: 60) writes "the state of being attached to a potential or possible future" incites gig workers to consent to exploitation. Workers become attached to gig work primarily because of the promises of flexibility and autonomy. Workers' coping strategies ostensibly allow them to manage their metrics to keep their jobs or even gain a competitive advantage. However, this hope can become "cruel" when workers realize "the object/scene of desire is itself an obstacle to fulfilling the very wants that bring people to it" (Berlant, 2011: 227). For instance, there are tensions between maintaining high system-generated behavioral measures and the flexibility of accepting valuable orders. Workers' everyday agency is often disrupted by difficult customers, information asymmetries, unfair dispute policies, and algorithmic opacity. The lack of actionable information also raises questions about whether workers can truly be treated as independent contractors when they cannot make informed decisions about their work. Gig workers are placed in a vulnerable position in which they are required to rationalize and cope with unpredictability in their everyday lives.

What is at stake here is not merely whether workers' performance should be evaluated, but the point that platforms put too much emphasis on ratings and make it difficult for workers to dispute unfair ratings. Metrics can be useful for building trust among total strangers and providing reference points about service quality. However, the discrepancy between intended purposes and actual uses of metrics is a common pitfall when metrics become dominant modes of evaluation (Espeland and Sauder, 2016). Scholars and policy makers have directed attention to how constant pressure for reputation management "put workers under considerable strain which creates a working environment that fuels stress and create risks for PPVH [i.e. psychosocial violence and harassment] where unpaid but necessary work creates unmanageable workloads" (Moore, 2018b: 6). The 2021 European Commission's (2021) proposed directive has suggested that ratings should be considered as management tools and suggested labor platforms to "evaluate the risks of automated monitoring and decision-making systems to the safety and health of platform workers" (p. 37). Consistent with the Fairwork Project's (2022) principle of fair management, possible solutions are to have platforms provide a meaningful explanation of ratings and allow workers to appeal against platforms' decisions.

The affective power of metrics goes far beyond the gig economy, especially considering how metrics play an ever-important role in shaping access to material and symbolic resources in our everyday lives (Fourcade and Healy, 2017). While this research compares the affective power of metrics across three types of geographically tethered gig work, further research is needed to document the convergent and divergent metric power in different work contexts. As in the three cases, we can observe that *not* all metrics matter, and even if they do matter, they may have unequal impacts on workers. Indeed, Van Doorn et al. (2022) argue that migrants make up a sizable portion of the gig economy, partly because platforms offer vulnerable migrants with seemingly flexible employment opportunities. There is an urgent need for considering how affective measures can disproportionally affect marginalized groups of workers and unevenly distribute OSH risks in the ever-expanding culture of metrification.

Acknowledgments

The author would like to express gratitude to Lee Humphreys, Brooke Erin Duffy, Malte Ziewitz, Tarleton Gillespie, and members of "New Media & Society Working Group" at Cornell University for giving feedback on earlier aspects of this project. I would also like to thank Matthew Zook for his editorial guidance and the three anonymous reviewers for their invaluable feedback. I am also grateful to the interviewees who generously shared their time and insights for this study.

Declaration of conflicting interests

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author received no financial support for the research, authorship, and/or publication of this article.

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Notes

1. This is part of a larger project (Chan, 2019a, 2019b) that began with the author's unpublished doctoral dissertation. It draws on a subset of the interview data from a case study of ride-hailing drivers. This study examines metrics' affective power and reactivity across three kinds of geographically tethered gig work.
2. The recruitment and interview procedure remain largely the same in the two phases. One major distinction about participant recruitment, however, is that participants received a stipend (US$20 gift card) in exchange for their time in the second phase.
3. I thank the reviewer for this point.

References

Ahmed S (2004) *The Cultural Politics of Emotion*. Edinburgh: University of Edinburgh Press.

Beer D (2016) *Metric Power*. London: Palgrave Macmillan.

Berlant L (2011) *Cruel Optimism*. Durham, NC: Duke University Press.

Braverman H (1974) *Labor and Monopoly Capital: The Degradation of Work in the Twentieth Century*. New York: Monthly Review Press.

Bucher T (2017) The algorithmic imaginary: Exploring the ordinary affects of Facebook algorithms. *Information, Communication & Society* 20(1): 30–44.

Cameron LD and Rahman H (2022) Expanding the locus of resistance: Understanding the co-constitution of control and resistance in the gig economy. *Organization Science* 33(1): 38–58.

Chan NK (2019a) "Becoming an expert in driving for Uber": Uber driver/bloggers' performance of expertise and self-presentation on YouTube. *New Media & Society* 21(9): 2048–2067.

Chan NK (2019b) The rating game: The discipline of Uber's user-generated ratings. *Surveillance & Society* 17(1/2): 183–190.

Christin A (2020) *Metrics at Work: Journalism and the Contested Meaning of Algorithms*. Princeton, NJ: Princeton University Press.

Christin A and Lewis R (2021) The drama of metrics: Status, spectacle, and resistance among YouTube drama creators. *Social Media+Society* 7(1): 2056305121999660.

Cotter K (2019) Playing the visibility game: How digital influencers and algorithms negotiate influence on Instagram. *New Media & Society* 21(4): 895–913.

Duffy BE (2020) Algorithmic precarity in cultural work. *Communication and the Public* 5(3–4): 103–107.

Duffy BE, Pinch A, Sannon S, et al. (2021) The nested precarities of creative labor on social media. *Social Media+Society* 7(2): 20563051211021368.

Dzieza J (2015) The rating game: How Uber and its peers turned us into horrible bosses. *Vox*. Available at: https://www.vox.com/2015/10/28/11620138/the-rating-game-how-uber-and-its-peers-turned-us-into-horrible-bosses (accessed 28 September 2022).

Espeland WN and Sauder M (2007) Rankings and reactivity: How public measures recreate social worlds. *American Journal of Sociology* 113(1): 1–40.

Espeland WN and Sauder M (2016) *Engines of anxiety: Academic rankings, reputation, and accountability*. New York: Russell Sage Foundation.

Espeland WN and Stevens ML (2008) A sociology of quantification. *European Journal of Sociology* 49(3): 401–436.

European Commission (2021) *Proposal for a Directive of the European Parliament and of the Council on Improving Working Conditions in Platform Work*. Brussels: European Commission.

Fourcade M and Healy K (2017) Seeing like a market. *Socio-Economic Review* 15(1): 9–29.

Gallie D, Felstead A, Green F, et al. (2017) The hidden face of job insecurity. *Work, Employment and Society* 31(1): 36–53.

Gandini A (2019) Labour process theory and the gig economy. *Human Relations* 72(6): 1039–1056.

Gregory K (2021) 'My life is more valuable than this': Understanding risk among on-demand couriers in Edinburgh. *Work, Employment and Society* 35(2): 316–331.

Griesbach K, Reich A, Elliott-Negri L, et al. (2019) Algorithmic control in platform food delivery work. *Socius* 5: 1–15.

Jarrahi MH, Newlands G, Lee MK, et al. (2021) Algorithmic management in a work context. *Big Data & Society* 8(2): 20539517211020332.

Jarrett K (2022) *Digital Labor*. Cambridge, UK: Polity.

Jhaver S, Karpfen Y and Antin J (2018) Algorithmic anxiety and coping strategies of Airbnb hosts. In: Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems, Montreal, QC, Canada. New York: ACM, pp. 1–12.

Jokinen E (2016) Precarious everyday agency. *European Journal of Cultural Studies* 19(1): 85–99.

Kalleberg AL and Vallas SP (2018) Probing precarious work: Theory, research, and politics. *Research in the Sociology of Work* 31: 1–30.

Kellogg KC, Valentine MA and Christin A (2020) Algorithms at work: The new contested terrain of control. *Academy of Management Annals* 14(1): 366–410.

Korczynski M (2009) The mystery customer: Continuing absences in the sociology of work. *Sociology* 43(5): 952–967.

Leidner R (1993) *Fast Food, Fast Talk: Service Work and the Routinization of Everyday Life*. Berkeley, CA: University of California Press.

LaRossa R (2005) Grounded theory methods and qualitative family research. *Journal of Marriage and Family* 67(4): 837–857.

Maffie MD (2022) The perils of laundering control through customers: A study of control and resistance in the ride-hail industry. *ILR Review* 75(2): 348–372.

Mason S (2019) Chasing the pink. *Logic*. Available at: https://logicmag.io/play/chasing-the-pink/ (accessed 28 September 2022).

Mau S (2019) *The Metric Society: On the Quantification of the Social*. Cambridge, UK: Polity.
Mennicken A and Espeland WN (2019) What's new with numbers? Sociological approaches to the study of quantification. *Annual Review of Sociology* 45(1): 223–245.
Moore PV (2018a) *The Quantified Self in Precarity: Work, Technology and What Counts*. New York: Routledge.
Moore PV (2018b) *The Threat of Physical and Psychosocial Violence and Harassment in Digitalized Work*. Geneva: ILO.
Pink S, Lanzeni D and Horst H (2018) Data anxieties: Finding trust in everyday digital mess. *Big Data & Society* 5(1): 2053951718756685.
Ragin C (1992) Introduction: Cases of "what is a case"? In: Ragin C and Becker H (eds) *What Is a Case? Exploring the Foundations of Social Inquiry*. Cambridge, UK: Cambridge University Press, pp.1–18.
Rahman HA (2021) The invisible cage: Workers' reactivity to opaque algorithmic evaluations. *Administrative Science Quarterly* 66(4): 945–988.
Ranganathan A and Benson A (2020) A numbers game: Quantification of work, auto-gamification, and worker productivity. *American Sociological Review* 85(4): 573–609.
Ravenelle AJ (2019) *Hustle and Gig: Struggling and Surviving in The Sharing Economy*. Oakland, CA: University of California Press.
Reid-Musson E, MacEachen E and Bartel E (2020) Don't take a poo!': Worker misbehaviour in on-demand ride-hail carpooling. *New Technology, Work and Employment* 35(2): 145–161.
Rosenblat A (2018) *Uberland: How Algorithms Are Rewriting the Rules of Work*. Berkeley, CA: University of California Press.
Schor JB, Attwood-Charles W, Cansoy M, et al. (2020) Dependence and precarity in the platform economy. *Theory and Society* 49: 833–861.
Stark D and Pais I (2021) Algorithmic management in the platform economy. *Sociologica* 14(3): 47–72.
Sun P, Chen JY and Rani U (2021) From flexible labour to 'sticky labour': A tracking study of workers in the food-delivery platform economy of China. *Work, Employment & Society*. Epub ahead of print 27 August 2021. DOI: 10.1177/095001702110
21570.
Sutherland W, Jarrahi MH, Dunn M, et al. (2020) Work precarity and gig literacies in online freelancing. *Work, Employment and Society* 34(3): 457–475.
The Fairwork Project (2022) *Gig Work Principles*. Available at: https://www.vox.com/2015/10/28/11620138/the-rating-game-how-uber-and-its-peers-turned-us-into-horrible-bosses (accessed 28 September 2022).
Ticona J and Mateescu A (2018) Trusted strangers: Carework platforms' cultural entrepreneurship in the on-demand economy. *New Media & Society* 20(11): 4384–4404.
Van Doorn N (2017) Platform labor: On the gendered and racialized exploitation of low-income service work in the 'on-demand' economy. *Information, Communication & Society* 20(6): 898–914.
Van Doorn N, Ferrari F and Graham M (2022) Migration and migrant labour in the gig economy: An intervention. *Work, Employment and Society*. Epub ahead of print 5 July 2022. DOI: 10.1177/09500170221096581.
Vasudevan K and Chan NK (2022) Gamification and work games: Examining consent and resistance among Uber drivers. *New Media & Society* 24(4): 866–886.
Veen A, Barratt T and Goods C (2020) Platform-capital's 'app-etite' for control: A labour process analysis of food-delivery work in Australia. *Work, Employment and Society* 34(3): 388–406.
Wood A and Lehdonvirta V (forthcoming) Platforms disrupting reputation: Precarity and recognition struggles in the remote gig economy. *Sociology*.
Wood AJ, Graham M, Lehdonvirta V, et al. (2019) Good gig, bad gig: Autonomy and algorithmic control in the global gig economy. *Work, Employment and Society* 33(1): 56–75.
Woodcock J and Graham M (2020) *The Gig Economy: A Critical Introduction*. Cambridge, UK: Polity.