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Algorithm Sensemaking: How Platform Workers Make Sense of Algorithmic Management

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Abstract

Algorithmic management can create work environment tensions that are detrimental to workplace well-being and productivity. One specific type of tension originates from the fact that algorithms often exhibit limited transparency and are perceived as highly opaque, which impedes workers' understanding of their inner workings. While algorithmic transparency can facilitate sensemaking, the algorithm's opaqueness may aggravate sensemaking. By conducting an empirical case study in the context of the Uber platform, we explore how platform workers make sense of the algorithms managing them. Drawing on Weick's enactment theory, we theorize a new form of sensemaking—algorithm sensemaking—and unpack its three sub-elements: (1) focused enactment, (2) selection modes, and (3) retention sources. The sophisticated, multistep process of algorithm sensemaking allows platform workers to keep up with algorithmic instructions systematically. We add to previous literature by theorizing algorithm sensemaking as a mediator linking workers' perceptions about tensions in their work environment and their behavioral responses.

Keywords: Sensemaking, Algorithmic Opacity, Algorithmic Transparency, Algorithmic Management

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1 Introduction

Online labor platforms like Uber, Upwork, TaskRabbit, and Amazon Mechanical Turk (MTurk) have changed millions of people's lives. In 2016 alone, about 8% of Americans earned money using such platforms.[1] Assuming that the existing growth continues at its current pace, by 2027, approximately 50% of the US population will be freelancing[2], many of them accessing job opportunities via online labor platforms.

By using algorithms to monitor and control the workforce and optimize the efficiency of matching processes (Kellogg et al., 2020; Lee et al., 2015; Rosenblat & Stark, 2016), online labor platforms have enabled the study of a new form of organizing. Scholars term this new form of organizing *algorithmic management*[3] (Gal et al., 2020; Jarrahi et al., 2021; Kellogg et al., 2020; Möhlmann et al., 2021, Newlands, 2021; Wiener et al., 2021). It refers to the "large-scale collection and use of data on a platform to develop and

[1] https://www.pewresearch.org/internet/2016/11/17/gig-work-online-selling-and-home-sharing/

[2] https://www.forbes.com/sites/elainepofeldt/2017/10/17/are-we-ready-for-a-workforce-that-is-50-freelance/?sh=3549bb7b3f82

[3] While algorithmic management is not limited to online labor platforms (Kellogg et al., 2020), prior studies have shown that algorithmic management is essential for these types of platforms (Lee et al., 2015; Rosenblat & Stark, 2016).

improve learning algorithms that carry out coordination and control functions traditionally performed by managers" (Möhlmann et al., 2021, p. 2001).

While algorithmic management can yield many benefits for platform companies, existing research suggests that it may create work environment tensions. Such tensions may result in frustration and confusion among platform workers (hereafter also referred to as "workers") and may also be detrimental to their well-being and productivity (Gal et al., 2020; Kellogg et al., 2020; Rosenblat & Stark, 2016; Tilson et al., 2021). One specific tension is that machine learning algorithms often exhibit limited transparency, given that they are complex, multicomponent systems with predictions that update in real time (Benbya et al., 2021).

Platforms are often reluctant to disclose detailed information about them to safeguard their company secrets. Workers tend to perceive respective algorithms as highly opaque "black boxes," which impede the understanding of their inner workings (Benbya et al., 2021; Burrell, 2016; Gal et al., 2020; Jarrahi et al., 2021; Kellogg et al., 2020; Marabelli et al., 2021). Previous work has shown that algorithmic opacity may cause Uber drivers to experience uncertainties about financial compensation and ride assignments (Möhlmann et al., 2021). Among some workers, such tensions trigger market-like responses, such as attempts to regain agency and work around the algorithms (e.g., gaming the system) (Cameron & Rahman, 2022; Möhlmann et al., 2021).

Although prior research has equipped us with meaningful knowledge, we still do not know how workers "make sense" of the tensions associated with algorithmic activities impacting their behaviors. Sensemaking "unfolds as a sequence" and is defined as "a significant process of organizing" where individuals "engage ongoing circumstances from which they extract cues and make plausible sense retrospectively, while enacting more or less order into those ongoing circumstances" (Weick et al., 2005, p. 409).

While algorithms often exhibit at least some transparency, which facilities sensemaking (see Maitlis & Christianson, 2014; Weick & Sutcliffe, 2001), their opaqueness may hinder sensemaking—potentially even fueling workers' desire to solve the tricky algorithm puzzle. Thus, algorithmic activities experienced in work environments may impact platform workers' sensemaking, while such sensemaking, in turn, most notably impacts their responses (see Figure 1). In sum, workers' sensemaking is essential for themselves and platform companies, yet we know little about it. To address this gap, we ask:

RQ: How do platform workers make sense of the algorithms managing them?

Before detailing how we answer the above research question, it is essential to note that workers' sensemaking is only one side of the coin. Successful platforms may instrumentalize the opaqueness of their algorithms to create a fine-tuned balance between, on the one hand, trying to induce trust and, on the other hand, trying to manipulate their platform workers. For example, some companies may expose platform workers to personalized push notifications that can manipulate and nudge them into behaviors that help maximize company profits (Möhlmann, 2021). While the intentions and resulting actions of the platform companies and algorithm creators are equally important, this other side of the coin is outside the scope of this study. Here, we focus solely on the platform workers' perspective and their sensemaking.

We examine the workers' sensemaking of the algorithms managing them in the empirical context of the ride-hailing platform Uber. In so doing, we draw on Weick's enactment theory, the primary evolutionary process of enactment-selection-retention assumed by sensemaking (Weick et al., 2005). Enactment theory is a helpful lens for answering our research question for two reasons. First, it explores specific sensemaking processes separately (e.g., enactment) and together (e.g., how the enactment of workers affects their selection of meaning and the different retention sources). Second, being an evolutionary process, it easily accounts for changes in platform workers' thinking and understanding, which is crucial for the context of algorithms since algorithms themselves are in constant flux.

We offer theoretical implications to the literature on algorithmic management and, as a secondary contribution, our findings speak to the sensemaking literature. To this end, we introduce a new form of sensemaking, which we call *algorithm sensemaking*. To avoid confusion, we note that we do not focus on the (related) notion of algorithm*ic* sensemaking (Min, 2019; Munk, 2019; Salge et al., 2022; Schildt et al., 2020), which addresses how algorithms, such as bots, make sense of information. Instead, our focus is on how humans, and platform workers specifically, make sense of the algorithms managing them.

We unpack algorithm sensemaking by theorizing its sub-elements (e.g., focused enactment, selection modes, and retention sources). Our findings suggest that algorithm sensemaking is a sophisticated, strategic, multistep process, allowing platform workers to systematically keep up with algorithmic activity (i.e., the app instructions). Our model extends previous research by suggesting that algorithm sensemaking acts as a mediating process, linking workers' perceptions about tensions in their work environment (antecedents) and their behavioral responses (consequences) (more details in Figure 1 and Table 3).

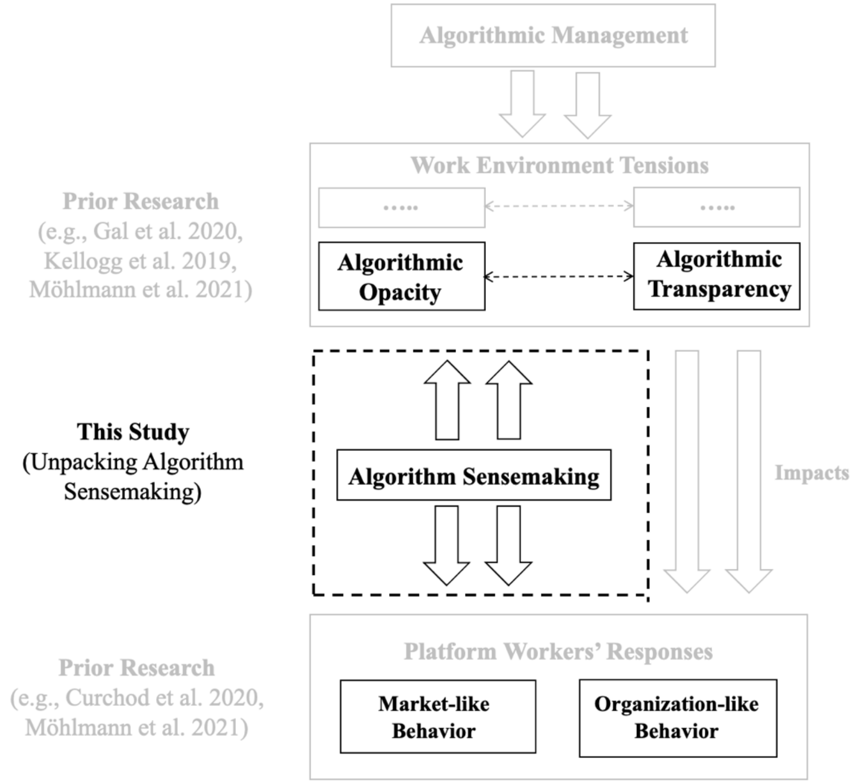

Figure 1. Positioning of This Study in Previous Literature

Studying algorithm sensemaking is theoretically and practically significant. From a theory perspective, without a process that explains how workers make sense of algorithms, scholars can be overwhelmed by the complexity of the different outcomes of algorithmic management and less informed on how to connect platform workers' responses to work environment tensions, accidentally generating disjointed knowledge clusters. By increasing knowledge about algorithm sensemaking, we provide insights into the links between work environment tensions and platform workers' responses.

Practically speaking, our findings contribute to the ongoing debate of how individuals are affected by the limited visibility of algorithms, and how algorithmic opaqueness may aggravate sensemaking. For example, in July 2020, UK drivers launched a data-protection complaint against Uber.[4] Drivers claim to have limited insights into how Uber's algorithms may use information about their ratings and customer interactions to manage platform workers based on their performance. The EU's GDPR not only gives EU citizens the right to information about the data stored about them but also requires companies to disclose the underlying logic of the data processing and how decisions are made based on their data. We suggest that online labor platforms that understand their workers' sensemaking can implement changes to their algorithmic management practices that can help facilitate algorithm sensemaking and lessen work environment tensions, potentially leading to more positive (e.g., job appreciation, satisfaction, or loyalty) and fewer negative responses.

In the following sections, we review previous research, introduce our empirical case study of Uber, and present our findings, which we then discuss in the context of prior work.

2 Algorithmic Management: Work Environment Tensions and Platform Workers' Responses

Online labor platforms, such as Uber, are increasingly employing algorithmic management (Curchod et al., 2020; Gal et al., 2020; Möhlmann et al., 2021; Newlands, 2021; Wiener et al., 2021). By using sophisticated every-second monitoring and surveillance techniques, these platforms collect large

[4] https://fortune.com/2020/07/20/uk-taxi-drivers-uber-gdpr-complaint-eu-privacy-algorithms

amounts of data about their workforce in real time (Kellogg et al., 2020; Newell & Marabelli, 2015; Zuboff, 2019). Machine learning algorithms then read such data, identify patterns, and guide meaningful decision-making through classifications and predictions (Benbya et al., 2021; Burrell, 2016; de Reuver et al., 2018; Faraj et al., 2018; Gregory et al., 2021; Lee et al., 2018; Pachidi et al., 2021; Schuetz & Venkatesh, 2020).

2.1 Work Environment Tensions Stemming from Algorithmic Management

Despite its manifold benefits for online labor platforms, algorithmic management is a double-edged sword. Workers exposed to algorithmic management often report that they experience tensions in their work environment (Gal et al., 2020; Kellogg et al., 2020; Möhlmann et al., 2021; Page et al., 2017; Tilson et al., 2021; Wiener et al., 2021). For example, while gig workers often experience high levels of autonomy and flexibility (Rosenblat & Stark, 2016), they still feel surveilled and controlled through real-time surveillance (Newell & Marabelli, 2015; Zuboff, 2019). Workers can be penalized and even (temporarily) banned from platforms for behavior classified as "undesirable" (Lee et al., 2015; Möhlmann et al., 2021; Rosenblat & Stark, 2016). Previous research has also suggested that platform workers may be victims of discrimination and algorithmic bias (Choudhury et al., 2020; Gal et al., 2020; Robert et al., 2020).

One specific type of tension stems from the limited transparency of the managing algorithms, resulting in platform workers' difficulty in understanding their inner workings (Gal et al., 2020; Marabelli et al., 2021). Compared to traditional forms of organizing, algorithmic management is "often more opaque in terms of how it directs, evaluates, and disciplines workers" (Kellogg 2020, p. 20). Indeed, machine learning algorithms are incredibly complex (Benbya et al., 2021). They are multicomponent systems potentially comprising thousands of data features trained on billions of examples and are weighted differently depending on the real-time inclusion of additional data points (Burrell, 2016; Faraj et al., 2018). Given that algorithms are learning and their input data is changing, algorithms are subject to dynamics and reconstructions (Gal et al., 2020; Gregory et al., 2021; Kellogg et al., 2020). To complicate matters further, the owners or developers of online labor platforms tend to have limited interest in disclosing detailed information about their algorithms to external stakeholders (Burrell, 2016). Thus, opaque and complex machine learning computations are difficult for the data science experts who design them to understand, let alone the nonexpert workers using them.

2.2 Platform Workers' Responses to Algorithmic Management

Previous research has reflected on how stakeholders outside organizations scrutinize algorithmic decision-making (Zuboff, 2019). Studies have also presented findings of platform workers' reactions to algorithmic management (Bucher et al., 2021; Cameron & Rahman, 2022; Curchod et al., 2020; Karanović et al., 2021; Möhlmann et al., 2021). For example, to feel part of a broader community and help one another navigate through the challenges imposed by their working environment, Uber drivers engage in informal communities (e.g., discussion in online forums and social media) (Lee et al., 2015; Möhlmann et al., 2021; Rosenblat & Stark, 2016). Platform workers affected by work environment tensions stemming from algorithmic management also exhibit a variety of response mechanisms, ranging from "organization-like responses" to "market-like responses" (Möhlmann et al., 2021, p. 37).

Organization-like responses refer to workers showing compliance or embracing and enjoying their work environment, while market-like responses refer to workers showing resistance and opposing the algorithm's instructions by showing agency (Cameron & Rahman, 2022; Curchod et al., 2020; Gregory et al., 2021; Karanović et al., 2021; Möhlmann et al., 2021). It is important to note that these two response categories are not necessarily always positive or negative (also, depending on the perspective, either the worker or the platform whose interests may not always be aligned). For example, while workers may enjoy embracing their loyalty (organization-like responses) they may be able to increase their earnings by gaming the system (market-like responses). Drivers gaming the system by strategically logging in and out of the app (market-like responses) certainly pose a significant challenge to platform companies.

However, it is noteworthy that only by allowing workers to show such responses can platforms such as Uber maintain their official classification as marketplaces (as compared to employers who are responsible for paying benefits).

Although previous work on algorithmic management has generated important insights, it is still unclear how platform workers make sense of algorithmic actions leading up to work environment tensions. It is also unclear how workers' sensemaking influences their work responses. We adopt a sensemaking perspective to address these gaps.

3 Sensemaking and Enactment Theory

Sensemaking has become a widely studied topic in information systems (IS) and management (Maitlis & Christianson, 2014; Mesgari & Okoli, 2019).

Sensemaking is a process whereby meaning is constructed "in an ongoing present in which past experience is projected upon possible futures" (Hernes & Maitlis, 2010). This means that sensemaking is retrospective but also continuing and grounded in identity construction (Weick, 1995). Cues, sometimes in the form of unexpected outcomes or violated expectations, are crucial for sensemaking. As Weick (Weick, 1995) writes, "Sensemaking is about the enlargement of small cues" (p. 113).

Because people making sense of ambiguous cues do not live in a vacuum but instead operate in a socio-material context where the mere presence of others influences their thoughts, feelings, and behaviors, sensemaking is also social (Maitlis & Christianson, 2014). In short, sensemaking is triggered by unanticipated violations of expectations, which calls for noticing and bracketing cues, where plausible meaning is developed through interpretation and action, resulting in a more organized view of the world.

3.1 Different Forms of Sensemaking

Prior research has shown that several forms of sensemaking have emerged over time (Maitlis & Christianson, 2014) and that scholars have also derived various sensemaking-related constructs, such as sense-giving (Gioia & Chittipeddi, 1991) and sense-exchanging (Ran & Golden, 2011). For example, Whiteman and Cooper (2011) presented an ethnographic tale from the subarctic to describe how people make sense of material landscapes and ecological processes ("ecological sensemaking"). Rather than challenging key ontological assumptions of the sensemaking perspective, they derived a new form of sensemaking specific and relevant to that context.

We adopt a similar approach in this study by relying on sensemaking to examine how Uber drivers make sense of the actions taken by the Uber algorithm. In so doing, we develop algorithm sensemaking.

3.2 Enactment Theory

In a 2005 study, Weick et al. use the label *enactment theory* to suggest that sensemaking "can be treated as reciprocal exchanges between actors (Enactment) and their environments (Ecological Change) that are made meaningful (Selection) and preserved (Retention)" (Weick et al., 2005, p. 414). Figure 2 shows this treatment of sensemaking.

As the label suggests, *enactment* is at the core of sensemaking. Weick (1969) writes that "Enactment is the only process where the organism directly engages an external "environment." (p. 130). He also defines two forms of enactment:

> *When differences occur in the stream of experience, the actor may take some action to isolate those changes for closer attention. That action of bracketing is one form of enactment. The other form occurs when the actor does something that produces an ecological change, which change then constrains what he does next, which in turn produces a further ecological change, and so on.* (p. 130)

In enactment theory, *selection* is the process that follows enactment. During the complex process of selection, the sense maker imposes various structures on bracketed cues to reduce their equivocality. These structures come from prior experience and represent cause maps that may help explain what happened. Weick (1969) writes:

> *"Selection often seems like a black box. One input to that black box is enacted raw data that potentially point to more than one feature of some ecological change. Another input is enacted interpretations that have worked in the past. Out of the black box comes an enacted environment and a moderately stable interpretation of what the person has recently been up to.* (p. 175)

The last stage of enactment theory is *retention*. For Weick (1969), "Retention involves relatively straightforward storage of the products of successful sensemaking, products that we call enacted environments. An enacted environment is a punctuated and connected summary of a previously equivocal display." (p. 131). Retained meanings are sensible; they gain further solidity and become enacted environments only when selected for retention. Enacted environments (or cause maps) are substantial because they represent a source of guidance for future action (Weick et al., 2005).

In IS, scholars have applied sensemaking to research the implementation of enterprise resource planning (ERP) systems (Tan et al., 2020), the affordances of systems in green transformations (Seidel et al., 2013), and the development of cultural frames in the context of IT outsourcing (Su, 2015), among many other types of phenomena (Baker et al., 2009; Berente et al., 2011; Tallon & Kraemer, 2007).

Despite these efforts in previous research, which have significantly contributed to our understanding, we still have limited knowledge about the role of technology sensemaking (Mesgari & Okoli, 2019). Although scholars have acknowledged the value of enactment theory (Iannacci, 2006) and have begun to explore algorithm sensemaking (Jarrahi et al., 2021), existing studies provide a superficial and descriptive account of this process. Thus, prior research leaves unexamined how workers make sense of algorithmic actions. We addressed this gap by analyzing the case of Uber with the help of enactment theory.

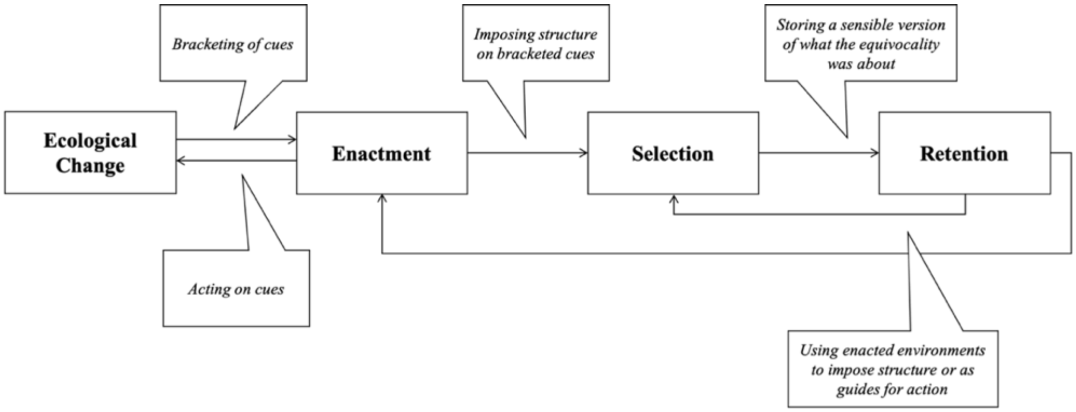

Figure 2. Enactment Theory (adapted from Weick, 1969 p. 132)

4 Methods

4.1 Research Setting

Founded in 2009, Uber Technology Inc. is a technology platform that offers various services, including ride hailing, food delivery, and courier services. We focused on Uber's ride hailing services that were available in as many as 10,000-plus cities worldwide by December 2021.[5] The Uber ride hailing app creates value by employing algorithms that efficiently match drivers with passengers seeking rides (Lee et al., 2015; Rosenblat & Stark, 2016). Drivers are primarily managed by an algorithm, leaving them with the feeling that they are "working for an algorithm" (Curchod et al., 2020).

We chose Uber as a single-case study to approach our research question, as it represents a common case concerning the variables of interest. Yin (2009) proposes a common case to be of theoretical value because it captures the mundane circumstances of everyday interactions. Uber drivers are exposed to algorithmic decisions and instructions on a daily basis, as are Deliveroo and MTurk workers, Amazon warehouse employees, and algorithmic traders. Because these algorithmic decisions and instructions influence workers' job performance (through ratings and earnings), it is no surprise that workers are motivated to make sense of them.

4.2 Data Collection

We interviewed Uber drivers based in London and supplemented this data set by interviewing Uber executives and customers (n = 46). We also harvested data from a local Facebook group of Uber drivers (n > 1,000 posts) and reviewed selected news coverage between 2019 and 2021. Table 1 summarizes the data collection for this study.

We conducted 15 nonrecorded interviews and observations (based on notes) of Uber drivers in London. We also engaged in more formal data collection by conducting 25 audio-recorded interviews with Uber drivers in London, three interviews with Uber executives based in different parts of the world, and three interviews with customers. In total, we conducted 46 interviews. The duration of the audio-recorded interviews was approximately 30-45 minutes each.[6]

Our interest in explicitly focusing on how Uber drivers make sense of the algorithms emerged after an observation that sparked the authors' intellectual curiosity during the data collection process. After finalizing a ride, an Uber driver asked one of the authors to remain in the car and share billing information that Uber shares with the customers via email just a couple of minutes after the finalized ride (i.e., how much Uber had charged for the ride). The driver intended to confirm the calculation of the route fee and whether customers and drivers receive the same billing information. As shown in the findings section, this type of enactment is not uncommon across drivers and is crucial to their sensemaking.

[5] https://www.uber.com (last accessed February 24, 2022)

[6] The lead author of this paper has also co-published a paper involving interviews with London Uber drivers in the *MIS Quarterly* (Möhlmann et al., 2021). Important to note is that the two data sets are different. The significant differences are: (1) In this paper we conducted all 15 informal interviews with drivers in London (compared to 15 informal interviews conducted in NYC); (2) the 25 audio-recorded interviews with Uber drivers analyzed in this paper have only been conducted in London (compared to 19 formal, semi-structured interviews with drivers in NYC and London); (3) this paper harvested the supplementary data from a Facebook group (compared to driver forums); (4) unlike Möhlmann et al. (2021), we conducted interviews with three customers to supplement the data set. Overlaps between the two data sets: 7 out of the 25 audio-recorded interviews with London drivers and the three interviews with Uber executives analyzed in this paper were also part of the Möhlmann et al. (2021) paper data set.

Table 1. Data Collection

	Data source and method	Topics
Nonrecorded interviews, and observations	Nonrecorded interviews with Uber drivers and observations of their day-to-day work environment in London (n = 15)	Uber drivers' relationships with customers and the platform company, and interactions with the Uber app
Audio-recorded interviews	Audio-recoded interviews with Uber drivers based in London (n = 25), supplemented with Uber executives (n = 3) and customers (n = 3)	Relationships among all platform participants, characteristics, and perceptions of (the transparency and opacity of) the Uber algorithm, and drivers' sensemaking of and reactions to the Uber app.
Facebook group posts	Random selection of posts from a local Facebook group of Uber drivers (UK–UBER DRIVERS) (n > 1000)	Drivers' community providing one another with ad hoc support for a wide variety of everyday challenges
Press releases	Selected Uber press releases identified using keywords such as Uber, transparency, algorithm	Uber's approach to the transparency and opacity of its algorithm

The interviews following this incident focused on three major topics: (1) relationships among platform participants, (2) participants' understanding of the Uber algorithm and especially their perceptions of (limited) transparency and complexity, and (3) drivers' sensemaking of the Uber algorithm and specific work responses. We provide a detailed overview of the interview guidelines in Appendix A. Figure 3 offers a roadmap of the methodological approach used in this study.

In addition to conducting 46 interviews, we randomly selected more than 1,000 posts from a Facebook group ("UK–UBER DRIVERS"). This additional data source was suitable for two reasons. First, prior research shows that social media posts have become a valuable extension of traditional data sets (von Hippel & Kaulartz, 2021). Second, many drivers reported that this group was the primary discussion forum for local Uber drivers in London. Finally, to gain better insights into the transparency (or opacity) and complexity of Uber's algorithm and learn more about the company's algorithmic management practices, we read selected news coverage and official press releases by Uber. Doing so allowed us to gain insights into upper management's perspective, for instance, through statements by Uber's CEO, Dara Khosrowshahi. Altogether, collecting data from a variety of sources allowed us to triangulate our case study findings and minimize research bias caused by relying too much on the perspective of a single stakeholder group.

4.3 Data Analysis

We employed grounded theory techniques to analyze the data (Charmaz, 2014). To this end, our data analysis was an iterative, multistep process (see Figure 3):

Early stages: We began our formal data analysis in the summer of 2020 with a broad research interest in drivers' sensemaking strategies and contextual topics such as goal conflicts among platform participants. We approached the data inductively through open coding and iteratively went back to relevant literature to guide the theorization. We went through the whole data set, and when text snippets triggered ideas or thoughts, we labeled them with short sentences representing first-order codes (Charmaz, 2014). We then clustered first-order codes into second-/third-order themes and theorized interrelationships between the different constructs (Charmaz, 2014), leading to an initial version of a model.

Later stages: We iteratively compared our emerging findings with relevant theory (Charmaz, 2014) and constantly revised the coding scheme and the study's scope. In the summer of 2021, we returned to the data to strengthen our narrative and more tightly connect our findings to sensemaking. In so doing, we narrowed the scope of our research question and consequently of our theoretical lens by adopting enactment theory (Weick, 1969; Weick et al., 2005). Yet, we remained open to novel data insights. As will be shown later in the findings, this openness was vital for developing algorithm sensemaking.

In this later stage of the analysis, we started by creating a new list of open codes. Next, we clustered first-order codes into second-order themes. The developed constructs were subject to interpretations and frequent discussions by the authorial team. We continued to compare our findings with relevant theory, specifically the three stages of enactment, selection, and retention (Weick, 1969; Weick et al., 2005). After further examination, the author team noticed overlaps between previously theorized constructs, which were merged into novel constructs. In the third and final stage of coding, we theorized interrelationships between the different processes and activities, which led to the development of algorithm sensemaking. Again, this process took many iterations, given that it was subject to interpretations (Walsham, 1995) and discussions by the authorial team and informed by previous theory. Figures 4, 5, and 6 list the first-order categories, second-order themes, and aggregated constructs.

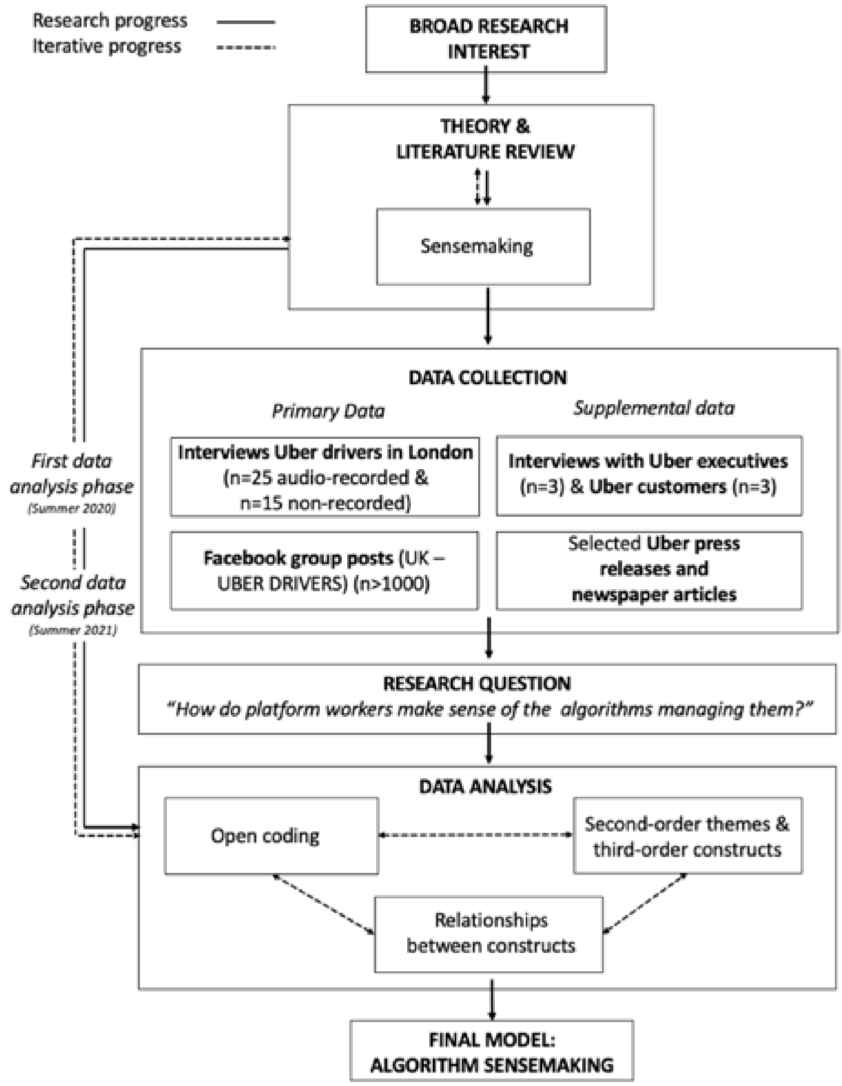

Figure 3. Data Collection and Analysis Roadmap

5 Findings

Five key aggregated constructs emerged from our analysis. The first aggregated construct captures platform workers' perceptions of the *continuum between algorithmic opacity and algorithmic transparency*. The following three aggregated constructs, *focused enactment*, *selection modes*, and *retention source*, were theorized by drawing on (and refining) previous research on sensemaking (Weick, 1969; Weick et al., 2005), specifically enactment theory. Lastly, reflecting previous research (Möhlmann et al., 2021), we outline different *platform workers' responses*, which represent an outcome of their algorithm sensemaking. Table 2 provides an organizer of the themes theorized in this paper.

5.1 The Continuum between Algorithmic Opacity and Algorithmic Transparency

While platform workers perceive the Uber algorithm to be more opaque than transparent, we find that the ride sharing algorithm also exhibits some level of transparency (in the eyes of drivers). As a result, we suggest that workers' views of opacity and transparency are not binary. Instead, they change along the lines of a continuum. For example, sudden changes (e.g., policy changes) may help alleviate (or worsen) opacity and move drivers' perceptions toward (or further away from) transparency. At the same time, familiarity with the system should increase their understanding of the algorithm and naturally pull drivers toward transparency. Since the Uber algorithm is constantly evolving, we expect drivers' perceptions of the algorithm, particularly opacity and transparency, to change over time.

Table 2. Organizer of Theorized Concepts

Concept	Definition
The continuum between algorithmic opacity and algorithmic transparency	
Algorithmic opacity	The difficulty of platform workers (as in their perceptions) to observe how the input data and inner workings of the algorithm affect algorithmic outputs.
Algorithmic transparency	The ease of platform workers (as in their perceptions) to observe how the input data and inner workings of the algorithm affect algorithmic outputs.
Focused enactment	
Information seeking	Platform workers' attempts to search for, request, and find cues from online communication platforms. Aimed at reducing the ambiguity and equivocality associated with a particular algorithmic action. It may take place outside working hours (or in between gigs).
Backward testing	Platform workers' attempts to validate a hunch associated with a particular algorithmic action through "data." It is only available while workers are active on the job.
Selection modes	
Finding glitches	Differentiating valid algorithmic action in the form of instruction or suggestion, from invalid algorithmic action. Invalid algorithmic action might be impossible to pursue or just plain dangerous given platform workers' vulnerable situation.
Discovering patterns	A time-consuming mental effort where the platform worker relies on a deep analysis of data to develop a stable interpretation after bracketing information associated with a particularly ambiguous and equivocal algorithmic action. The data can be internal (e.g., their memory of events) or external (e.g., app transaction history), or both. This interpretation is novel (does not come from retention), is perceived as accurate by the worker, and can be derived during or outside working hours.
Retention sources	
Physical encounter	The platform worker's storage of an enacted environment from an offline first-hand incident. It takes place on the job and is often more memorable than being exposed to information about successful sensemaking shared by others (e.g., on social media).
Digital space	Digital space is the platform worker's storage of an enacted environment by consuming (permanently) accessible content shared (by others) from an online communication platform.
Platform workers' responses	
Market-like behavior	Some platform workers "assumed free-market agency (i.e., market-like)." Embracing their role as independent contractors in a marketplace rather than employees, they use the outcomes of the algorithm sensemaking process to regain agency, for example by identifying loopholes or gaming the system (Möhlmann et al., 2021).
Organization-like behavior	Other platform workers showed more cooperative behavior (i.e., compliance or loyalty), similar to that observed among employees or members of an organization (Möhlmann et al., 2021).

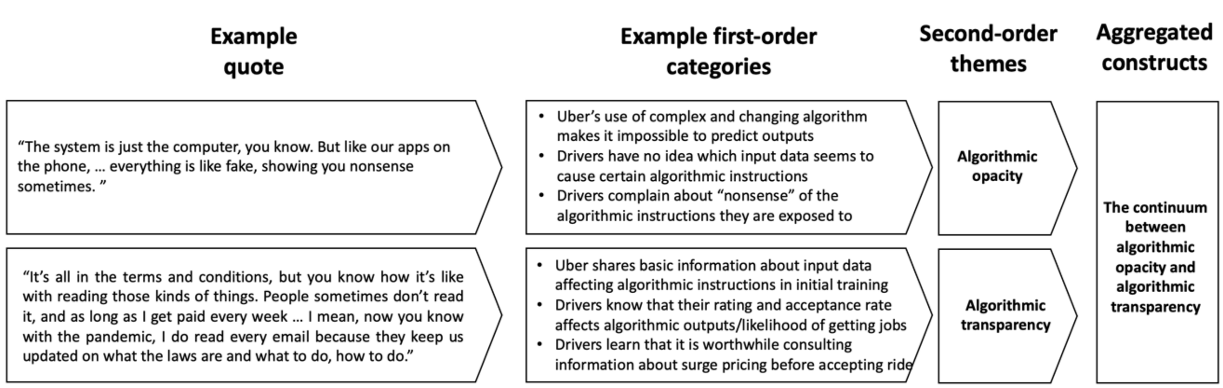

Figure 4. Example Quote, First-Order Categories, Second-Order Themes, and Aggregated Constructs I

In what comes next, we describe the continuum between algorithmic opacity and algorithmic transparency by its polar ends (algorithmic opacity first and algorithmic transparency next). By focusing on the extremes, we also describe and explain the continuum's impact on sensemaking.

5.1.1 Algorithmic Opacity

Algorithmic opacity refers to the difficulty of platform workers (as in their perceptions) to observe how the input data and inner workings of the algorithm affect algorithmic outputs.

Among others, perceived opacity stems from drivers' inability to understand the underlying logic of Uber's machine learning algorithms. Such algorithms are subject to constant dynamics and reconstructions and become more complex over time. They dynamically adjust to changing environments and personalized instructions. As one executive explained:

> *It [the algorithms] kind of evolved over time … In the old days, it was a very simple matching. It was literally just closest mixing. … And then over time, it got more, it got refined … we got what's called batched matching. Instead of just every time a request comes in from a rider doing the closest driver, it would wait for a couple of seconds and it could match five riders and five drivers and optimize to the lowest wait turn for the whole system.* (Uber executive, interview)

According to the Uber executive, these changes are often "very small and incremental," making it almost impossible for drivers to predict their effects. For strategic reasons, Uber does not disclose very detailed information about its complex algorithm and the changes it implements (Rosenblat & Stark, 2016). Thus, algorithmic instructions are perceived to be unpredictable (from the drivers' point of view), accentuating drivers' perceptions of opacity.

Generally, drivers report having "no idea" which input data (i.e., a driver's behavior) causes which data outcomes. For example, one driver said that he'd received a notification that his account was "temporarily on hold," triggering discussions among the Facebook community about what may have caused such an outcome.

Another driver speculated that using the rider app while online may have caused Uber to place the account on hold ("Do you use the rider app while online?"), while a third driver thought that not obeying the traffic rules may be a reasonable explanation for the same. Importantly, none of the drivers was sure about what had caused the temporary blocking of the account, indicating that drivers, at times, have trouble observing what leads to specific algorithmic output/instructions.

Other examples show that drivers face inconsistent algorithmic instructions. This inconsistency creates confusion about the algorithm's inner workings, as the same input can result in different algorithmic outputs. For example, sometimes those drivers who refuse a job would get another job opportunity (that suited them better).

> *I can refuse [certain ride jobs] but I say just okay, don't worry. I can refuse. But is no good, if I refuse a lot … [after you do] they switch off for two, maybe ten minutes … I can't log into the system [for] ten minutes.* (Uber driver, interview)

Other times, they were penalized for declining jobs, as Uber would switch them off. These inconsistencies in their own experience, but also the information they received from other drivers, resulted in confusion among the drivers:

> *If you're sat in an airport queue when your job comes to you, can you reject that job and still maintain your place in the queue? Or do you just have to accept that job?* (Uber driver, Facebook)

Whether it affected the assignment of jobs, the exact calculation of the waybill, or the computation of their average peer rating, drivers complained about unpredictable algorithmic outputs and the "nonsense" instructions they received—triggering perceptions about algorithmic opacity:

> *The system is just the computer, you know. But like our apps on the phone, … everything is fake, showing you nonsense sometimes.* [Uber driver, interview)

Although perceptions of algorithmic opacity likely hinder drivers' sensemaking ("the less you see, the less you know"), the resulting confusion and surprise can also trigger their sensemaking. Confusion, in particular, can motivate drivers to increase their understanding of the algorithm because resolving ambiguity increases knowledge, and more bits of knowledge mean more capability to optimize on-the-job behavior.

5.1.2 Algorithmic Transparency

Algorithmic transparency refers to the ease of platform workers (as in their perceptions) to observe how the input data and inner workings of the algorithm affect algorithmic outputs.

While Uber does not share very detailed information about its complex algorithms and the changes it implements, we found that the company wants to disclose at least some high-level information to its drivers. To this end, Uber publicly presents itself as being committed to some level of transparency. In 2018, Uber CEO Dara Khosrowshahi told staff members:

> *Ultimately, we came to the shared belief that being a true leader requires that we do the right thing, which means acting with transparency, embracing accountability, and making decisions without fear of bad headlines.*[7]

Uber uses various channels to disclose basic information about some of the input variables that play a role in explaining specific algorithmic outputs, and thus, algorithmic instructions. For example, all Uber drivers must attend an introductory training course when they sign up on the platform. One driver mentioned that on this occasion, Uber staff members explained that the commission rate is one of the significant factors determining ride compensation:

> *They explained it. You know that the commission rate is X%. They'll let you know. They have to or they'll be breaking the law. So, they explained the prices.* (Uber driver, interview)

Uber then remains in contact with the drivers by sending emails about changes to terms and conditions (e.g., changes in the calculation of the waybill) and occasionally calling them. One driver said that Uber regularly reaches out to drivers by email to keep them updated on new regulations and policies (data input) that may affect the algorithmic instructions they receive.

> *It's all in the terms and conditions, but you know how it's like with reading those kinds of things. People sometimes don't read it, and as long as I get paid every week ... I mean, now you know with the pandemic, I do read every email because they keep us updated on what the laws are and what to do, how to do.* (Uber driver, interview)

Finally, drivers can access basic information about relevant input data that may directly affect algorithmic instructions via the app interface or Uber website. Here, drivers are generally aware that ratings and acceptance rates may affect ride assignment, while surge pricing may substantially impact ride compensation. While driving for Uber, drivers have learned that consulting information shared via the app is worthwhile before accepting a job.

> *There doesn't have to be [a] surge but you can see it [as it is displayed on the app interface] ... You can either accept or decline [the ride].* (Uber driver, interview)

Still, information disclosure by Uber is relatively high level and rarely moves into specifics. In other words, the company is more likely to share information about primary input data and less likely to share information about the inner workings of the algorithm. Previous research corroborates this observation by indicating how different variables are weighted, such as what exact rating, acceptance rate, or traffic situation would help drivers get more rides (Möhlmann et al., 2021; Rosenblat & Stark, 2016).

5.2 Enactment in Algorithm Sensemaking

As mentioned earlier, platform workers who notice unexpected, surprising, or confusing algorithmic actions can be motivated to make sense of them. This motivation can lead workers to employ bracketing techniques by filtering unexpected incidents for closer investigation. Given the complexity and opaqueness of machine learning algorithms, surprising or confusing algorithmic actions are perceived as ambiguous (i.e., devoid of meaning) and equivocal, as Weick suggests.[8]

Along these lines, an Uber driver reported on Facebook that "… recently i have noticed, that my rating went down … ," or "so last few days tryed to remember unussual cases." This bracketing of (ambiguous and) equivocal cues is the first form of enactment proposed by Weick (1979).

The second form of enactment involves individuals' actions that produce changes in the environment (Weick, 1979). We refine this second form of enactment based on our findings by proposing two behaviors relevant to algorithm sensemaking: *information seeking* and *backward testing*. We use the term *focused enactment* to describe such behaviors because they represent sensemaking activities aimed to reduce ambiguity and equivocality.

5.2.1 Information Seeking

We define information seeking as the platform worker's attempt to search for, request, and find cues from online communication platforms. Again, this behavior is unique because it aims to reduce the ambiguity and equivocality associated with a particular algorithmic action. Information seeking may occur outside working hours (or in between gigs).

[7] https://www.forbes.com/sites/jasonwingard/2019/12/13/ubers-transparency-gamble-how-troubling-safety-disclosures-are-actually-helping-the-company/?sh=15ba70f57b0e

[8] According to Weick (1979), equivocal inputs have multiple significations, being difficult to manage precisely because they can fit numerous classifications and might be indications of any one of several states of the world.

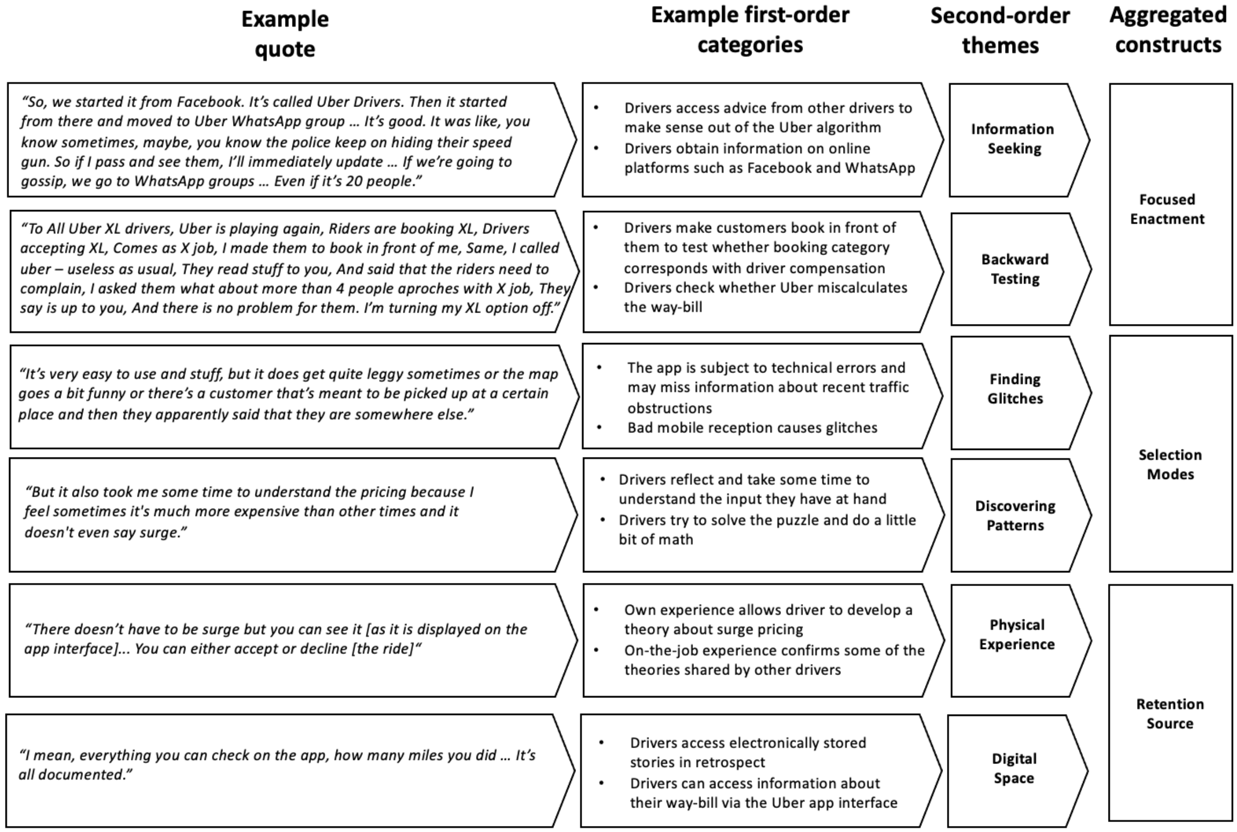

Figure 5. Example Quote, First-Order Categories, Second-Order Themes, and Aggregated Constructs II

At the time of our study, the central communication forum in London was a local Facebook group. In some cases, hundreds of local drivers were seeking information on Facebook. The following quotes exemplify this type of focused enactment. Here, a driver posted a question in the Facebook group, hoping that another driver would comment and help explain why Uber may have flagged his account for fraudulent activity:

> *Account on hold for fraudulent activity. I only did 10 trips so far, in 30 days. Response: Brother you are too fast Response: what do you mean to fast?? Response: What did you do wrong Response: nothing wrong. Have no idea. ve told them i have a dash cam front and back that keep data for a month, they can come and se it if they like it! I have done nothing.* (Uber drivers, Facebook)

Interestingly, many drivers sought information from this local Facebook group before contacting the Uber service hotline, meaning that information seeking is crucial for their sensemaking. In one case, a driver had received a notification from Uber that he had reached the "MAXIMUM TRIP TIME." Without hesitation, he reached out to other Uber drivers in the community and got their feedback on how to make sense of this information:

> *Is this something new? What are your thoughts Response: It's been there for few years now Response: It is not new mate. Response: After a guy had accident after 21hrs of driving!!* (Uber drivers, Facebook)

Drivers also sought information from other online communication platforms. At times, their conversations moved to WhatsApp groups, a more private setting including fewer drivers, allowing them to speak more openly about all kinds of issues.

> *So, we started it from Facebook. It's called Uber Drivers. Then it started from there and moved to [the] Uber WhatsApp group … It's good. It was like, you know sometimes, maybe, you know the police keep on hiding their speed gun. So, if I pass and see them, I'll immediately update … If we're going to gossip, we go to WhatsApp groups … Even if it's 20 people*. (Uber driver, interview)

This quote implies that drivers enjoy mingling with other drivers in online communities, as airing their frustration and "gossiping" allowed them to access information for sensemaking while at the same time entertaining them.

5.2.2 Backward Testing

Backward testing reflects platform workers' attempts to validate a hunch associated with a particular algorithmic action through "data." It is only available while workers are active on the job.

Our findings reveal that, like social science researchers, platform workers test how a change in an input variable affects the outcome of an algorithmic process. Here, they already have a hypothesis for what may have influenced an algorithmic activity. The focus is on seizing an opportunity to test their theory by getting additional evidence. Workers can verify or reject their algorithm hypothesis by deliberately acting to change the environment. When their hypothesis is validated by backward testing, ambiguity is reduced, and the story becomes factual rather than just plausible (more about this below).

In addition, backward testing can be a collaborative effort, as drivers may involve customers in their research. To this end, we find that drivers may ask customers to share information they receive from the app and compare it with the information they receive via their app interface, checking for potential irregularities that help support their hypothesis.

As previously mentioned, we initiated this paper after a driver asked one of the authors to remain in the car until Uber had emailed her the bill for the ride. The driver wanted to test whether Uber shares different information about waybills with drivers and customers (he hypothesized that Uber did that).

This type of behavior is more common than one might expect. Our interviews show that several drivers engaged in backward testing. For example, one driver had a hunch that Uber was only compensating drivers for UberX rides, whereas customers were booking the more expensive/more profitable UberXL rides. In the Facebook forum, he explained what he did to validate this hypothesis:

> *To All Uber XL drivers, Uber is playing again, Riders are booking XL, Drivers accepting XL, Comes as X job, I made them to book in front of me, Same, I called uber—useless as usual, They read stuff to you, And said that the riders need to complain, I asked them what about more than 4 people aproches with X job, They say is up to you, And there is no problem for them. I'm turning my XL option off.* (Uber driver, Facebook)

Another driver theorized that Uber might sometimes miscalculate the waybill or submit false claims. To verify his hypothesis, he occasionally checked the invoice after some of the rides. As he explains in the quote below, the goal was to make sure that crucial information, such as distance or the length of the ride, was accurately reflected in the invoice:

> *At times, it miscalculates. At times, there are some trips they don't calculate for you. They forget. You have to complain to them. That is why as soon as I drop you now, I check. I know how much I had from the last update. I check it again to see if they updated it. It could be.* (Uber driver, interview)

Backward testing in the form of hypothesis testing implies that Uber drivers take on the role of researchers—systematically approaching sensemaking to keep up with the sudden ad hoc changes of the algorithmic instructions presented to them.

5.3 Selection in Algorithm Sensemaking

Weick (1969) theorizes selection to follow enactment. Here, we draw on and refine his work by introducing two different *modes of selection* specific to algorithm sensemaking: *finding glitches* and *discovering patterns*. Before discussing these two modes in greater detail, we note that while enactment is about noticing and bracketing (first form) and behavioral acting (second form), selection is about seeing (Weick, 1969). Consequently, we point out that finding glitches and discovering patterns are not based on actions taken by workers but instead reflect a mental effort; two different ways of seeing and interpreting the bracketed ambiguous and equivocal actions of the algorithm.

5.3.1 Finding Glitches

We define finding glitches as differentiating valid algorithmic action, in the form of instruction or suggestion, from invalid algorithmic action. Invalid algorithmic action might be impossible to pursue or just plain dangerous given platform workers' vulnerable situations.

We interviewed drivers who stressed that the algorithm is subject to technical errors. Some of these errors may be caused by the Uber app's limited access to accurate real-time data, resulting in missing information about recent traffic obstructions. Drivers find glitches by comparing algorithmic instructions or suggestions against real-time road conditions. If the guidance provided by the Uber algorithm is inappropriate or unsafe, they "find a glitch" and do not follow the algorithm's instructions. Below is an example of finding glitches reported by one driver:

> *Uber sometimes is taking us through dead ends, no left turns. So, I have to follow the*

> *road. I'm not going to follow set path if it says that I'm not allowed to drive there.* (Uber driver, interview)

Algorithmic instructions may also deviate from their intended purpose in case of other technological issues, such as an outage or a malfunctioning of broadband connection or mobile reception. As is shown in the quote below, erroneous instructions sent by the algorithm can disrupt the service provided by the worker.

> *It's very easy to use [the Uber app] and stuff, but it does get quite leggy sometimes or the map goes a bit funny or there's a customer that's meant to be picked up at a certain place and then they apparently said that they are somewhere else. (*Uber driver, interview)

Finding technical glitches is a crucial part of the drivers' selection process. It allows them to "clean the data" at hand, paving the way for differentiating invalid algorithmic instructions from valid ones, with the latter being most valuable to job performance.

5.3.2 Discovering Patterns

We define discovering patterns as a time-consuming mental effort where the platform worker relies on a deep analysis of data to develop a stable interpretation after bracketing information associated with a particularly ambiguous and equivocal algorithmic action. The data can be internal (e.g., their memory of events) or external (e.g., app transaction history), or both. This interpretation is novel (does not come from retention), is perceived as accurate by the worker, and can be derived during or outside working hours.

Drivers use the information they bracketed during enactment to deeply reflect and take "some time to understand" the input they have at hand. It is during such a profound reflection that they develop intersubjective meaning. As one driver explained:

> *But it also took me some time to understand the pricing because I feel sometimes it's much more expensive than other times and it doesn't even say surge.* (Uber driver, interview)

Similarly, another driver explained how he had recently noticed that his rating had gone down, which then initiated a profound thought process, allowing him to conclude that not letting passengers sit in the front negatively affected his rating score:

> *... recently i have noticed, that my rating went down- so last few days tryed to remember unussual cases- conclussion is- You will not get ★★★★★ if do not let people sit at the front- what a reasons they have got to convince me and let them at the front 😂.* (Uber driver, Facebook)

In this mode of selection, platform workers are trying to solve a "puzzle." One driver described this timely effort as doing "a little bit of math," for example, when calculating how much money he could save driving for Uber competitors, such as Ola or Bolt.

> *I will get similar thing if it's Ola or if it's Bolt. And the commission if we say 15%, this one says 20%, that 5% is huge. ... I do a little bit of math ... That's why I open the two, whichever one comes first, depends on location.* (Uber driver, interview)

Some drivers we interviewed said they "imagine" or are "under the impression" that certain input variables fed into the Uber algorithm correlate with one another. These assumptions, although potentially erroneous, are necessary because they allow workers to develop intersubjective meaning about the algorithm's inner logic. Due in part to the "black box" aspect of selection (Weick, 1969), many of the cause maps developed by workers fail, either because they are not helpful or because they are inconsistent with reality.

5.4 Retention in Algorithm Sensemaking

Retention is the third and last process of Weick's (1969) enactment theory. We propose two *retention sources* for the specific context of algorithm sensemaking: the *physical encounter* and *digital space*.

5.4.1 The Physical Encounter

The physical encounter is the platform worker's storage of an enacted environment from an offline firsthand incident. It takes place on the job and is often more memorable than being exposed to information about successful sensemaking shared by others (e.g., on social media).

Drivers experienced many physical encounters that helped them store successful outcomes of sensemaking, covering all aspects of their work environment. For example, in the quote below, one driver shares how his physical on-the-job experience (and interaction with the app that displays surge pricing on the screen) allowed him to develop and retain a valid "theory" about surge pricing.

> *There doesn't have to be [a] surge but you can see it [as it is displayed on the app interface] ... You can either accept or decline [the ride]* (Uber driver, interview)

In the following quote, a different driver reports his learning of how certain types of requests can negatively impact drivers' ratings.

> *Uber has not taken this into consideration that some riders will give a driver a lower rating for not taking 4 passengers. Or even I've had because requested they wear a mask. The rating system is unrealistic in the real world. But don't worry about your rating it doesn't impact on the trips you receive.* (Uber driver, interview)

Below, another driver explains how his own on-the-job, physical experience ("this happened to me today") confirmed a theory shared by another driver:

> *This happened to me today! There were four people. I refused to take them and canceled the trip! They ordered xl in front of me and then I took the trip.* (Uber driver, Facebook)

In sum, drivers are likely to remember incidents they experience themselves. These incidents can help validate a theory put forth by others or can help validate their hypotheses (physical encounter retention originating from focused enactment through backward testing).

5.4.2 Digital Space

Digital space is the platform worker's storage of an enacted environment by consuming (permanently) accessible content shared (by others) via an online communication platform.

As mentioned earlier, Uber drivers frequently exchange information on online communication platforms such as Facebook and WhatsApp. This exchange allows them to access electronically stored stories and theories that capture created meanings about algorithmic activity—even in retrospect. Having this type of accessibility is essential, as sensemaking is an ongoing process. It may take a few iterations and several responses from community members before an issue is solved or a question receives a meaningful answer. To this end, one driver explained:

> *He's in a Facebook group about Uber and that last week or so, they got this weird message about being blocked because apparently, they did something wrong and no one really knew what they were talking about, and then he went to this Facebook group and then he found out that many people got the same message and he was blocked for like a whole day. And then they said, "Oh, it was a technical mistake."* (Uber driver, interview)

In addition to accessing stored conversations on public forums, valuable information is available through the Uber app. Indeed, Uber provides some basic information in the app by documenting drivers' past rides and payments (see Appendix). Drivers can access this type of information at any point in time.

> *I mean, everything you can check on the app, how many miles you did… It's all documented.* (Uber driver, interview)

Digital space as a source of sensemaking retention is less memorable than a physical encounter. Yet because workers share a lot of information online, communication platforms like Facebook and WhatsApp become valuable resources they can always access to help them remember a particular incident.

5.5 Platform Workers' Responses

We find that some drivers use insights gained through algorithm sensemaking to their advantage. Our findings show that algorithm sensemaking about specific incidents can directly feed into *market-like behavior*. For example, drivers who believed they could observe and understand the algorithms' inner workings were inclined to regain agency, for example by exploiting loopholes for financial advantage and gaming the system. On the other hand, we found that drivers abstract away from specific algorithm sensemaking incidents to conclude that, overall, they were satisfied with the opportunities Uber was offering them. This insight led platform workers to act cooperatively (*organization-like behavior*).

5.5.1 Market-Like Behavior

Consistent with previous research (Möhlmann et al., 2021), we found that some drivers "assumed free-market agency (i.e., market-like behavior)" (p. 31). Embracing their role as independent contractors in a marketplace rather than employees, they use the outcomes of the algorithm sensemaking process to regain agency, for example by identifying loopholes or gaming the system. For example, one driver explained how (due to algorithm sensemaking) he realized that a sudden drop in his ratings "was caused" (in his view) by a reluctance to let customers sit in the front. To maintain a high rating, get more rides, and receive a higher income, this particular driver decided to cancel rides for customers who requested a front seat even though this may not be in Uber's best interest. Canceling rides certainly allows drivers to regain some agency:

> *…recently i have noticed, that my rating went down- so last few days tryed to remember unusual cases - conclussion is … better cancel that trip - if they want travel in four- and u do not let them- 99% you will get less than 5 star on the end.* (Uber driver, Facebook)

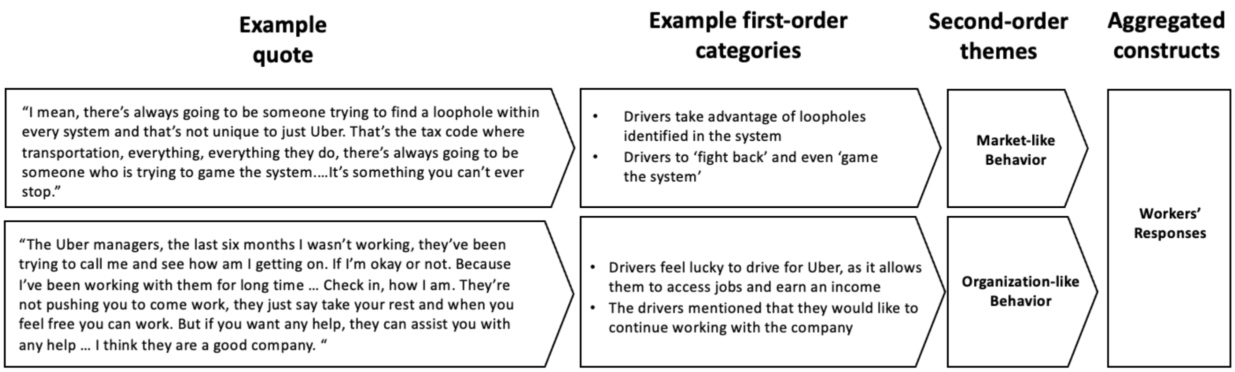

Figure 6. Example Quote, First-Order Categories, Second-Order Themes, and Aggregated Constructs III

Our findings also reveal that drivers use what they learn from algorithm sensemaking to identify loopholes in the system. In so doing, they implement strategies to increase profitability. One driver explained:

> *I mean, there's always going to be someone trying to find a loophole within every system and that's not unique to just Uber. That's the tax code where transportation, everything, everything they do, there's always going to be someone who is trying to game the system.… It's something you can't ever stop.* (Uber driver, interview)

Other drivers don't necessarily try to find loopholes yet they still "game" the system by "fighting back" at some of the suggestions proposed by the algorithm. Another driver explained:

> *Many of you will not agree with this, but if I come across a fare that is Uber's new "lower base fare" then I will simply just take the longer route to make up the difference!* (Uber driver, interview)

5.5.2 Organization-Like Behavior

In line with prior studies (Bucher et al., 2021; Möhlmann et al., 2021), we also found that other platform workers showed more cooperative behavior (i.e., compliance or loyalty), similar to those observed among employees or members of an organization. These drivers more generally reflected their algorithmic interactions and sensemaking, concluding that, they are satisfied with their work overall.

For example, some drivers felt lucky to have the opportunity to drive for Uber, as it allows them to earn money and maintain flexibility. One driver stressed that Uber presents a win-win situation that creates jobs for drivers and that he is happy to do the job:

> *I don't have any good qualification. I am not gas engineer or not lawyer, I'm not the engineer, I'm not whatever. And my father, my father is not rich as well, yeah. This is my job. I come, I start to work, eight hours, ten hours, five hours. Okay. … This is they give the job, they take the commission, and they give me eighty per cent of that. I cannot create the Uber, can I? Can I? Can I create Uber? No. Because million, million, million pounds, billion pound they spend, they created this job.* (Uber driver, interview)

In particular, during the COVID-19 outbreak, several drivers mentioned that they felt supported by the company. Uber offered assistance and handed out free support kits with sanitizers and face masks. The drivers said that they plan to continue working with the company in the future:

> *The Uber managers, the last six months I wasn't working, they've been trying to call me and see how am I getting on. If I'm okay or not. Because I've been working with them for long time … Check in, how I am. They're not pushing you to come work, they just say take your rest and when you feel free you can work. But if you want any help, they can assist you with any help … I think they are a good company.* (Uber driver, interview)

By replicating previous research about market-like and organizational-like workers' responses (Bucher et al., 2021; Cameron & Rahman, 2022; Karanović et al., 2021; Möhlmann et al., 2021), we sought to illustrate links of our findings on algorithm sensemaking to previous research on algorithmic management.

Finally, in Figure 7, we illustrate the different processes (enactment, selection, and retention), behavioral activities (information seeking and backward testing), modes of thinking (finding glitches and discovering patterns), storage sources (physical encounter and digital space), and platform workers' behaviors (market-like and organization-like) derived from our data analysis. We show they are not stand-alone entities but are instead very much connected.

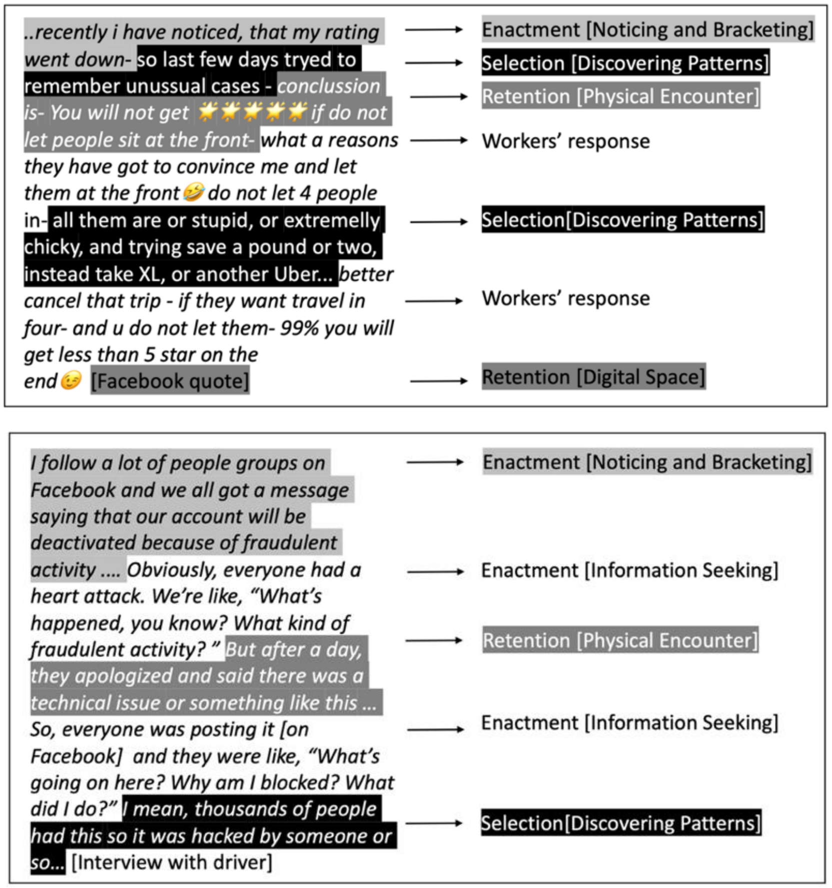

Figure 7. Empirical Evidence for Interconnections between Aggregated Constructs

6 Theoretical Integration: A Framework of Algorithm Sensemaking

Figure 8 depicts our model of algorithm sensemaking. We theorize five aggregated constructs and how they all hang together: The antecedents of algorithm sensemaking, the continuum between algorithmic opacity and algorithmic transparency, followed by the three steps of algorithm sensemaking, focused enactment, selection modes, retention source, and finally, platform workers' responses, which is the consequence of algorithm sensemaking.

First, the model illustrates platform workers' perceptions of algorithmic opacity and algorithmic transparency. Unlike previous research, we argue that algorithm perceptions reflect a dynamic continuum between (the extreme poles of) algorithmic opacity and algorithmic transparency. In the Uber case, workers' perceptions tend to lean more towards opacity. While algorithmic opacity can hinder sensemaking, algorithms like Uber's ride-sharing system often exhibit at least some transparency, which facilities sensemaking.

As the first step in the sensemaking process, workers who experience surprising or confusing algorithmic activity employ bracketing techniques by filtering those ambiguous incidents for closer investigation. Embedded in our framework is a new concept of focused enactment, a process that captures two particular behaviors enacted by workers to reduce algorithmic ambiguity.

The first behavior, information seeking, describes how workers search for, request, and find cues on online communication platforms. The second behavior, backward testing, explains how workers validate a hunch associated with a particular algorithmic action through "data" acquired on the job. Platform workers bracket and notice the information they seek from various communication platforms and the information they get through backward testing. Sometimes, the information that workers obtain through these focused enactment efforts is valuable.

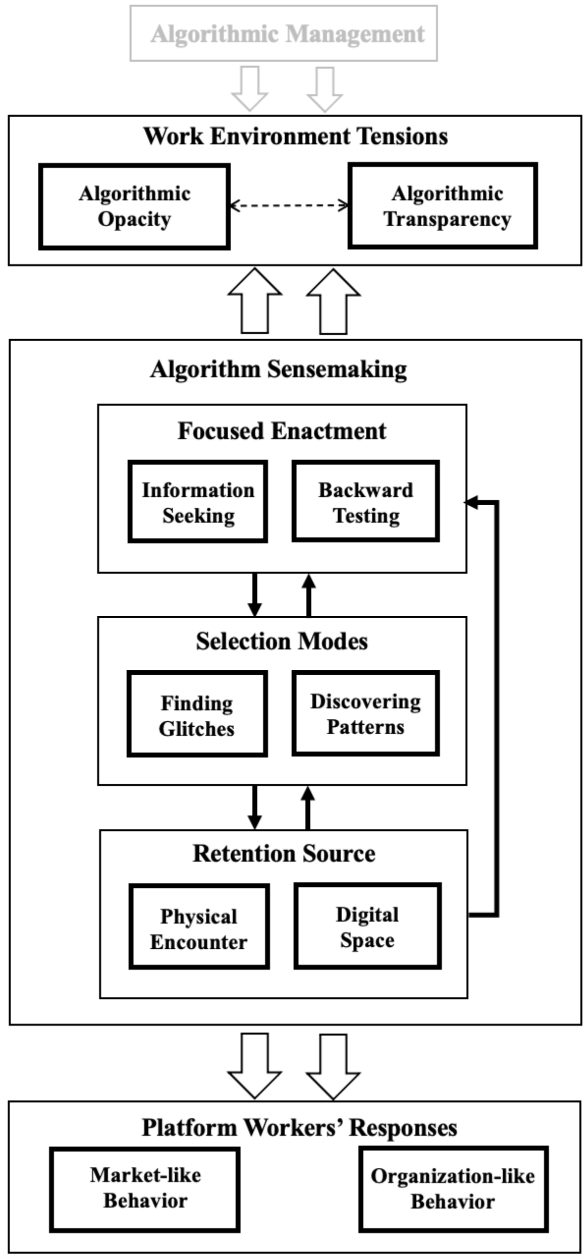

Figure 8. Model of Algorithm Sensemaking

For example, workers engaging in backward testing may get information that confirms their hypothesis. In this case, their (provisional) hunch is supported and retained as an enacted environment. Other times, however, the information is not valuable. Think of content (shared by another driver or a customer) unrelated to the ambiguous incident at hand that already details something the worker knows. Furthermore, workers may not always receive information back (e.g., a never-answered question posted in the Facebook group).

When workers do not (1) confirm a hypothesis through backward testing or, (2) receive "sense" from others answering their questions in online communication platforms, they usually move from enactment to selection to try and create subjective meaning about what they have bracketed and noticed.

Through our case study of Uber, we also theorize two different modes of selection. The first mode is finding glitches. Here, workers do not superimpose cause maps on bracketed content. Instead, they derive new cause maps by differentiating valid algorithmic actions from invalid ones. Although workers can find glitches outside working hours, this type of "seeing" is potentially caused by temporary technical errors, usually occurring during the job (e.g., Uber drivers seeing and not following dead-end signs suggested by the algorithm).

The second selection mode is discovering patterns. This mode refers to the careful analysis of data to develop a new but stable interpretation of what happened. In examining data, workers may try to find connections between what they remember from previous events and the outputs of algorithmic actions. They can also try to find these connections by "seeing and studying" what was registered by the system. In contrast to finding glitches, we suspect that this mode of selection takes place more frequently outside working hours since it requires deep reflection on the part of workers (e.g., one driver described it as "doing a little bit of math").

Regardless of which mode of selection occurs, workers must arrive at a moderately stable algorithm interpretation. Such an interpretation will likely be stored and used as a guide for future action, enabling strategic change in workers' behavior. Following Weick (1969), the last process of algorithm sensemaking is retention. In this study, we detail two different sources of retention. The first source, the physical encounter, captures workers' storage of enacted environments from offline incidents, whereas the second source, digital space, involves registering enacted environments by consuming accessible content shared (by others) online.

Although enacted environments selected from offline, personal incidents are more memorable, those retained from online communication platforms are resourceful and valuable, especially for learning more about algorithms in general. When integrated into the framework we offer, the different focused enactment behaviors, selection modes, and retention sources formalize and extend sensemaking to human-AI interactions.

Finally, we theorize that algorithm sensemaking triggers different reactions from platform workers. In line with previous research (Bucher et al., 2021; Curchod et al., 2020; Karanović et al., 2021; Möhlmann et al., 2021), we show that algorithm sensemaking allowed workers to regain agency, for example by spotting loopholes in the system and by fighting back and even gaming the Uber algorithm (market-like responses). We also find that other workers had the impression that the platform represents a win-win situation for everyone involved. Such workers behave cooperatively, similar to those observed among employees or members of an organization (organization-like responses).

7 Theoretical Contribution and Implications

This paper explores how platform workers make sense of the algorithms managing them. Our key theoretical contribution is the *model of algorithm sensemaking* (see Figure 8). In the following section, we discuss the theoretical implications of our work to the literature on algorithmic management. As a secondary contribution, our findings speak to the sensemaking literature.

7.1 Literature on Algorithmic Management

Previous literature has suggested that there are direct links between platform workers' perceptions about the algorithm and their work environment tensions (such as perceived algorithmic opacity and transparency) (Gal et al., 2020; Jarrahi et al., 2021; Kellogg et al., 2020; Rosenblat & Stark, 2016), and workers' behavioral responses (Bucher et al., 2021; Curchod et al., 2020; Karanović et al., 2021; Möhlmann et al., 2021).

Our model extends previous research by suggesting that algorithm sensemaking acts as a mediator, linking platform workers' perceptions about tensions in their work environment (antecedents) and their behavioral responses (consequences) (see Figure 1 in the introduction). Algorithm sensemaking explains how workers being managed by algorithms act, think, and retain information associated with ambiguous algorithmic actions. Our findings will allow scholars to identify the relationships and interdependencies between those antecedents and consequences, and how they hang together. To this end, our findings imply that algorithm sensemaking is a substantial factor explaining platform workers' behaviors on the job and thus presents valuable insights into the management of the platform workforce.

In particular, we unpack algorithm sensemaking—which has been addressed rather superficially in the previous literature (Jarrahi et al., 2021)—by theorizing its sub-elements (focused enactment, selection modes, and retention source) and subthemes (e.g., information seeking, backward testing, finding glitches).

Our findings imply that algorithm sensemaking is a sophisticated, multistep process. We find that platform workers' approach to algorithm sensemaking resembles some characteristics of social science research. For example, we extend previous literature by theorizing the new construct of backward testing, referring to workers systematically acquiring "data" on the job (similar to data collection in social science research). Similarly, we find that in the stage of selection, workers find glitches (similar to data cleaning in social science research) and identify patterns in the data (similar to data analysis, by some described as doing "a little bit of math").

Our findings offer an alternative perspective from the previous research which tends to picture "low-skilled" workers who conduct simple work tasks (e.g., assembly line work or driving a car) as rather limited in their attempts to exhibit coordinated and strategic behavior. Reactions to algorithmic management, for example in the form of gaming, have often been pictured as ad hoc reactions triggered by power asymmetries, frustration, or the feeling of being mistreated (Curchod et al., 2020; Karanović et al., 2021; Rosenblat & Stark, 2016; Wiener et al., 2021).

Alternatively, it has been suggested that workers' reactions are driven by a desire for entertainment. For example, in Roy's (1959, p. 158) study, a group of factory workers who performed simple, repetitive work invented games to entertain themselves because they were "going nuts" in the "monotonous work environment." While previous research has largely neglected the cognitive efforts involved in algorithm sensemaking (Jarrahi et al., 2021), our findings suggest that platform workers strategically, and often persistently, attempt to solve the complex "puzzle" of algorithmic management.

Mirroring previous research, we find that due to algorithmic opacity, platform workers face difficulties in understanding the algorithms' inner workings (Burrell, 2016; Gal et al., 2020; Kellogg et al., 2020; Marabelli et al., 2021). However, our empirical findings suggest that reality is more complex. Unlike previous research, we theorize that the managing algorithms are perceived to exhibit algorithmic opacity and algorithmic transparency alike, as perceptions about the algorithm can be represented on a continuum. Some workers gain some visibility of the algorithm, as they have access to historical data they can analyze (at any day and any time) to discover patterns and show market-like behavior by gaming the system. We extend previous research by theorizing how perceptions about algorithmic opacity and algorithmic transparency feed into algorithm sensemaking, which in turn triggers certain platform workers' responses (and how these hang together).

One implication of our findings is that dispensing algorithmic transparency but maintaining a level of opacity enables the platform company to enforce policies and strategies without revealing details to the workers. A lack of independent access to data and insight into the nature of the opaque algorithms operating on this data allows the platform company to engage in hidden surveillance, nudging, and manipulation. While this practice can enable platform companies to maximize revenue, it may be less beneficial to their workers (Kellogg et al., 2020; Möhlmann et al., 2021; Newlands, 2021; Zuboff, 2019). To this end, previous work has found that Uber exposes drivers to push notifications to nudge them into driving longer hours (Möhlmann, 2021). Maintaining some algorithmic opacity allows the platform company to maintain control points with no real opportunity for workers to hold the central platform to account (Kellogg et al., 2020; Tilson et al., 2021).

Furthermore, some of our findings mirror previous research which widely accepts that platform workers' behavior is influenced by the personalized, algorithmic instructions presented to them. In turn, platforms monitor and track their workers' "every move," feeding this information back into their learning algorithms (Benbya et al., 2021; Faraj et al., 2018; Gregory et al., 2021; Möhlmann et al., 2021; Newell & Marabelli, 2015). Yet our findings show that platform companies' algorithms and workers' behaviors are interconnected through a mutual learning loop.

Our findings indicate that workers' behavioral input into the algorithm is not only the passive and reactive provision of data, as suggested by previous research. Rather, workers create intersubjective meaning through algorithm sensemaking (e.g., by finding glitches or discovering patterns); they actively learn themselves and may adjust their behavior based on this learning curve. Likewise, a platform company's algorithmic management efforts are shaped by strategic decisions (e.g., upper management makes decisions about drivers' compensation) and technology design choices (e.g., dynamic, learning algorithms).

The result is a constant back and forth between algorithm, algorithm*ic*, and platform managers' sensemaking, based on mutual learning and influence. Here, we suggest that some companies may be able to leverage algorithm sensemaking to their advantage. In some contexts, algorithm sensemaking may improve human-algorithm interactions, as learning about the algorithm may enable workers to complete their work tasks more accurately or efficiently. Table 3 summarizes our work's theoretical contributions and implications for algorithmic management.

7.2 Literature on Sensemaking

We introduce a new form of sensemaking—algorithm sensemaking—which prior research has only described superficially (Jarrahi et al., 2021). We contribute theoretically to a specific understanding of sensemaking by unpacking and refining the contextual aspect of algorithms in the enactment, selection, and retention model introduced by Weick (1969) (more details in Appendix C).

While previous research has focused on how more transparent, less complex sensemaking unfolds in organizations (Maitlis & Christianson, 2014), it has overlooked how it develops in less transparent, more complex nonorganizational settings (such as those characterized by algorithmic opacity). It has examined trusted advisors, leaders, and employees within traditional organizations (Strike & Rerup, 2016; Tallon & Kraemer, 2007) but has focused little on how independent contractors make sense of "manager algorithms."

Table 3. Overview of Theoretical Contributions and Implications

	Assumptions made in previous research	How we extend or refine this previous research
Literature on algorithmic management		
1	Suggests direct links between workers' perceptions about the algorithm/their work environment tensions (Gal et al., 2020; Möhlmann et al., 2021) and workers' behavioral responses (e.g., Curchod et al., 2019; Möhlmann et al., 2021)	We theorize that algorithm sensemaking acts as a mediator linking workers' perceptions about tensions in their work environment (antecedents) and their behavioral responses (consequences).
2	Tends to picture "low-skilled" workers as rather nonstrategic. Responses such as gaming have often been pictured as ad hoc reactions triggered by power asymmetries (Curchod et al., 2020; Karanović et al., 2021; Rosenblat & Stark, 2016; Wiener et al., 2021) or the desire for entertainment (Roy, 1959).	Our findings suggest that algorithm sensemaking is a sophisticated, strategic, multi-step process, which resembles social science research. It allows platform workers to systematically keep up with algorithmic instructions.
3	Focuses on algorithmic opacity and how it may affect an individual's understanding of the algorithm's inner workings (Burrell, 2016; Gal et al., 2020; Kellogg et al., 2020).	We theorize the continuum between algorithmic opacity and algorithmic transparency. Perceptions about algorithm visibility directly feed into algorithm sensemaking (e.g., algorithmic opacity may harm or motivate sensemaking).
4	Widely accepts that a platform company's algorithms and workers' behaviors are interconnected (Gregory et al., 2021, Zuboff, 2019), as algorithms learn from workers who passively supply behavioral data.	We suggest "mutual learning" and show that platform workers' behavioral input into the algorithm is not only passive and reactive, but through algorithm sensemaking, they also actively learn and may adjust their behavior based on a rising learning curve.
Literature on sensemaking		
5	Weick et al. (2005) introduced the enactment-selection-retention model that theorizes different stages in the sensemaking process. Sensemaking has mainly been addressed in rather *transparent* settings. Sensemaking is *social*. • Enactment: Focused on bracketing, noticing, and *ecological change* • Selection: Focused on selecting a *plausible* story • Retention: Focused on *memory* (Please consult Appendix C for a more detailed explanation)	We introduce algorithm sensemaking as a new form of sensemaking that occurs in *less transparent and complex technology* settings in which platform workers make sense of "manager algorithms." While algorithm sensemaking is also social, it is more *informational* than anything else. • Enactment in algorithm sensemaking: Focused on bracketing, noticing, and *ambiguity reduction* • Selection in algorithm sensemaking: Focused on selecting an *accurate* story • Retention in algorithm sensemaking: Focused on *accessibility* (Please consult Appendix C for a more detailed explanation)

In addition, while past work has suggested that sensemaking is driven by plausibility (Weick, 1995), our findings show that workers seem to strive for accuracy. Focused enactment is exemplified by accuracy-driven activities of information seeking and backward testing. These activities add value in two ways. First, they explain what workers do to remediate their lack of algorithmic knowledge and transparency. Second, they show the actors (other drivers and customers) that workers reach out to when in doubt about something.

Two main features distinguish algorithm sensemaking from traditional sensemaking (Weick, 1995, Weick et al., 2005). First, algorithm sensemaking is characterized by complexity; thus, this notion helps unpack contextual factors and accounts for essential elements in this setting. Algorithm sensemaking reminds us to look more deeply at technology's role in sensemaking (Mesgari & Okoli, 2019) and how people managed by algorithms perceive and react to the automated activity imposed on them (Page et al., 2017). By studying how the Uber algorithm impacts drivers' sensemaking, we emphasize how technologies and algorithms matter. We find that an algorithm can trigger a desire for accuracy. For example, we show that algorithmic opacity may motivate workers to discover patterns and show market-like behavior. When combined with their desire for financial gain, the algorithmic opacity faced by workers motivates them to "get it right!" Our study emphasizes this general insight for sensemaking—workers are driven by the same token: That of accuracy, not plausibility (as argued by Weick, 1995).

Table 4. Overview of Directions for Future Research

Theorized aggregated constructs	Directions for future research
The continuum between algorithmic opacity and algorithmic transparency	• How can platforms design algorithmic management to facilitate, rather than hinder, algorithm sensemaking? • Which types and levels of information disclosure (or lack of thereof) trigger what aspects of algorithm sensemaking?
Focused enactment (information seeking and backward testing)	• What are different platform workers' approaches to information seeking? What type of information do they search for/posted by whom/on which platforms? • What are the challenges of information seeking? When are platform workers likely to end up in social media "rabbit wholes" when seeking information? • What is/are the backlash(s) of backward testing? Might consumers (or other stakeholders) show negative reactions to backward testing (when directly involved)? • Given that algorithms are subject to changes/evolve and instructions are subject to personalization, how often do tentative sensemaking theories need to be "retested"? • Do workers reflect on the fact that the information they are exposed to is perhaps provided as a deliberative attempt to manipulate or nudge them into behavior beneficial to the company but not themselves?
Selection modes (finding glitches and discovering patterns)	• How is finding glitches related to on-the-job improvision, or the ability to perform on the job without algorithmic reliance? Do drivers who are good at finding glitches show better job performance? • How does an algorithmic manager (compared to a human manager) affect workers' perceptions of fairness and predictability of the patterns they discover? • Given that workers seek accuracy, can they become obsessed with discovering patterns? If yes, what are the issues and how can they be mitigated? • Does pattern discovery keep drivers up at night? Do they enjoy/feel entertained by solving the endless "Uber puzzle"? • What types of data do workers analyze when discovering patterns?
Retention sources (physical encounter and digital space)	• Does work experience trigger physical encounters—is sensemaking easier for experienced platform workers? Why? • Do digital space retention sources and information seeking go hand in hand? How can perceived benefits from information seeking trigger digital space retention? • How can drivers learn from others through digital spaces despite being exposed to personalized algorithmic instructions?

Furthermore, while our findings show that algorithm sensemaking is social (Weick, 1995), we also find that, most importantly, algorithm sensemaking is informational. Often, the platform worker is information hungry. The process of selection best exemplifies this specific interest.

Weick (1969) argued that selection is somewhat of a black box, as little is known about what happens between enactment and retention. We contribute to the previous research by shedding light on this unknown by introducing two modes of selection: Finding glitches and discovering patterns. While finding glitches requires quick observations from imposed actions, discovering patterns demands careful analysis of previous events. However, both heavily require information.

For example, the sharp observations in finding glitches come from comparing and contrasting algorithmic instructions or suggestions (from algorithms) to real-time conditions (from the physical world). Without either type of information, finding glitches would not be possible. Such a focus on information in algorithm sensemaking appears to be different from that of sense makers described in previous studies (Berente et al., 2011; Lockett et al., 2014; Seidel et al., 2013).

Altogether, our study offers a more nuanced view of sensemaking for algorithms by capturing the complexity of varying perceptions of algorithmic opacity and algorithmic transparency and exposing a more granular characteristic of the social in the informational.

8 Future Research

While we generally encourage others to investigate how our model might play out in other industries, non-platform settings, and over time, we also provide more specific avenues for future research in Table 4.

A fruitful area for future research is related to our findings on focused enactment (information seeking and backward testing). For example, it would be valuable to examine different information-seeking approaches and identify the specific types of information that workers search for when making sense of algorithms (e.g., posted by whom / on which platforms, technical versus nontechnical).

It would also be worthwhile to investigate how workers react to potential challenges when seeking information, such as exposure to non-accurate details (e.g., because they end up in social media "rabbit holes"). Likewise, there may be backlashes involved in backward testing that would be important to investigate. For example, consumers may react negatively to drivers' specific requests, resulting in platform workers' need to carefully evaluate whether potential benefits outweigh risks, such as receiving negative customer ratings.

We also encourage future researchers to unpack additional selection modes and connect these to the different types of focused enactment behaviors. Because selection is crucial for sensemaking and meaning development, we suspect that specific information-seeking approaches may be more valuable than others in helping workers discover new patterns. We call on researchers to further examine how the selection modes of discovering patterns may be affected by workers being managed by an algorithm (compared to a human) and how this may impact workers' perceptions of the fairness and predictability of the patterns they discover.

Finally, although retention from physical encounters can be memorable, they are often anecdotes that may not be as generalizable as those retained from digital spaces. Thus, a study examining the amount and variety of learning generated by these different retention sources could shed light on workers' responses and where to go to learn more deeply about algorithms. We share more specific avenues for future research in Table 4. In the following, our last section, we reflect on the policy implications of our research and conclude.

9 Policy Implications and Concluding Remarks

While workers understandably demand algorithmic transparency, there are technical boundaries to increasing the visibility of complex machine learning algorithms (Burrell, 2016; Faraj et al., 2018; Gal et al., 2020; Gregory et al., 2021). Digital platforms are left with the tricky task of responding to the conflicting demands of providing algorithmic transparency to the platform participants while safeguarding against participants and competitors potentially reengineering the system to the company's detriment.

The (limited) transparency of Uber's algorithm is a timely topic that has been subject to heated discussion in the media (Möhlmann & Henfridsson, 2019). In July 2020, UK drivers filed a lawsuit against Uber, seeking to force the company to disclose information that allows them to make sense of the underlying logic of the algorithm employed by Uber. The suing party argues that Uber is failing to comply with the EU's GDPR.[9] This or similar lawsuits are likely to shape the EU's (and eventually even other countries') regulatory response to the transparency of "manager algorithms," which in turn effect workers' ability to make sense of them.

Given that algorithm sensemaking is a crucial topic for all kinds of algorithm-mediated platform interactions, we are confident that our research provides relevant insights beyond the Uber case. Tech giants such as Facebook and Google must also deal with ownership of platform participants' data and, more importantly, questions relating to the transparency of the data being processed. Likewise, platform companies can expect that those affected by algorithmic instructions may be very strategic and persistent in their attempts to solve the algorithm "puzzle."

Our research is timely. We contribute to an important debate by theorizing a new form of sensemaking that we label as algorithm sensemaking. While this research takes a small step in advancing understanding of this important area, we humbly encourage researchers to build on our model in their future research.

[9] https://fortune.com/2020/07/20/uk-taxi-drivers-uber-gdpr-complaint-eu-privacy-algorithms

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Appendix A: Questionnaire for Semi-Structured Interviews with Drivers

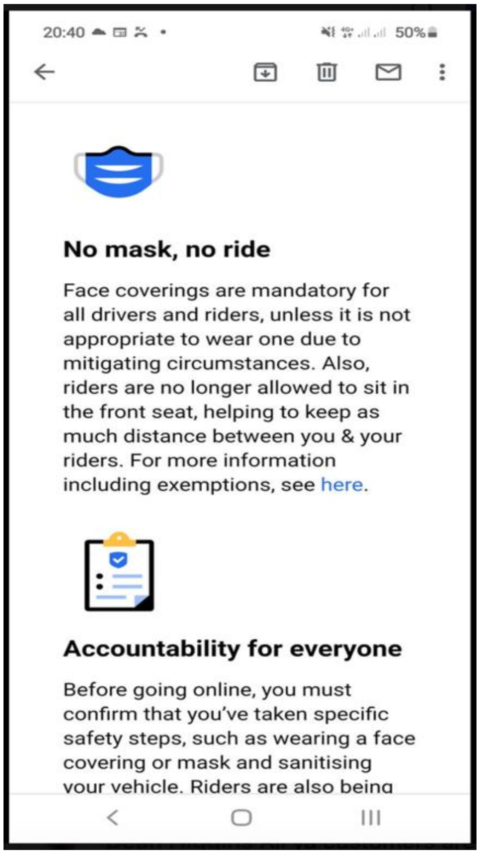
Thank you for participating in this study. At [university x], we are conducting an academic study about Uber drivers. All information you share with me is confidential and will be anonymized. Your identity will never be revealed. Our conversation will be recorded.

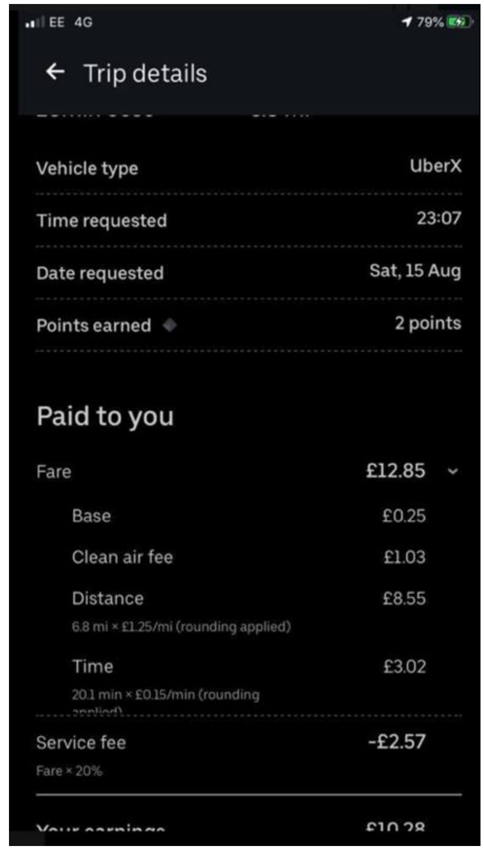
First, we are interested in your experience with Uber and the customers. How do you like driving for Uber? What does the typical interaction with Uber look like? How do you interact with customers? Do you think the Uber platform is a "win-win" situation for everyone involved? Do you remember situations of conflict, either with the Uber platform or the customers? How was the conflict solved? What do you dislike about the Uber company and the customers?

Second, we are interested in your perceptions of the Uber app. Has the app ever been explained to you? What information about the app does Uber share? Do you remember incidents of the app not working properly? Why do you think that is? Do the app's instructions sometimes surprise you? Has the app changed over time? Do you think the app is transparent—or is it opaque? Uber employs algorithms to match drivers and customers. Do you think its algorithm is transparent—or is it opaque?

Third, we would like to learn more about how you make sense of the Uber app. How familiar are you with the app? Is it important to you to understand the underlying logic of how the app works? If you get suspicious about instructions, what do you do? Do you speak to other drivers about the app? How do drivers communicate with each other? Have you heard about Uber drivers "gaming" the app? If so, how?

Appendix B: Screenshots Shared on the Facebook Group "UK–Uber Drivers"





Appendix C: Main Differences between Sensemaking and Algorithm Sensemaking

	Sensemaking (Weick, 1969)	**Algorithm sensemaking (this paper)**
Enactment	Focused on bracketing, noticing, and **ecological changes:** "When differences occur in the stream of experience, the actor may take some action to isolate those changes for closer attention. That action of bracketing is one form of enactment. The other form occurs when the actor does something that produces an ecological change, which change then constrains what he does next, which in turn produces a further ecological change, and so on." (p. 130). "Enactment is the only process where the organism *directly* engages an external "environment." (p. 130).	Focused on bracketing, noticing, and **ambiguity reduction:** Still two forms of enactment. But the second form is distinct. It is not limited to all actions producing ecological change. Rather, it is focused on behaviors that help reduce algorithmic ambiguity (and opacity, to some extent). One behavior, information seeking, describes how workers search, request, and find cues from online communication platforms. The other behavior, backward testing, explains how workers validate, through "data" acquired on the job, a hunch associated with a particular algorithmic action.
Selection	Focused on selecting a **plausible** story: "In the formula "How can I know what I think until *I see what I say*?" selection is *seeing*. Selection is the organizational process that generates answers to the question "What's going on here?" … The selection process houses decision-making" (p. 175) "The meanings that are tried come both from previous experience (signified by the causal arrow from retention to selection) and from patterns implicit in the enactments themselves (signified by the causal arrow from enactment to selection)" (p. 175) "The number of possible meanings gets reduced in the organizing process of selection. Here a combination of retrospective attention, mental models, and articulation perform a narrative reduction of the bracketed material and generate a locally plausible story." (Weick 2005, p. 414)	Focused on selecting an **accurate** story: Because the ambiguity is algorithmic, the formula is now changed to "How can I know *if* what I think *about the algorithm is valid* until *I test what I say is valid*?" which means selection is *validating*. People try to *create* novel interpretations *for what they don't know and have almost no visibility into (the algorithm). And when something seems valid, they look for opportunities to test it.* The meanings that are tried come both from previous experience *and information channels* (signified by the *double* causal *arrows* from retention to selection) as well as from patterns implicit *and explicit* in the enactments themselves (signified by the *double* causal *arrows* from enactment to selection). *Explicit patterns represent deliberate attempts to test the validity of novel interpretations created during selection (signified also by the causal arrow from selection to enactment)* The number of possible meanings gets reduced in the organizing process of selection. Here a combination of retrospective attention, *validated* mental models, and articulation perform a narrative reduction of the bracketed material and generate a locally *factual* story. Though possible, the story that is selected is also *anecdotal* and provisional.
Retention	Focused on **memory:** "storage of interpreted segments for future application" (p. 45) "Retention does have a straightforward connotation: "retention means liability to recall, and it means nothing more than such a liability. The only proof of their being retention is that recall actually takes place" 1979 p 207 "The issue of retention takes on added interest if we review the sensemaking recipe, "How can I know what I think until I see what I say?" The relevant modification for retention is, "*How can I know what I think because I forgot what I said*" The only way the sense-making recipe works is if you can remember the things you've said so that they're available for reflection" (p. 207)	Focused on **accessibility:** Two specific types of interpreted segments for future application: digital space and physical encounter. Retention is not *only* about the liability to recall (this is true for a physical encounter, which should be no major problem since they are memorable), but also about the *capability to access* (true for digital space). Thus, the proof of their being retention is that both recall and access actually take place. The change for this contextualized form of retention is, "*How can I know what I think because I forgot or do not have access to what I or others said*" The only way the sense-making recipe works is if you can remember *or access* the things you've said so that they're available for reflection.
Note: Traditional sensemaking is described as social. While algorithm sensemaking is also social, it is more informational than anything else.		

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