The Rise of Algorithmic Work: Implications for Organizational Control and Worker Autonomy

by

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ABSTRACT

In less than a decade the on-demand economy, a labor market characterized by short-term contracts where work is coordinated through algorithms, has radically reshaped organizations, employment relationships, workers' lives, and consumer behaviors. Despite optimistic and pessimistic predictions, few studies have examined how algorithms affect work and workers in practice. This dissertation focuses on understanding the impact of algorithms on workers in an environment where the entire human resource cycle is coordinated by algorithms. Existing organizational theories suggest that algorithmic systems will tighten the iron cage by providing more comprehensive and invasive methods of control. This dissertation, however, reveals the myriad ways that workers find autonomy in an algorithmic work environment.

To theorize this central finding, I draw upon field work collected from the ride hailing industry, the largest sector in the on-demand economy. I begin with an overview of some of the changes in the contemporary workplace highlighting how they may challenge and extend mainstream organizational theories. I follow with a review of the on-demand economy, including its predecessors of production and service work, and how it affects workers, consumers, and communities. Next, I describe how algorithm-based control systems differ from prior systems and conceptualize *algorithmic work*—a set of job-related activities that are structured by algorithms—drawing on a synthesis of literature across six social science disciplines. I conclude this chapter with unexplored questions at the nexus of work, workers, and algorithms.

In the two empirical papers, I draw on participant observation (including three years as a driver and a rider), longitudinal interviews, online archival data and focus groups. In the first study, I examine how workers interpret the insecure work conditions inherent in the on-demand economy. Focusing on the practices and perspectives of the two most salient features of their work environment—customers and technology—I explore how these interactions lead drivers to understand their work. Seeing their relationship with work as either an alliance or as adversarial, workers tend to view features of the work environment as either working on their behalf or against them. Over time these practices and perspectives culminate in different outcomes.

In the second study, I begin by describing how algorithm-based control systems differ from prior systems and conceptualize *algorithmic work*. Algorithms manage by structuring choice at each human-algorithm interaction, to which drivers respond with a set of tactics: compliance, engagement, or deviance. While these tactics appear to be at odds, drivers describe their responses as evidence of their personal autonomy, in that the system allows them to maximize earnings and create a continuous stream of work from a discontinuous set of tasks. This autonomy demonstrates that although the algorithmic-manager may be an unforgiving taskmaster, workers perceive otherwise, thus suggesting that workers feel they have more autonomy in algorithmic rather than traditional work.

This dissertation provides several theoretical and empirical contributions. First, I summarize perspectives of algorithms across the social sciences laying out several unanswered questions at the intersection of work, organizations, and algorithms. Further, I propose a definition of how algorithms operate in the workplace which I expand on. In contrast to iron cage metaphors, this dissertation suggests that workers do indeed experience a great deal of autonomy in the algorithmic workplace. This study thus has implications for our understanding of algorithms, organizational control, autonomy and the meaning of work.

CHAPTER 1

Introduction

In less than a decade the on-demand economy,[1] a labor market characterized by short-term assignments where work is coordinated through platforms, has radically reshaped organizations, employment relationships, workers' lives, and consumer behaviors. Jason Tanz, editor of *Wired*, notes, "many of these companies have us engaging in behaviors that would have been seen as foolhardy five years ago. We are hopping into strangers' cars (Lyft), welcoming them into our spare rooms (Airbnb), dropping our dogs off at their houses (DogVacay), and eating food in their dining rooms (Feastly)." Not since the industrial revolution have more people chosen to work outside of traditional organizations, moving between short-term assignments (Katz & Krueger, 2019). The rise of the on-demand economy is coupled with the increasing role of algorithms in our lives. Already we rely on algorithms to direct public transport (Hodson, 2014), recommend books, films, music, and vacation spots (Gomez-Urive & Kent, 2016; Orlikowski & Scott, 2014; Seavers, 2014), help us find romantic partners (Devendorf & Goodman, 2014), and protect our homes and neighborhoods (Benlian, Klompe & Hinz, 2019;

[1] This phenomenon can go by a number of names including: gig economy (Friedman, 2014), sharing or gifting economy (Hyde, 1983; Stephany, 2015), hybrid economy (Lessig, 2008), collaborative economy (Botsman & Rogers, 2010), crowd-based capitalism (Sundarajan, 2016), peer economy (Bauwen, 2005), 1099 economy (Hill, 2015), and the renting economy (Trikha, 2014). I am unaware of any consensus on a definition on any of these terms leading to further clarity. Gig economy, a term commonly used by the media, is misleading as gigs could apply to work assignments that are not enabled by a web platform (e.g., a musician's gig). Sharing implies the loaning of personal resources, typically with minimal (if any) financial gain, and applies more to organizations on the gift economy of the spectrum, such as CouchSurfing, where consumers make friends with the person whose couch they stay on, as opposed to OneFineDay, a competitor to Hyatt where customers rent out luxury villas and have no contact with homeowners. Therefore, in the interests of greater precision and clarity, as well to be inclusive to the myriad of on-demand platforms, I've chosen to use the word on-demand economy.

Saunder, Hunt & Hollywood, 2016). Indeed, algorithms, and their sophisticated cousin, artificial intelligence, are already substituting for the work of journalists (Smith, 2015), human resource managers (Miller, 2015), medical lab technicians (Tufecki, 2015), and equities traders (Popper, 2016). Multiple forecasts predict that nearly half of US occupations are at risk of becoming automated over the next 20 years and that 70% will require interaction with digital technology by 2020 (Frey & Osborne, 2013; Muro et al., 2017, 2019). Summing up these trends in the changing relationship between employment and technology in their book, *The Four Global Forces,* Dobbs, Manyinka and Woetzel (2015) asses that "compared with the Industrial Revolution, we estimate that this change is happening ten times faster and at 300 times the scale, or roughly 3,000 times the impact."

Short-term work assignments, aka gigs, are not new. Nor are the questions that arise with the integration of algorithms in the workplace. With the introduction of new technologies, scholars have questioned how technology will change organizational practices and workers' lives (Barley, 1986; Mann & Hoffman, 1960; Orlikowski, 2007; Zuboff, 1989). Take, for example, the transition from an agricultural to an industrial society. Despite fears that automation would make workers obsolete, job loss was eventually offset by gains in manufacturing and services (Autor, 2015). The introduction of innovative technologies to manufacturing processes intensified the physical labor required for production in and around new machines (Samuel, 1977). For example, when power looms automated an estimated 98% of the labor required to weave a yard of cloth, consumer demand increased so sharply that the number of weaving jobs actually rose and workers' skills became increasingly valuable (Bessen, 2015). Further, for workers, the shift from life-long employment to short-term tasks may make the experience of work closer to what is was like in the agricultural age (Barley & Kunda, 2001). In sum, the effects of technology on work are nonlinear and complex; understanding the conditions that give rise to variable configurations of work, workers, and technologies requires examination of the organizations in which they are embedded.

Vivid portrayals of the "doing of work" have always aided scholars in staking out the contours of organizational processes, especially in light of widescale societal change. In-depth accounts of the Tennessee Valley Authority, Forest Service, shop floor, gypsum mine, corporate boardroom, and technicians' labs, for example, led to some of the foundational theories on organizational processes. These thick descriptions reflecting the challenges individuals face at work and in their daily lives force researchers to grapple with the relationships between organizations, workers, and society at-large, often bringing overlooked issues to the public's attention (Desmond, 2016; Edin & Schaefer, 2015; Goffman, 2015; Hochschild, 2018). Although widely optimistic and pessimistic projections on the algorithms and the future of work abound (e.g., Daugherty & Wilson, 2018; Domingos, 2015; Pasquale, 2015; Sundarajan, 2016), grounded accounts about the relationship between technology and work are the exception rather the norm (Barley et al., 2017). Accounts such as these would encourage researchers to move beyond the simple binary that algorithms are either good or bad and to think about the entwined relationship between technological advancements, organizations, workers, and society.

In this vein this dissertation aims to vividly depict how work gets accomplished and is experienced in the context of a workplace riddled with algorithms. Specifically, I ask two questions: "How do workers navigate the tensions between organizational control and individual needs for autonomy in an algorithmic workplace?" and "How do workers make meaning of their work in such a sterile environment?" I explore these contexts in the ride hailing industry, the largest employer in the on-demand economy where work is coordinated by algorithms largely with no direct contact with managers or co-workers.

To ground my findings, I begin in Chapter 2 by describing a sector where these changes are at the forefront—the on-demand economy. I start by discussing two forms of work that preceded and shaped the on-demand economy, namely production and customer service. I then layout the main features of the on-demand economy and review the literature that discusses how the on-demand economy affects workers, consumers, and communities.

In Chapter 3, I delve deeper into the coordinating mechanism of the on-demand economy—algorithms. Algorithms coordinate on-demand work in that they assign tasks, set pay rates, and evaluate work. I begin with a broad definition of the term algorithm, drawing from its roots in the mathematical and physical sciences, before explaining the limitations of this definition for the social sciences. I then provide an overview of how six major social science disciplines (economics, law, information science, communications/cultural media studies, organizational studies) define the term before concluding with a definition of algorithms that is more applicable for studies on the world of work. I conceptualize the idea of algorithmic work as *a set of job-related activities that are structured by algorithms which are, in turn, a set of logic steps, typically written in software code, that are set to maximize a predictive outcome.* I then review the recent literature about how algorithms are embedded in different stages of the work process.

In Chapter 4, I describe my empirical context of the ride hailing industry, the largest industry in the on-demand economy. I begin by tracing the history of the industry, the challenges it faces, and the hiring, evaluation, and firing process workers undergo. Next I describe my four data sources (observation, interviews, focus group, social media data) collected over a three-year period that inform the following two empirical chapters. I conclude with an inventory of all my research participants including their demographics, prior work experience, motivation for entering ride hailing, and their current work status.

In Chapter 5, the empirical companion to the literature review in Chapter 2, I explore how workers interpret the precarious work conditions inherent in the on-demand economy that ultimately shape their perspectives to their working arrangements. Drawing on my qualitative data, in particular the longitudinal interviews (n=117), I examine how these workers make meaning of their work by focusing on the practices and perspectives of the two most salient features of their work environment—customers and technology. I explore how these interactions lead drivers to understand their relationship with their work as either an alliance or as adversarial in that workers believe the features of the work environment are working on behalf or against drivers. Over time these work practices and perspectives culminate in different expected psychological, emotional, and behavioral outcomes. This paper contributes to the understanding of how workers make meaning of their work in the contemporary workplace.

In Chapter 6, the empirical companion to the literature review in Chapter 3, I explore how workers navigate the tensions between organizational control and individual needs for autonomy in an algorithmic workplace. Algorithms manage by structuring choice at each human-algorithm interaction, to which drivers respond with a set of tactics: compliance, engagement, or deviance. While these tactics appear to be at odds, drivers describe their responses as evidence of their personal autonomy, in that the choices allow them to maximize earnings and create a continuous stream of work from a discontinuous set of tasks. This autonomy that is conditional on time and the work demonstrates that though algorithms may be seen as an unforgiving taskmaster, workers perceive otherwise. Further, by continually offering choice and requesting consent from workers at each stage of the work process, algorithmic systems enact control without authority. This paper contributes to the understanding of the tension between control and autonomy in organizations by describing a new control system and theorizing how algorithms can be a means of exercising control through enabling autonomy.

Finally, in Chapter 7 I conclude with a brief overview of how the findings in this dissertation address some long-standing questions in organizational theory and organizational behavior around control and autonomy. I then consider further questions that this study raises and future avenues of research to be explored.

Lastly, it should be noted this work is neither critical nor laudatory of algorithms in the workplace or the on-demand economy more generally. Instead, my desire is to present the experiences, interactions, and meaning-making around work in the algorithmic workplace as vividly as both I and workers I interviewed lived it. As James Spradley noted in *The Ethnographic Interview* (1979/2016):

> I want to understand the world from your point of view. I want to know what you know in the way you know it. I want to understand the meaning of your experience, to walk in your shoes, to feel things as you feel them, to explain things as you explain them. Will you become my teacher and help me understand?

It is to the workers and the algorithms themselves that I ask these questions. Ultimately, I hope to prove Kranzberg's (1986) last law of technology, "Technology is a very human activity."

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CHAPTER 2

The Workplace of Today: The On-Demand Economy

The emergence of internet-enabled platform technology has accelerated the speed and reach of information flows bringing together participants on both the demand and supply side of labor. A key feature of the on-demand economy is that work and workers are continually available, i.e., on-demand. Freed from the contractual obligations of life-long employment, contract employers are able to hire workers to complete tasks only when needed, saving on labor costs, and workers have greater flexibility in choosing their assignments and designing their schedules. The on-demand economy combines features of two older types of work: production and customer service work. Similar to production work, on-demand work tends to be repetitive, narrow in scope, paid at piece-rate, and have minimal autonomy. The work is highly visible, making it possible for workers to be surveilled—in this age, by cameras and algorithms as opposed to by a foreman. On-demand work is facilitated by a digital platform forming a tri-party employment relationship between worker, employer, and the platform. As with other types of service work, customers evaluate work with ratings that serve as reputation signals for future employers and the platform at-large. As the platform only brokers work, without human managers, customers have more power as their ratings substitute for performance appraisals. This novel way of organizing affects how work is structured, evaluated, and experienced. In the remainder of this chapter, I give greater context to the on-demand economy first by looking at its historical predecessors and then through a detailed description of what has come to constitute the on-demand economy. In the final section I explore how the on-demand economy affects consumers, workers, and communities.

Predecessors to the On-Demand Economy

Production Work. Three defining features of production work include 1) its narrow task scope, 2) highly visible tasks that make the work easily monitorable, and 3) a system of pay coupled with output. The manufacturing industry, the exemplar of production work, is the birthplace of many foundational organizational theories (e.g., Taylor, 1911; Mayo, 1933; Roethlisberger & Dickson, 1939; Roy, 1952). In the mid 1800s, most manufacturing operations were small with owner-entrepreneurs living and working close to workers. For such firms, control and motivation were handled through informal relationships as it was easy for owner-entrepreneurs to observe and correct workers (Smith, 1850; Edwards, 1974). As firms grew in size, control structures evolved to compensate for the absence of personal relationships. Foremen oversaw production (Roy, 1952), wages were linked to output (Burawaoy, 1974), and technology, such as the assembly line, regulated the production process (Taylor, 1911; 1947). The narrow and discrete nature of the task further allowed work to be easily monitored, tracked, and paced. With the rise of non-unionized and non-production work in the mid-twentieth century, managerial interest turned to how to absorb workers into organizations through bureaucratic processes and structures (Gouldner, 1954; Blau, 1956). Edwards's (1974) categories of control provide a useful typology to understand production work. Workers are expected to march under the overseer's gaze (simple control), dance at the pace of assembly lines (technical control), and toe the line following procedures and processes laid out by management (bureaucratic). Even jobs that were enriched through optimizing the task variety, task identity, task significance, feedback, and autonomy available within the job were ultimately another tool to control workers (Hackham & Oldham 1975; 1976). Recent advances in technology have enabled more invasive and fine-grained surveillance, such as real-time location tracking through counters (Pierce, Snow, & McAfee 2013), RFID trackers (Boyce, 2011), and GPS systems (Levy, 2015).

Customer Service Work. Three defining features of service work are its 1) interactions with customers, 2) reliance on routines and scripts, and 3) emotional labor. As of 1980, the service industry overtook manufacturing as the largest industry in the US (Westcott and Bednarzik, 1980). Unlike manufacturing, service work entails a complex three-way interaction, dubbed the service triangle or triangle of power, between workers, employers, and customers (McCammon & Griffon, 2000). The presence of the customer in the service interaction produces more uncertainty than is typical in manufacturing jobs. To manage this uncertainty, employers try to structure service encounters to elicit specific, predictable reactions to promote what they view as quality service. At Disneyland, for example, supervisors can watch employees from multiple attractions at blind observation posts (Van Maanen & Kunda, 1989). Grocery store registers and check-out lines regulate the speed of worker-customer interactions (Tolich, 1993). And, in a form of bureaucratic control, McDonald's tightly scripts exchanges between workers and customers in what Liedner (1993) calls routinized service work. Emotional labor, or the process of managing feelings and expressions for economic value (i.e., to fulfill the emotional requirements of a job), are integral to service work (Hochschild, 1983). To provide "authentic"— i.e. friendly, caring, and smiling— service encounters, employers select, train, and socialize to meet management's desires (Hochschild, 1983; Gittell, 2003). Customer service interactions can be empowering or alienating for workers (Korczynski, 2009; Korczynski & Ott, 2004;). When workers have repeated contact with the same customer, emotionally fulfilling, generative relationships may develop. On the other hand, pseudo-relationships or one-off exchanges with customers may lead to alienation and burnout (Gutek, 1995; Gutek & Bhuppa, 1999). In sum, the service triangle raises new questions about how control dynamics evolve and sustain themselves that are still under investigation by scholars (Lopez, 2010). With an emphasis on technical control and customer interaction, the on-demand economy combines elements of both the production and customer service industry.[2]

The On-Demand Economy

The on-demand economy is a hybrid of production and customer service work. In 2016 the US Commerce Department proposed the first governmental definition of the on-demand economy, identifying four characteristics: 1) the use of information technology to facilitate peer-to-peer transactions, 2) the use of ratings systems, 3) flexibility for workers to choose hours, and 4) worker-provided tools and assets necessary to do the job (Telles, 2016). While helpful, these criteria can be criticized on the grounds of being too broad as they ignore the traditional sharing and market exchanges on which the on-demand economy is based. Anthropologists and sociologists, who emphasize its shared consumption practices, define the on-demand economy as a form of access-based consumption where economic transactions may be market-mediated but where no transfer of ownership takes place (e.g., Bardhi & Eckhardt, 2012; Schor & Fitzmaurice, 2014; Belk, 2014). In contrast, economists and management scholars, who emphasize its market-

[2] A distant cousin to the on-demand economy is the sharing economy. Although there are key distinctions between the sharing and the on-demand economy, with the largest being that exchanges in the sharing economy are not economic based, the sharing economy socialized the public to sharing what were typically thought of as private goods such as cars and homes, which the on-demand economy then built upon (see Sundarahan, 2016; Schor, 2014; 2019 for extensive reviews of the sharing economy).

based practices, view the on-demand economy as a new form of capitalism (Sundarajan, 2016) that heightens economic efficiencies (Horton & Zeckhauser, 2016), increases consumers' buying power (Zervas, Proserpio & Byers, 2016; Cohen, Hahn, Hall, Levitt & Metcalfe, 2016), and improves labor conditions, often describing the work as micro-entrepreneurship (Ravenelle, 2017). Both perspectives recognize what is innovative about the on-demand economy: that strangers—rather than kin and communities—exchange goods and services, and that the exchanges are made possible by technology. More recent work has sought to categorize the on-demand economy based on organizational control and wages (Kalleberg & Dunn, 2017), services offered and clientele (Schor, 2013), and sector, size, and intended consumers (Sundarajan, 2016).

Platforms or apps are a defining feature of the on-demand economy, serving as workplaces and storefronts where employers, workers, and customers connect. These apps enable short-term employment contracts, or gigs, ranging in length from minutes to months. Across apps there is a wide range of tasks, so that workers can build a "task portfolio" based on their resources, availability, and skills. A lower-skilled worker without a car, for example, could dog walk, copy-edit, or mystery shop all within a single day. Within an app, task variety fluctuates, with platforms providing extremely (e.g., mystery shopping on Gigwalk), moderately (e.g., household tasks on TaskRabbit), or minimally varied work (e.g., driving on Via). Pay rates can be set by the employer (e.g, HourlyNerd) or the on-demand organization (e.g., Lyft). Performance is evaluated through customer ratings. Some platforms require minimum rating for continued access (e.g., Uber) while in other platforms prior customer ratings serve as a reputation system signaling work quality that can be used by future clients (e.g., Upwork). Shifting evaluations from managers to customers places even more pressure on worker-customer interactions. Workers may feel pressured to make all interactions, even one-time, 30-second interactions, an "experience," increasing emotional labor (Hoschild, 1983; Van Maneen & Kunda, 1998; Liedner, 1996). While customer ratings have always influenced service workers' performance evaluations, sometimes disproportionally (McCammon & Griffon, 2000), final authority has rested in the hands of managers who provided some protections, legal and/or otherwise, for workers.

How the On-Demand Economy Affects Consumers, Workers, and Communities

Over 90% of Americans have heard of the on-demand economy (Pew Research, 2019) and a 2016 study showed that over 70% of adults in the US had purchased on-demand goods or services (Smith, 2016a). An important line of recent research, crossing information sciences, media studies, economics, and sociology, examines the behavior of these consumers. A number of factors motivate consumers to participate in the on-demand economy, including the enjoyment of sharing (Hamari, Sjoklint, & Ukkonen, 2016), economic gain (Eckhardt & Bardhi, 2015), lifestyle improvement (Catulli, Lindley, Reed, Green & Hyseni, 2013), cost saving (Neoh, Chipulu, & Marshall, 2015), community belonging, (Milanova & Mass, 2017), novelty (Milanova & Mass, 2017), and familiarity, utility, and trust (Mohlmann, 2015). Many studies have found that even in the context of the same service, for example, car sharing (Akbar et al., 2016; Bardhi & Eckhardt, 2012; Benkler, 2004; Hellwig et al., 2015; Lamberton & Rose, 2012; Mohlmann, 2015; Meijkamp, 1998), the motives for using the on-demand economy seem to vary. These mixed motivations, as well as rotating sets of platform companies, may explain the fickle consumer behavior that is typical in the on-demand economy. Compared to consumers of traditional products, they have less brand loyalty and are more likely to jump between platforms (Bardhi & Eckhardt, 2012). The on-demand economy is often portrayed as a buyer's market, yet consumers still face discrimination as workers sometimes prefer certain assignments (e.g., Nsoko & Tadelis, 2015; Zhang & Wang, 2016) or prioritize work for those in majority racial groups (e.g., Ge, MacKenzie, Knittel & Zopef, 2016; Edelman, Luca, & Svirsky, 2017).

Another line of inquiry looks at the experiences, motivations, and behaviors of workers, ultimately offering critiques on whether on-demand work is good or bad. While estimates of the number of on-demand workers vary, recent reports suggest a range between 0.4% and 0.8% of the US workforce (Harris & Krueger, 2015; Katz & Krueger, 2016; 2019), which represents between 650,000 and 1 million workers in the United States.[3] Although a relatively small part of the overall US workforce, participation in on-demand work has increased more than 300% in less than five years (Farrell & Greig, 2016), and venture capital funding for these types of businesses has increased fivefold (Hartnett, 2017; Manning, 2017). Given that workers may juggle multiple work-assignments across apps alongside traditional employment, labels such as "full-time" or "part-time" have become less meaningful. Workers are increasingly dependent on income from on-demand employment, and some estimates suggest that as many as 40% of on-demand workers depend on these wages to meet basic needs (Farrell & Greig, 2016; Schor et al., 2017).

The on-demand workforce is constantly in flux and thus it is challenging to present an accurate portrait of the "average" on-demand worker. Media exposés, survey polls, and research-based consulting reports do provide insights, however, and popular press and survey polls have highlighted that on-demand workers value autonomy, flexibility, and task variety (e.g., Smith, 2016b; MBO Associates, 2016; Kelly Report, 2015). Qualitative studies provide further insights about workers' motivations. Manyika and colleagues (2016) propose a four-part typology of on-

[3] Survey polls are more generous, suggesting that in the mid-2000s, between eight and 28% of the US population earned income in the on-demand economy, and up to 30 million adults worldwide (Smith, 2016b; Manyika et al.; 2016; MBO Associates, 2016).

demand workers: free agents (who prefer and rely on on-demand work as primary income), casual earners (who do not rely on on-demand work as primary income), reluctants (who work full-time in the on-demand economy yet would prefer traditional employment), and the financially strapped (who do on-demand work out of necessity). Avery and colleagues (2016) developed a similar typology that distinguishes between those who choose on-demand work based on values (e.g., autonomy), life history (e.g., criminal background and unable to find traditional employment), and career objectives (e.g., entrepreneurs who are using platform to launch their own venture). Looking across domestic and international surveys, white-collar workers and those in the Global North (e.g., Smith, 2016b; MBO Associates, 2016; Kelly Report, 2015) tend to report higher levels of satisfaction than blue-collar workers and those in the Global South (e.g., George & Chattopadhyay, 2015; Kuek et al., 2015). As expected, those who enter the on-demand economy by choice, regardless of number of hours worked, report higher levels of job satisfaction (Manyika et al., 2016; Smith, 2016b). Correspondingly, Rockmann and Ballinger (2017) find that when individual needs (e.g., autonomy) are met, workers are more likely to experience intrinsic motivation and identify with the organization. In contrast, those who are unable to meet basic needs through platform-work report more stress and uncertainty (Schor et al., 2017).

Yet another line of inquiry considers how the on-demand economy affects labor and working conditions. Some researchers concur with popular discourse and marketing materials and highlight the positive aspects of this work, noting the increases in employment opportunities (Azevedo, 2016), the possibility for flexible hours (Sherk, 2016), the formalization of informal labor (Mahesh, 2014), and the potential for greater inclusion of those with disabilities (Avery et al., 2016). Others have shown that in spite of the discourse of open access and equality of opportunity, patterns of bias, discrimination, and inequality remain (Schor et al., 2016). Unstable work schedules (Hodson, 2014), opacity about job requirements and pay (Martin, O'Neill, Gupta, & Hanrahan, 2016), invisibility (Irani & Silberman, 2016), minimal access to benefits (Cato & Rosenblat, 2017), and confusion around taxes (Donovan, Bradley, & Shimabukro, 2016) heighten the power asymmetry between organizations and workers. Workers must be radically responsible (Fleming, 2017), bearing the cost of their own labor investment. Furthermore, on-demand workers are not protected by national labor laws, such as the Fair Labor Acts and National Labor Relations Act (Donovan et al., 2016), leading to additional opportunities for racial and gender biases and discrimination (e.g., Hannak et al., 2017). Ultimately, it is unwise to label the on-demand economy as good or bad as it produces both good (e.g., stable) and bad (e.g., exploitive) jobs (Kalleberg & Dunn, 2016). It does, however, remain clear that even in such a decentralized working context organizations retain significant control over work processes and worker behavior.

Similarly, there is ongoing debate about the broader implications of the on-demand economy on geographic-based communities. On-demand services are hypothesized to reduce overall consumption and environmental impact as well as increase leisure time (Jarrenpaa & Majchrzak, 2016), yet empirical evidence is limited, with the majority of evidence from studies in the ride-hailing industry. The introduction of ride-hailing platforms within a city is associated with more successful entrepreneurship (Burtch, Carnahan & Greenwood, 2017), lower incidences of rape (Park, Kim, & Lee; 2016), and a reduction of alcohol-related homicide (Greenwood & Wattal, 2017). In a study of ride-hailing riders and drivers, Dillahunt and colleagues find that driving facilitates the accumulation of economic, social, and cultural capital for riders living in neighborhoods with low SES (Dillahunt, 2014; Kameswaran, Cameron, &

Dillahunt, 2017). On the other hand, the ride-hailing industry depresses the wages of taxi drivers (Morris, 2017) and is also associated with an increase in road congestion (Fitzsimmons & Hu, 2017) and traffic accidents (Emeterio, 2016).

Unexplored Questions about On-Demand Work

Taking into account the previous points, studying the on-demand economy raises the following questions. From the production work lens, questions arise about how work is being structured, controlled, and coordinated in light of new technologies. From the service work lens, questions arise about how workers will experience and navigate these new technology control structures, especially as they place more power in the hands of customers. In the next section I will explore the technology that enables coordination in on-demand work, algorithms, with a focus of how algorithms may affect work and workers.

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CHAPTER 3

Perspectives on Algorithms Across the Social Sciences

Though algorithms have become more and more integrated into the human resource cycles, the theoretical work in the corresponding literature has struggled to keep pace. In part, this is due to the many ways algorithms can be 1) integrated throughout the human resources cycle (hiring, evaluation, firing) and 2) studied across levels, below and above the application programming interface (API). The API specifies the computer program's "rules of engagement" providing instructions of how the algorithm is to communicate to users through a common language. Existing research on algorithms in the workplace focuses on the two ends of the human resource cycle, hiring and firing, and the two extremes of the API, back-end coders and individual experience decontextualized of algorithms. This research aims to address this dual gap by focusing on the "messy middle" of the execution of the work itself, exploring how workers experience actually working with an algorithm. Not only is this an underexplored area of research, but it also offers important insights about how perceptions, or the social construction of technology, affect work practices and organizations. In this section, I first cover how algorithms are explored from a number of different perspectives in the social sciences before reviewing how algorithms have been studied in workplace contexts. I conclude with unexplored questions of algorithms in the workplace, laying out several potential avenues for future research.

The Conceptual Landscape: Theoretical Perspective on Algorithms

To begin I provide a definition of the word algorithm as it has been widely used by both academics and the popular press. The Oxford dictionary defines an algorithm as a "process or a set of rules to be followed in calculations or other problem-solving operations, especially by a computer." Similarly, Gillespie (2014:167), a communication scholar, defines an algorithm as "transforming input data into a desired output, based on specified calculations." Reflecting the roots of the algorithm in the mathematical and physical sciences, both of these definitions view the algorithm as an organized and finite set of instructions that can be followed to solve a problem (Chabert & Barbin, 1999).[4] These logic steps of the algorithm are all observable and, once identified, can be verified and reproduced by others. A computer hacker working at the National Security Agency in 2019, a lab manager setting a budget in 1980, a university mathematician working on a proof in 1940, and a doctor establishing treatment procedures in 1890 might have all claimed, correctly, to be working on algorithms. However, when applied to social phenomena, this definition of the algorithm is lacking as the logic steps between entities is not as easily defined. Social science is based on probability or estimated co-occurrence of relationships between individuals, their psychological states and social practices. This limits the understanding and the interpretability of algorithms and their intended effects due to their opacity.

First, algorithms are designed and maintained by organizations, specifically data scientists, who code the algorithm and often have proprietary knowledge of that code and what it

[4] The term *algorithm* was initially defined and named after eighth-century Persian mathematician Muhammad ibn Musa al-Khwarizmi. The concept of algorithms and symbolic logic were further developed by the 17th-century mathematician Gottfried Leibniz, who designed the first calculating machine, and later by mathematicians George Boole, Charles Babbage, and Ada Lovelace. It was not until the Allied and Cold War defense strategists that symbolic logic and programming acquired great practical purpose. See Brezina (2006), Chabert & Barbin (1999), and Dourish (2016) for a more detailed history on algorithms.

is supposed to do. A form of intellectual property, this opacity is intentional corporate secrecy limiting how much those outside the organization can understand about the algorithm itself (Burrell, 2016). Yelp, for example, not only hides how its algorithms decide what to filter, but also the fact there is a review-filtering algorithm at all (Eslami et al., 2019). A second level of opacity stems from the capacity to write (and read) code. The design of algorithms is a specialized skill that is inaccessible to the majority of the population; thus, even if code became public, it would be uninterpretable. The closed nature of these algorithms raises questions about the degree to which algorithms are indeed fair and efficient. Emerging research suggests that algorithm-based pricing mechanisms disproportionately benefit early adopters in the industry and the organization as opposed to the workers (e.g., Chen, Mislove, & Wilson, 2015b).

Further heightening opacity is that algorithms take into consideration many shifting environmental inputs, further limiting the interpretability of the algorithm. In a study of music recommendation systems, Seavers (2014, 2017) demonstrates there is rarely one algorithm that results in, say, a particular song playing on Pandora, as results are personalized based on a "technological ecology" of interlocking inputs from advertising networks, users, and moderators. In another example, geography interacts with pricing algorithms. Consumers on on-demand platforms, such as GigWalker and TaskRabbit, pay higher rates to complete tasks in areas that are less dense or of lower socio-economic status (Thebault-Spiekier, Terveen, & Hecht, 2015; 2017).

Even seemingly objective algorithms—such as search algorithms, performance ratings, and resumés—are prone to human biases. In a field test of how an algorithm promoted job opportunities in the STEM field, Lambrecht & Tucker (2019) found that the ad was shown disproportionally to men although the ad was gender-neutral. This study suggests that simply optimizing cost-effectiveness in ad delivery will deliver ads that were intended to be gender-neutral in an apparently discriminatory way, as women are a prized demographic and more expensive to show ads to.[5] Likewise, Google images for some careers support gender underrepresentation (i.e., although 56% of authors are women, only 25% of the images are of women) and gender stereotypes (e.g., a woman construction worker being shown in a bikini posed over a jackhammer), which influence unconscious bias (Kay, Matuszek & Munson, 2015). These examples show how algorithms in practice can produce an output independent of and regardless of its intent. More directly linked to employment, women and minorities are given lower ratings by clients on online labor markets (Chan & Wang, 2017; Hannack et al., 2017; Luca & Zervas, 2016), which affects their placement in search results. Taken together these studies suggest a technical illiteracy, both on behalf of the general public, which cannot decipher code, and even programmers, who cannot possibly know all of the output of a given algorithmic sequence.

Lastly, and perhaps more fundamentally, behavior is challenging to model as human behaviors and the organizations they design are not perfectly rational (March & Simon, 1958). In other words, their behaviors cannot be composed of discrete components in which the relationship can be easily specified. Take, for example, an algorithm determining whether to offer a loan through computing a score based on variables such as race, gender, whether the person owns a home or rents, income, earnings potential, and credit history. The algorithm is making a prediction based on a certain set of items that were (likely) true at one moment in time.

[5] In another example of algorithms not being able to program away bias regardless of the programmer's intent, in 2015, Google apologized for its image AI for categorizing images of black people as monkeys or chimpanzees (Alcine, 2015). As of 2018, Google had not "fixed" the algorithm, instead restricting the algorithm from identifying monkeys, chimpanzees, and black people at all—i.e., a search on black women will return images of women wearing black and white clothes, but not sorted on race (Vincent, 2018). Similar fixes have been reported at Amazon (Marr, 2019) and Xerox (O'Neil, 2016).

While the code could be run again with the same input and (likely) the same outcome, there is, of course, a gap between the actual variable, what can be measured about the variable of interest, and what is actually programmed. Even when algorithms learn, such as in machine learning, there is still a probabilistic reasoning on what would occur between the given inputs and outputs (Burrell, 2016; O'Neil, 2016). This opacity arises from the characteristics of the algorithm itself and is inherent in the way algorithms operate.

Given these endemic challenges in examining algorithms in relation to social phenomena, social science disciplines have developed their own definitions of algorithms to apply to their research settings. (See Table 3-1 for an overview.) Economists' view of algorithms are most closely aligned with definitions in the mathematical and physical sciences, seeing algorithms as an equilibrium mechanism to forecast demand (Cohen, 2016), set prices (Borg, Candogan, Chayes, Lobel, & Nazerzadah, 2014), optimize capacity rates (Matsubara & Kagifuku, 2016), and eliminate discrimination (Horton & Zeckhauser 2016; Schweitzer & Cachon, 2000). Legal scholarship examines algorithms in relation to transparency and employment. Legal technologists suggest ways that algorithms and platforms can improve legal processes, such as calculating income-variable fines (O'Neill & Prescott, 2019), combatting police discrimination (Goel, Perelman, Shroff, Sklansky, 2018), identifying tenants at risk of landlord harassment (Johnson et al., 2019), and providing information for individuals to resolve their disputes in the local courts (Prescott, 2017). Employment law debates whether algorithms are merely monitoring or coordinating work or are controlling work and substituting for managers and, if the latter, determining if workers are properly classified as independent contractors (Cato & Rosenblat, 2016; Dubal, 2017b; Harris & Krueger, 2015). Information sciences, communications and media studies, and organizational studies have more seriously considered social practices surrounding algorithms. As a whole the information sciences, which has both more computational (economic, computer science) and relational (human-computer interaction, user design) subdisciplines, broadly tries to identify how technology can improve efficiencies both in markets, code, and for workers (e.g., Chen & Wilson, 2017; Dillahunt, Kameswaran, Li & Rosenblat, 2017; Kameswaran, Cameron, & Dillahunt, 2018; Wei, Wang, Wo, Liu, & Xu, 2016). In contrast, communication studies focus on how algorithms are being used in cultural and communication practices. One line of study looks at folk tales or stories individuals make up about the algorithms (DeVito, Hancock, French & Liu, 2018; DeVito et al., 2018; French & Hancock, 2017), while another describes how online forums can facilitate information sharing and informational arbitrage (e.g., Irani & Silberman, 2016; Rosenblat & Stark, 2016). Lastly, psychological studies focus on the conditions necessary for people to trust decisions made by an algorithm (e.g., Eslami et al., 2018; Jugo, 2019). Compared to the other social science disciplines, research on algorithms in organizational science is less developed, primarily focused on algorithms as reputation systems (e.g., Curchod et al., 2019; Rahm, 2019) with more recent work looking at how algorithms affect employment processes.[6]

[6] While a complete discussion of the relationship between technology, artificial intelligence, machine learning, and algorithms are beyond the scope of this dissertation, I would like to offer some distinctions. Technology is an umbrella term and includes medical systems (Barley, 1986), cameras (Sewell, Barker & Nyberg; 2012), smartphones (Mazmanian, Orkilowski & Yates, 2013), and software (Anthony, 2018). Thus, while a specific technology might include an algorithm, an algorithm is not necessarily in all technology. For example, a surveillance camera viewed by a security guard would not involve an algorithm, but a surveillance camera whose output is fed to an algorithm for screening any suspicious events would be an example of algorithms being integrated in the work process. Algorithms vary in their complexity, performing everything from simple calculations to forecasting budgets (Mazmanian, Beckman & Harmon 2017) to high-frequency trading (Yadav, 2015). Both machine learning and artificial intelligence (AI) signify more complex processes. Artificial intelligence is the broader concept of machines being able to carry out tasks in a way that we would consider as smarter or more efficient than humans. Most AI-developments are applied, such as to sell stocks, as opposed to general "readiness" to handle any task. Machine learning, which is mostly closely aligned with the latter, is a current application of AI based on the idea that by giving machines access to data they can learn for themselves. An example is giving an algorithm a number of faces to discern sexual orientation (Wang & Kosinski, 2018) or criminality (O'Neill, 2019). See Brynjolfsson & McAffee (2014) for a more detailed review.

The Empirical Landscape: Review of Algorithms in the Workplace

Algorithms in Hiring, Scheduling, and Firing. Recognizing that algorithms, as they relate to social phenomena, are inherently opaque and based on probability, I go on to explore the consequences of algorithms throughout the human resources cycle with a focus on selection, assigning and assessing work, and firing. From the organization's perspective, algorithms can be embedded in all three stages of the hiring process: planning for what skills to hire, searching for potential employees, and screening and evaluation of candidates' skills.[7] Shifts in technology mean that jobs are continually being redesigned making it more challenging for employers to identify suitable candidates. Using data about the tasks that compose these news jobs, Dewitt (2019) shows that companies can advertise for jobs by identifying similarity between the new jobs' tasks and tasks for already familiarl jobs. On online labor markets, such as Upwork and Care.com, algorithms rank workers based on skills and customer evaluations, making high-ranked workers more visible to potential employers (Ticona & Mateescu, 2018). Automated hiring platforms solicit increasingly personal information from applicants (e.g., personality assessments for hourly workers), and in turn, the algorithms use this information to perpetuate human biases and cull "riskier" job-seekers (Ajunwa & Greene, 2019). Consequently, those being evaluated by hiring algorithms report the hiring process as lacking procedural justice, as it lacks contextual information about the applicants (Newman, Fast, & Harmon, 2019). Further, hiring algorithms are prone to gender and racial bias. Textio, a platform that screens for gender-hostile language in job advertisements, was launched after a series of complaints about the gender and racial biases encoded within hiring algorithms and platforms (EEOC, 2007).

[7] For job seekers another part of the process is job searching or the act of looking for employment/work. This, too, can be influenced by algorithms, such as the types of jobs advertised to seekers (Kay, Matuszek & Munson, 2015; Lambrecht & Tucker, 2019).

Increasingly, retail and other service workers are subject to predictive scheduling—being told when to show up for work based on algorithms that are optimizing on traffic, weather patterns, and consumer demand, among other factors (Ho & Vaughn, 2012; Hodson, 2014; O'Neil, 2016). Workers have complained that these algorithmically-derived schedules can be inhumane, spreading shifts too far apart so workers cannot work enough hours to make a living or bunching the shifts too close together, not leaving enough time to rest in-between (Kantor, 2014; Greenhouse, 2015).

A related line of research examines how algorithms can coordinate on-demand workers into computationally-created teams of crowd experts (e.g., Retelny et al., 2014). By encoding the crowd's division of labor into de-individualized roles and continually reassembling these structures, flash organizing allows for the development of complicated open-ended and complex products, including product design, online course development, software development, and game production (e.g., Valentine et al., 2017).

Algorithms also measure and monitor work to evaluate performance, comparing work output to a benchmark that, if not met, leads to termination. Dubbed "replacement algorithms," these computations quickly identify low-accuracy workers (Ramesh et al., 2012). Documents from Amazon warehouses detail hundreds of firings: "Amazon's system tracks the rates of each individual associate's productivity and automatically generates any warnings or terminations regarding quality or productivity without input from supervisors" (Lecher, 2019). A quantifiable, objective, and publicly available measure of reputation, ratings are a proxy for performance. Scholars have argued that public ratings allow for market transactions to be more efficient as employers can quickly assess prior work performance, which can serve as a "shadow of the future" (Heide & Miner, 1992; Resnick, Zeckhauder, Kuwabara & Friedman, 2000). In online labor markets, such as Upwork, client ratings are vital and often the primary criterion for hiring decisions, serving as a signal of work quality (Gao, Liu, Li & Fang, 2016). These ratings are particularly crucial for being selected for assignments that are outside workers' primary skill set (Leung, 2014). Similarly, in the context of web journalism, Chrétien (2018) found that managers make significant decisions based on metrics or "web clicks." In closed labor markets, such as Uber and Lyft, ratings serve as an evaluation of work quality, but do not influence future hiring decisions, as workers are assigned tasks automatically by algorithms (Rosenblat, 2018). A small and growing stream of research highlights how the algorithms governing reputational ratings can also lead to systematic discrimination, inflation, and other drawbacks that threaten to challenge the effectiveness of rating systems and digital platforms (Cato & Rosenblat, 2017; Horton & Golden, 2015; Luca & Zervas 2016; Rahm, 2019). For example, Hannak and colleagues (2017) found that algorithms used for workers on TaskRabbit and Fiverr consistently display minorities (women, black, and Asians) lower than whites in search results, making it less likely that they would be selected for assignments.

Algorithms Embedded in Work. How humans and algorithms interact in the context of work is relatively unexplored, leaving open questions about how workers interpret and respond to the algorithm. I begin with an assumption and a definition. First, I use the term algorithmic not in the mathematical sense, but instead as a set of logic steps, typically encoded in software code, based on a set of variables that are set to maximize a predictive outcome. Thus, algorithms are in themselves not fixed entities but probability equations suggesting an outcome. Second, I limit my interest in algorithms to how they shape social interactions within the workplace relating to the actual doing of the work. Thus, I define algorithmic work as a ***set of job-related activities***

that are structured by algorithms which are, in turn, a set of logic steps, typically written in software code, that are set to maximize a predictive outcome.

The information sciences and communications disciplines have done the most research to begin to explore the concept of algorithmic work. These scholars have explored workers' complex emotions in response to the algorithms, generally drawing the conclusion that the algorithms are an exploitative agent that workers counter and manipulate. In one of the first case studies, Lee et al. (2015) explore how drivers counter an algorithm's nudges by declining less profitable work or hiding "in plain sight" so the algorithm will not assign them work, but they can earn a guaranteed hourly wage. Other information studies explore how workers use online forms to perform information arbitrage by workers sharing information about how to "outsmart" the algorithms. Workers on the MTurk platform, for example, can use the TurkOptican forum to share complaints about assignments that are insufficiently compensated for their time/effort, or not paid at all (Irani & Silberman, 2016). Similarly, driver forums allow drivers to share information about high-demand areas, changes in pay structures, and how to navigate remote support (Rosenblat & Stark, 2016; Rosenblat, 2018). Studying an online food delivery company, Shapiro (2018) finds workers becoming disgruntled by falling wages and exiting for other work. A common theme across this research is that algorithms systematically exacerbate the power asymmetry between organization and workers, and disadvantages workers, such that "the wealthy and informed get the edge, and the poor are more likely to lose out (O'Neil, 2016:114).

More broadly, psychologists have explored how workers interpret and respond to algorithms. Interactions with technology and humans is a different psychological experience, even when the tasks and objectives are the same, as they experience less social evaluation concerns when interacting with technology (Raveendhran & Fast, 2019b). Individuals generally agree that algorithms make more accurate, objective, and quicker decisions than humans (Logg, Minson, & Moore, 2019a), especially for more mechanical tasks such as predicting when machinery will malfunction (Lee, 2018). However, individuals tend to lose trust in algorithms when they see they make an error, even if overall they are more accurate than humans (Dietvorst, Simmons & Massey, 2015). This aversion is only overcome if individuals are given some ability to modify, even slightly, the algorithm (Dietvorst, Simmons, & Massey, 2016). While humans are averse to algorithms making subjective (Lee, 2018) or ethical/moral decisions (Jago, 2019) as they lack a human mind (Bigman & Gray, 2018), recent advancements help make people more comfortable trusting algorithms. Anthropomorphizing algorithms—such as naming a search algorithm "Siri," "Alexa," or "Ask Jeeves"—increases humans' ability to rapidly build trust in algorithm-based services, such as autonomous cars (Waytz, Heafner & Epley, 2014), smart home assistants (Benlian, Klumpe & Hinz, 2019), or avatars (Lucas, Gratch, King & Morency, 2014). Yet this trust comes at a cost as the rise of products and services built around algorithms make privacy more vulnerable (Fast & Jago, 2019). Fast & Jago (2019) suggest that diffusion and convenience of algorithms erode people's capacity and psychological motivation to take meaningful action against algorithms, as they are rationalizing their potential harm and believe privacy loss is inevitibile. And, in some cases, individuals may prefer to interact with an algorithm than a person, due to the perceived lack of social judgement and anonymity (e.g., Raveendran & Fast, 2019b).

Unexplored Questions about Algorithmic Work

Overall, this literature reveals many exciting unexplored questions about the algorithmic work at varying levels of analysis. The two major sub-questions are: Where in the organizational structure are we studying algorithms? And with whom are the algorithms interacting? Let us address the second question as it has insights for the first. Similar to the customer service triangle in the service workplace (Liedner, 1996, 1999; Lopez 2010), the algorithmic workplace has various constituents or users—managers, data scientists, employees/workers, customers, and consumers—that interact with the algorithms. One helpful way to categorize these workers is if they interact with the algorithm above or below the application programming interface or API. The API specifies the computer program's "rules of engagement" with those on the back-end designing, programming, and directly modifying the algorithms. Front-end users interact with the output of, respond to, and may indirectly modify the algorithms. This rich web of interactions illustrates how a wide variety of users think about and respond to algorithms and how this influences other levels and processes in the triangle. (See Figure 3-1.) Some of the questions to be explored in the dissertation and in future research are described below.

> *Worker ←→ Algorithm.* How do workers interact with and communicate with the algorithm and vice versa. How do these interactions matter? What are the psychological and behavioral outcomes of working with algorithms? How does the algorithm communicate with workers and how does it modify itself based on these interactions? Do workers see the algorithms as a contract, suggestion, or a promise? What are the consequences if the algorithm breaks the agreement?

> *Customer ←→ Algorithm.* How can customers interact with and communicate with the algorithm and vice versa? How do these interactions matter? What are the psychological and behavioral outcomes of interacting with algorithms? How does the algorithm communicate with customers and how does it modify itself based on these

interactions? Do customers see the algorithms as a contract, suggestion, or a promise? What are the consequences if the algorithm breaks the agreement?

Organization ←→ Algorithm. How are algorithms designed, modified, and monitored? Does having access to the code matter for organizational managers? How are managerial suggestions about the algorithms encoded by programmers and interpreted by data scientists? Does the organization see the algorithms as a contract, suggestion, or a promise? What are the consequences to the organization if the algorithm breaks the agreement?

Algorithmic Work Triangle System Dynamics. How is power and control exercised in this four-way interaction? How do customers affect the organization and/or workers via the algorithm, or vice versa? How do the algorithms communicate with the different constituents? How do different users interpret the algorithms? What happens when these interpretations differ?

This dissertation takes on several of these challenging questions, focusing on the human-algorithm interactions in the "messy middle," or the execution of work. I explore these questions in the ride-hailing industry, a context where work is coordinated completely by algorithms, using qualitative methods that are the most well-suited to emerging phenomena and theory-building in nascent literatures. In the next section, I detail my research setting and data collection methods in greater detail.

Figure 3-1: Algorithmic Work Triangle

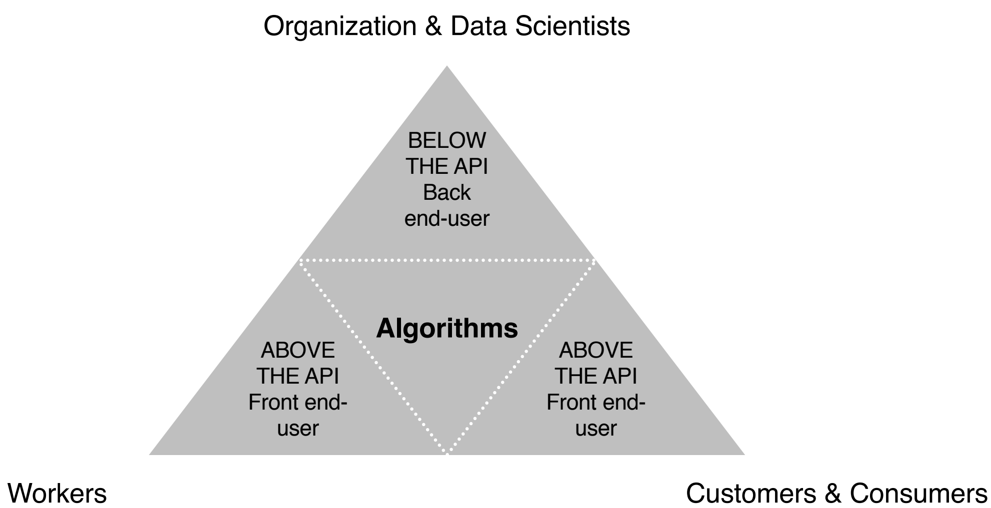

	Table 3-1: Perspectives on Algorithms and Work in the Social Sciences					
	Economics	**Law**	**Information Sciences**	**Communications and Media Studies**	**Organization Studies**	**Psychology**
Conceptualization of Algorithms	Tool to set equilibrium between supply and demand, typically via price	Legal tool, contract, stand-in manager	Intermediary between market and social conditions	Social tool, agent of organization	Technical system, reputation system, architects of organization structure	Unknown technical tool
Illustrative Processes and Outcomes	Equilibrium for price mechanisms, maximum utilization of vehicles	Increasing access to legal information, reducing harassment, worker classification	Highlighting inequalities, algorithm-based work persists and offering tech-based improvements	Information asymmetry, informational arbitrage, reputation bias, myths	Controlling workers, practices leading to ratings construction, changes in organization design	Whether people trust decisions made by a human or algorithm more
How Changes in Algorithm Occur	Programmed by data scientists, dynamic inputs from environment	Programmed and controlled by organization	Programmed by data scientists, dynamic inputs from environment	Programmed by data scientists	Workers' interpretation and practices	Doesn't change, only the tasks it accomplishes and peoples' perceptions change
How Workers Respond to Algorithm	Conform to	Are informed by, follow and abide by	Interact with	Are influenced by, make up stories about	Interpret and shape, are controlled by	Don't (usually) trust
Key Phrases and Metaphors	Machine, optimization, efficiency	Transparency, fairness, regulation	Lever, amplifier, improvement	Information asymmetry, folk myths	Iron cage, panopticon, control, reputation, social construction	Trust, uncertainty, black box, fairness
Example of Questions Addressed	How does the rise of a platform in industry X effect traditional work in industry X? How do utilization rates compare? How do workers respond to incentives? Are minorities being discriminated against?	What regulations are being put on on-demand companies? Are they appropriate? How are workers being classified? How do consumer protection laws apply in the digital age?	How do human and social practices interact in technology mediated work? How can technology systems improve worker inefficiencies?	How do algorithms make practices obscure from and visible to workers? How does the ratings system in platforms ensure those ratings are unbiased? Is there a way to combat bias?	How are ratings and evaluation systems socially constructed? How is the rise of algorithms shaping organizational design and workers? How do algorithms surveil and control workers?	Under what conditions do individuals trust algorithms? How can systems increase people's trust in algorithms?
Exemplar Papers	Cohen, 2016; Cramer & Krueger, 2016; Hall & Krueger, 2016; Zerves, 2016;	Cato & Rosenblat, 2017; Rahesh, 2014; Caleb, 2015; Stokes, 2017;	Lee et al., 2015; Bean 2016; Castillo et al., 2017; Dillahunt et al., 2017; Kameswaran et	Stark & Rosenblat, 2016; Shapiro, 2018; Christin, 2018b; Seavers, 2018; French & Hancock, 2015	Curchod et al., 2019; Orlikowski & Scott, 2014; Rahm, 2019; Shestakosfsky,	Jago, 2019; Raveendran & Fast, 2019b; Lee, 2018; Eslami et al., 2019

	Angrist, Caldwell &Hall, 2017; Edelman, Luca & Svirsky, 2016	Tomassetti, 2016; Cherry, 2017; Hubley, 2016; DeStanfo, 2016	al., 2018; Irani, 2015		2018; Christin, 2018a; Valentine et al., 2017;	

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CHAPTER 4

The Ride-hailing Industry: Research Settings, Design, and Methods

As of 2019, at the publication of this dissertation, ride-hailing services were available in more than 170 countries. The industry includes companies that are both global (e.g., Uber, Lyft, Via) and regional (e.g., Kareem in the Middle East, Didi in China, Juno in New York City) in scope. In this section, I provide a brief overview of the ride-hailing industry, focusing on the four largest companies in the United States: Uber, Lyft, Via, and Juno.

The early ride-hailing industry arose from the sharing economy, an economy where goods or services are shared among a group of users (Sundarajan, 2016). Precursors to the ride-hailing industry include Zipcar, a car sharing service founded in 2000, and BlahBlah car, an online marketplace for carpooling founded in 2006.[8] Advances in smartphone technology enabled the rise of app services, such as Taximagic, an app-based service for hailing taxis founded 2008). Uber, then called Ubercab, was incorporated in 2009 and launched in May 2010, offering luxury sedan services in San Francisco at 1.5 times the price of a cab. As of mid 2019, Uber was in over 600 cities in 60 countries and began offering lower-cost services with economy cars, Uber X (Iqbal, 2019). In the same year Via, a shared ride service where multiple riders share the same car, launched with the two largest companies, Uber and Lyft, quickly following

[8] In contrast to Uber, Lyft, Juno, and Via which are on-demand access platforms, BlahBlah is a true sharing platform with a community-based ridesharing model. Other variants of the shared car model include Zimride, a service where an organization-sponsored ridesharing platform. See Acquier, Daudigeous, and Pinkse (2017), Schor (2013), and Sundarajan (2016) for further theoretical and empirical distinctions between platform types. It is due to these distinctions that I refer to Uber, Lyft and other companies as ride-hailing companies as opposed to ride*sharing*.

suit offering shared rides. As part of a strategy to attract and retain workers, Juno launched in New York City in 2016 taking smaller commissions and offering drivers equity. Over the years ride-hailing companies have added additional services including, food and pet delivery, bus-like services with designated pick-ups and drops, and helicopter service. A 2019 study from Pew Research states that 97% of Americans have heard of ride hailing and 36% of have taken a ride -- more than double from 2015 - and as of 2018 there were around 830,000 drivers in the US (Jiang, 2019).

Since inception, the ride-hailing industry has faced many challenges, including allegations of misrepresenting workers as independent contractors (Mischel & Nicholas, 2019), artificially hiking customer rates (Sidiqui, 2017), deliberately shortchanging drivers' pay (Scheiber, 2017), circumventing local regulations (Issac, 2017), and fostering divisive internal company cultures (Fowler, 2017). The most serious challenge faced during the duration of this study (2016-2019) was the removal of the Uber CEO after a video of him verbally harassing a driver went viral. This was followed by an internal review and a series of actions meant to promote drivers' rights, including the institution of employee-like protections for drivers required by the city of New York, such as guaranteed hourly wages, which resulted in both Lyft and Uber starting driver caps. In spite of these challenges, both Lyft and Uber successfully went public in early 2019, with valuations of $24 billion and $82 billion (de la Merced & Conger, 2019; Ungarino, 2019).

Several factors distinguish ride-hailing companies from liveries, resulting in their classification and regulation as technology companies. While both ride-hailing drivers and taxi drivers are independent contractors, ride-hailing drivers own or lease vehicles from an approved third-party vendor as opposed to owning a medallion. More importantly, the app coordinates the entire work process including hiring, assigning rides, setting wages, directing drivers, and evaluating performance. Unlike taxis, ride-hailing cars only pick up riders who request a ride and are matched by the app. Thus, the ride-hailing company has demographic and financial information about customers, leading drivers to believe that passengers are "safer" than street pick-ups. Lastly, ride-hailing work is even more decentralized and isolating than taxicab work as there are no dispatchers, taxi stands, or garages for maintenance. Further, taxicab drivers often are required to complete additional exams and knowledge checks (i.e., "the knowledge," a course of study for prospective London drivers which consists of 320 routes). As a result, ride-hailing drivers typically report lower levels of occupational identity than taxi drivers (Dubal, 2017). Taken together, these factors lower the barrier for work entry, so that anyone with a car and clean driving record can begin working. In the next section, I describe the process of how drivers complete the employment process.

The Employment Process

Drivers complete an on-line application providing information about their vehicle (make, model, year) and current insurance and inspection documents. Motor vehicle, and sometimes criminal, background checks, are requested through a third-party, with most ride-hailing companies requiring a record free of moving violations in the past three years. Some platforms require reference checks[9] or an in-person meeting with a fellow driver. Once all documents are approved, which can take from three days to three weeks, workers can start working.

The organization communicates with drivers through the app. From the app, drivers can go "on-line" and begin work, view high-demand areas, see upcoming promotions, navigate to past work history (e.g., hours driven, wages). Once drivers go "online" they are matched with

[9] My mother and sisters were sent a text, "Is Lindsey a good driver?" with a ☺ and ☹ as possible responses.

riders and given directions to the pick-up location and destination. Drivers are required to rate the ride before being matched with the next ride. More on this process is described in Chapter 6.

Customer ratings are the most visible form of performance evaluation. All platforms use a 5-star rating scale and drivers need to maintain a score of 4.5 or above to remain active on the platform, although drivers may be immediately blocked from the app after an incident. Some platforms also track acceleration and deceleration speeds and acceptance and cancellation rates. Riders may leave qualitative feedback or select feedback from a range of options (e.g., "Good conversationalist"). Drivers earn badges (visual icons of trophies or slogans) if they receive multiple items of positive feedback. Drivers can contact support via the app or through staffed "hub" centers, available in major cities, if they have any problems. While phone support became more readily available in mid-2018, most drivers report requesting support through the app.

Each company operates a different pay-for-performance system, however, drivers are generally paid a flat, pick-up fee for each ride along with a varying amount based on miles driven and time. Companies may also offer incentives such as hourly guarantees, increased fare during high-demand periods or bonuses for completing a certain number of rides in a short time period. Due to expenses and deprecation it is challenging to estimate drivers' net pay. Estimates range between $8 and $20 an hour, with a recent study putting average pay at $10.81 (Mischel, 2018).

Data Collection

Given the emerging nature of on-demand work and my interest in theory development, I designed a multiple-sources qualitative study, spending three years in the field. I used five overlapping data sources, which I triangulated to bolster validity (Eisenhardt, 1989): participant observation (160 hours as driver),[10] conversational interviews (*n* = 112), semi-structured interviews in eleven North American cities (*n* = 107),[11] focus groups with riders (*n* = 5), and social and print media (e.g., blogs, Reddit forums, magazines and newspapers articles).

Participant Observation. To understand how algorithms were deployed and experienced, I participated in the ride-hailing industry as a driver and rider. From 2016 to 2019, I worked as a driver for several platforms in a major US city using both my personal car and rental car, the latter obtained through a platform-sponsored program. I varied my driving times and routes to widen my range of experiences. I drove the weekday morning commute, the evening bar shift, timed my airport runs with the international flight arrivals, visited higher and lower income neighborhoods, and worked major holidays, including two New Year's Eves (the busiest day of the year). I also conducted mini-experiments on myself. Some days I would try to maximize my income by chasing surges and bonuses, while other times I purposefully ignored surges and did not check my earnings until the day's end. Sometimes I manipulated the app to try and confine my trips to a certain area, while other times I let the app "drive" to see where I would end up. To gain perspective of drivers' experience in a different area, I enlisted a research assistant to drive in another US city. Our ethnographic notes included reflections on: work performance, busyness, ratings, surge pricing and bonuses, pay, interactions with support, breakdowns, accidents, car care, and weather, traffic, and road conditions. I also attended several classes on defensive driving and my legal rights as a driver organized by a local activist group. As a rider, I kept notes

[10] One hundred of driving hours were completed by the first author. As ride-hailing platforms restrict driving to the state where the car is registered, a research assistant completed the remaining hours in a different state.

[11] Geographic break-down of informant locations are as follows: 34% Ann Arbor or Detroit Michigan, 33% Washington, DC, 33% other cities. Interviews were conducted in two phases. Sixty-one individuals were interviewed during the first phase of data collection, from January 2016 to November 2017. Approximately one year after the initial interview, all participants who had driven more than 10 hours/month over the past year (83% of all Phase 1 interviewees) were asked to complete a follow-up interview, of which 84% accepted. Some declined to participate because they were no longer driving, had moved, or were no longer interested in the study. When possible, I conducted a short exit interview.

of nearly all rides (n = 112) taken during the same time period. These rides were personal and specifically for the sake of this research as I would often spend afternoons taking rides around an area of town I have not visited before. Logs included information about how I hailed the ride, the car's condition, app malfunctions, and overall impressions of the ride including my driver rating.

Semi-Structured Interviews. I conducted two rounds of interviews with drivers, roughly a year apart. In my first round of data collection, I conducted 63 semi-structured interviews with drivers working in twenty-three North American cities and towns.[12] The interview protocol began with grand-tour questions: "Tell me about driving?" "What's a good day working?" "Describe a positive (negative) interaction you've had with a customer." Roughly one year after the initial interview, I contacted all regular drivers[13] for a follow-up of which 44 drivers (76%) were interviewed.[14] Second-round interviews were more focused and followed up on themes that came up in the participant's first interview. All interviews except one were conducted in English, and all interviews except two were professionally transcribed. In total, I conducted 107 interviews with 63 drivers of which 19 (30%) were female. Fifty (70%) reported driving as their primary source of income and all except one reported driving to meet essential household expenses, such as utilities, health care, and child support. Twenty-four drivers (38%) were active on at least two apps, though not all participants lived in cities with multiple ride-hailing companies. Amount of time driving ranged from two weeks (10 rides) to seven years (18000

[12] I interviewed drivers in Ann Arbor (Michigan), Atlanta, Austin, Baltimore, Boston, Charlottesville (Virginia), Chicago, Denver, Detroit, Houston, Lewiston (Maine), Los Angeles, Missoula (Montana), Montreal (Quebec), New Haven (Connecticut), New York City, Palo Alto (California), Port Huron (Michigan), Philadelphia, Sacramento, San Francisco, Seattle, and Washington, DC.
[13] Using Katz and Krueger's (2015) definition of regular driving as more than 10 hours per month, I did not contact four drivers for follow-up interviews. An additional participant was not contacted again as ride-hailing was now banned in their city.
[14] Of the 44 drivers who were interviewed again, four were no longer driving and so I conduced a short exit interview. The remaining drivers (14) declined a follow-on interview either because they were no longer driving (3) or not interested.

rides), with my sample averaging fourteen months driving and 1,800 trips completed with a 4.87/5.0 rating. See Table 1 for a participant inventory.

I used several sampling approaches to ensure maximum variation and participant anonymity.[15] I initially met roughly half my informants directly through hailing—either as part of my everyday life (e.g., traveling to the airport or in a different city for a conference) or through expeditions where I would visit an unfamiliar area of a new city and hail rides. Research assistants also travelled to cities to recruit potential informants. Further, to increase my participants' anonymity, I would often hail rides from family and friends' platform apps. The other half of my sample was recruited in-person at locations where drivers congregate (e.g., airport parking lots, vehicle inspection stations), online from advertisements in forums and discussion groups, convenience sampling (from friends and friends of friends), and snowball sampling. By far, snowball sampling was the least lucrative sampling technique because most drivers did not know other drivers.[16] Whenever possible I tried to oversample on drivers who were female, white, or part-time to gain more minority perspectives. Though I recruited informants in-person, due to drivers' variable schedules, I conducted the majority of interviews over the phone. Interviews ranged from 35 minutes to 2.5 hours with an average of 65 minutes. Lastly, I collected data across multiple cities because ride-hailing and new features (e.g., shared rides, deluxe rides) were introduced at varying times and places. For example, shared rides, a car-pooling type service that matches drivers with multiple riders traveling in the same direction, were first introduced in 2015 and are only available in larger cities. Interviews included cities

[15] News media have reported that riders and drivers have been blocked from the app due to taking grievances public (Issac, 2017, 2019).
[16] Three drivers had multiple members of their household driving. I chose not to interview more than two people from the same household.

where the industry was well-established (e.g., San Francisco, Philadelphia), nascent (e.g., Ann Arbor, Missoula), banned (e.g., Austin, Montreal), and faced pressure from unions (e.g., New York City, Seattle).

One important consideration is potential biases from my sampling technique. The majority of ride-hailing work is completed by a minority of workers. In other words, drivers who work the least are the majority of the population of drivers; however, the majority of rides are given by drivers who work the most hours. Further, unsatisfied workers are more likely to stop working before drivers who are satisfied. The majority on my sample was recruited while driving, hence my sample is skewed to drivers who driver longer hours and are more satisfied. I have described how my sampling affects my findings in the methods section in Chapters 4 and 5.

Focus Groups. To gain a deeper understanding of the riders' experience, I conducted focus groups (n = 5) with heavy users (n = 27) who had regularly taken five or more rides per week over the past three months. Focus groups were recruited from a university subject pool and included students, staff, and community members. Conversations were recorded and a research assistant, who did not participate and sat in a side room, took notes while I led the group. Themes covered included trip experiences, how riders use the app, app malfunctions, and the rating system.

Archival and Social Media. Archival materials served as useful support for triangulation (Shah & Corley, 2006) and included newspaper and magazine articles, social media posts, Youtube videos, how-to guides, blogs, forums, and company websites. Social media sources were chosen by a popularity measure from Alexa, a web traffic analytics company. The most popular website, *The RideShare Guy: Blog and Podcast For Rideshare Drivers,* featured weekly posts by a rotating cast of drivers across North America. From these materials, I created several analytical aids, such as a timeline of the industry and a compilation of interviews with industry leaders. This was an unobtrusive form of data collection (Webb & Weick, 1979) that provided important information about the social, legal, and political challenges in the industry as well as additional perspectives on drivers' experiences.

Data Analysis

I analyzed data using a grounded theory approach (Charmaz, 2006; Locke, 2001; Strauss & Corbin, 1990) with field observations, interviews, and forum postings as my primary data sources. Chapter 5 and 6 each describe the specific analysis used for their respective findings.

Table 4.1: Participant Inventory

Name	Sex	City	Co-Current/Prior Work	Multiple Job Holder	Prior Experience in Driving Industry	Expressed Motivation	Length of Time Driving, in months	Number of Rides, across platforms	Driver for Multiple Platforms
Sarah	F	Chicago	Care Work	Y	N/A	Income, FT job reduced hours	12	500 - 800	N
Jared	M	Seattle	Service - Restaurant	Y	Delivery	Income, multiple job holder; Social, drivers when bored	12	500	N
Jamal	M	Ann Arbor, MI	Service - Restaurant	N	N/A	Income, fired	5	250	N
Leo	M	Ann Arbor, MI	Service - Restaurant (manager/owner)	N	N/A	Income, in-between jobs	7	3000	Y
Karen	F	Detroit	Care Work; Social Security (disability)	N	N/A	Income, pay for medications	15	1700	Y
Jonathan	M	Washington, DC	Manual Labor; Sales; Driver	Y	Taxi, Limo	Income; Schedule Flexibility, illness	6	Not known	Y
Frank	M	Baltimore	Taxi; Retail (manager)	N	Taxi	Income, in-between jobs	18	5040	N
Winnie	F	Washington, DC	Security Guard	Y	N/A	Income, pay for daughter's college	30	1500	Y
Chapman	M	Detroit	Manual Labor	N	N/A	Income, laid off prior job	18	5000	N
Kentucky	M	Philadelphia	Student	N	N/A	Income, trying to start own business	1	350	N
Polly	F	Philadelphia	Retail; Care work (unpaid)	N	N/A	Income; Schedule Flexibility for eldercare	12	4000	N
Forest	M	Detroit	Manual Labor; Social Security (disability)	N	Commercial	Income, laid off, supplmenet social security; Boredom - get out house	36	1150	Y
Porris	M	Boston	Retail	N	N/A	Income, laid off	18	1500	Y
Tabitha	F	Detroit	Service - Restaurant	N	N/A	Income, quit prior job because of boss	1	200	N
Lillian	F	Baltimore	Service - Restaurant; Care Work (unpaid)	Y	N/A	Income, to meet unexpected expenses	6	10 (not a typo)	N
Mary	F	Detroit	Call Center; Retail	Y	N/A	Income, laid off	14	1200	Y
Ernest	M	Los Angeles	Clerical/Office Work	Y	N/A	Income, wanted extra money to spoil grandchildren	18	1000	N
Myrtle	F	Boseman, MT	Clerical/Office Work	Y	N/A	Income; Curiousity; Schedule Flexibility, new mother	4	400	Not an option
Nathan	M	Charlottlesville, VA	Driver - Food Delivery	N	N/A	Income, couldn't find other job	36	N/A	Y
Joel	M	Detroit	Sales	Y	Taxi	Income, save money for retirement and help mom	11	5000	Y
Jay	M	Washington, DC	Sales	N	N/A	Income, laid off prior work	60	4000	Y
Chase	M	Washington, DC	Manufacturing (technican)	Y	N/A	Income, no more overtime	1	25	N
Aaron	M	Ann Arbor, MI	Care Work; Student	Y	N/A	Income, problems with prior boss; Schedule Flexibility with school	7	2000	N
Catherin e	F	Port Huron, MI	Clerical/Office Work	Y	N/A	Income for extra expenses; Boredom, likes being busy	4	300-350	N
Seth	M	Washington, DC	Clerical/Office Work	Y	N/A	Income, Schedule Flexibility	24	5000	N

*N Not known means either a) Driver did not know their number of rides and did not want to check their app in the interview or b) Author forgot to ask.

Participant Inventory

Name	Sex	City	Co-Current/Prior Work	Multiple Job Holder	Prior Experience in Driving Industry	Expressed Motivation	Length of Time Driving, in months	Number of Rides, across platforms	Driver for Multiple Platforms
Eleanor	F	Detroit	Call Center; Retail - Food Services	N	N/A	Income, for medication and 'fun'; Social, meeting new people	18	500	Y
Roger	M	Washington, DC	Pilot (Contract)	N	Pilot	Income not able to find enough pilot work; Schedule Flexibility with other work	6	1200	Y
Sheldon	M	Ann Arbor, MI	Driving Industry - Dispatcher	Y	Dispatcher	Income, not enough overtime at other job	36	2250	Y
Kristen	F	New Haven, CT	Care Work; Driver-Food Delivery	N	Delivery	Income, lost job	9	580	Y
Sean	M	San Francisco	Civic	Y	N/A	Income, extra money; Boredom, wanted to spend time productive	3	200	N
Carlos	M	Baltimore	Manufacturing (technican)	Y	N/A	Income, no raise at curent job; Curiosity, new experience	4	12 (not a typo)	N
Pound	M	Detroit	Sales	N	N/A	Income, in-between jobs	33	18000 (not a typo)	Y
Colorado	M	Lewiston and Portland, Maine	Service - Food Industry; Student	Y	N/A	Income, extra money for a student	0.5	10 (not a typo)	N
Japan	M	Denver	Call Center	Y	N/A	Income, student loan/debt	14	657	Y
Tyrone	M	Boseman, Montana	Service - counseling	Y	N/A	Income, multiple job holder	9	1500	Y
Vox	M	Montreal, Quebec	Manufacturing	N	N/A	Income, couldn't find other work	18	Not known	Not an option
Sebastien	M	Detroit	Driver - Commercial	N	N/A	Income, student loan/debt payments	9	3000	Y
Nancy	GF	San Francisco	Research	Y	N/A	Income; Schedule Flexibility works to/from her primary job	2.5	150	N
Andre	M	Detroit	Manufacturing (self-employed)	Y	N/A	Income, to supplement side business	18	2000	Y
Casside	F	Houston	Clerical/Office Work	Y	N/A	Income, lost job and supports adult daughter	60	800	N
SueEllen	F	Denver	Interior Design; Care work (unpaid)	N	N/A	Income, car payment; Social, meet people	6	536	N
Charlotte	F	Ann Arbor, MI	Care work; Student	Y	N/A	Income; Schedule Flexibility, in school	2	70	N
Lisa	F	Austin	Call Center	Y	N/A	Social, meet people and get out of house	12	125	Y
Maria	F	Boston	Service - Retail; Service - Food Industry	N	N/A	Income, in-between jobs	24	500	Y
Abraham	M	Washington, DC	Real estate broker (self-employed)	N	N/A	Income, not enough income from regular job	8	1000	N
Zara	F	Washington, DC	Service - trainer (Self-Employed)	Y	N/A	Income, multiple job holder	10	Not known	N
Jackson	M	Philadelphia	Manual Labor	N	N/A	Income, pays more than other work	20	4000	N
Ralph	M	Detroit	Service - Food Industry	N	N/A	Income, in- between jobs	36	8000	Y

*N Not known means either a) Driver did not know their number of rides and did not want to check their app in the interview or b) Author forgot to ask.

Participant Inventory

Name	Sex	City	Co-Current/Prior Work	Multiple Job Holder	Prior Experience in Driving Industry	Expressed Motivation	Length of Time Driving, in months	Number of Rides, across platforms	Driver for Multiple Platforms
Andrew	M	Washington, DC	Service - Food Industry	N	N/A	Income; Schedule flexibility	4	650	N
Morris	M	Chicago	Real estate broker (self-employed)	N	N/A	Income, left other job	18	1700	N
Calvin	M	Washington, DC	Retail; Service - trainer (self-employed)	Y	N/A	Income, laid off	18	500	N
Lincoln	M	Boston	Driver - Food Delivery	N	Delivery	Income, in-between jobs	20	4000	N
Albert	M	Boston	Driver - Taxi; Manufacturing	N	Taxi	Income, in-between jobs; Schedule Flexibility, sick child	3	2000	N
Robert	M	Detroit	Service - Food Industry	N	Delivery	Income; Schedule flexibility, primary caretaker of children	8	1500	N
Kenny	M	Baltimore	Manual Labor	N	Commercial	Income, in-between jobs	12	Not known	N
Sam	M	Detroit	Manufacturing (management)	Y	Works in auto plant	Income, daughter's college fund; Social, meet people	14	1700	N
Anton	M	Detroit	Service - Food Industry	N	Delivery	Income, could not find other work	18	2100	Y
Chuck	M	Washington, DC	Retail	N	Taxi	Income, in-between jobs	5	Not known	Y
Nixon	M	Washington, DC	Sales; Service - trainer	N	N/A	Income, laid off	10	Not known	Y
Slim	M	New York City	Sales; Driver - Limo	Y	Limo	Income; Schedule Flexibility, illness	30	6500	Y
Chad	M	New York City	Service - Food Industry	N	N/A	Income	18	1500	Y
Zack	M	New York City	Sales	N	N/A	Income; Schedule Flexibility, illness	30	4500	Y
Laina	GF	Sacramento and San Francissco	Office/Clerical	N	N/A	Income, quit job	3	356	Y
Marvin	M	San Francisco, CA	Engineer	Y	N/A	Income, child support	30	8000	Y

*N Not known means either a) Driver did not know their number of rides and did not want to check their app in the interview or b) Author forgot to ask.

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CHAPTER 5

Allies or Adversaries?: Making Meaning of the "New" Gig Employment Relationship

> I have a double feeling about the company. It's a great way to survive. When you don't have another job, when you need to make ends meet, to put some bread on the table - it's a great place to be. [Long pause.] On the other hand you make ends meet - not more. It will look like you earn a lot, but it's only an impression. We are all miserable... we kill to pay for the car, to pay for gas, and put aside money for the next car because this car will be junk very soon. And hopefully there is some leftover money that can be used to buy bread. [Nervous laugh.] (Lincoln)

Caviar. Crowdflower. Catalant. The contemporary workplace is rapidly changing. Over the past decade the number of nonstandard workers has more than doubled with around 14% of the US workforce working as "free agents" moving between gigs. Much of this work is precarious with workers encountering temporary employment contracts, variable pay, and unsafe working environments (Kalleberg, 2009; Katz & Krueger, 2019). While emerging research has explored these structural changes (Curchod et al., 2019; Gray & Suri 2019; Lee et al. 2015; Shapiro, 2017), it has not yet explored how these changes are shaping workers' experience and meaning-making, particularly in the rapidly growing on-demand economy, a labor market where work is always available and facilitated by digital platforms. Are workers grateful for the opportunity to work, or resentful at its conditions? How do these emotions affect the way they approach work and interact with clients, or their perspectives on the company? The "double feeling" that Lincoln describes highlights the complex and sometimes conflicting meanings workers give to the changing workplace. This paper goes beyond the dichotomy of "good job, bad job" (Kalleberg, 2011) to explore how those in precarious, on-demand jobs experience and make meaning of their work.

Meaning making is a fundamental human endeavor (Baumeister, 1990; Brief & Nord, 2000; Hall & Mirvis, 2004*)*. Interpreting what work signifies and the role it plays in life has been encouraged by industry, business leaders, and in popular writing from the earliest days of capitalism to today (Hurst, 2017). Prior work has primarily considered meaning making in the aftermath of a trigger (Weick, 1995; Weick, Sutcliffe & Obstfeld, 2005) or in the event of the work that has significance or meaningfulness (Dobrow, 2012; Bunderson & Thompson, 2009) or both (Maitlis, 2009; Schabram & Maitlis, 2017). Much less research examines the types of meaning constructed in the everyday. Several features of gig work complicate what we already know about meaning-making. Literature on the meaning of work has largely focused on how one's values, beliefs, and attitudes can give individuals a sense of identity, purpose, and contribution through fostering a sense of authenticity, belonging, and self-efficacy. However, for many individuals, financial insecurity, often as a result of gig work, can make the economic value of work more manifest. Classic "strong" situations such as poverty or financial insecurity (Leana, Miettal & Stiehl, 2012) may crowd out the single sources of meaning typically identified in meaning-making studies.

An emerging stream of research looks at the roles of others, such as managers and coworkers, in shaping meaning-meaning, arguing these individuals offer cues from which workers can then interpret (Salancik & Pfeffer, 1978; Wrzesniewski & Dutton, 2001). Meaning can be constructed from managers normalizing stigmatized activities (Ashforth, Kreiner, Clark & Fugate, 2017), job titles (Grant, Berg & Cable 2014), professional development activities (Sonenshein, Dutton, Grant, Spreitzer & Sutcliffe, 2006), and connections to a broader purpose, such as serving the sick (Dutton, Debebe & Wrzesniewski, 2016) or animal welfare (Schabram & Maitlis, 2017). Yet, a common feature of gig work is its decentralized and distributed nature—workers are classified as independent contractors, with no long-lasting ties to the organization, work remotely, with little (if any) direct contact with organizational members, and are often assigned micro-tasks devoid of context—all of which limit the interpersonal and organizational cues available for meaning-making. In sum, the contemporary workplace puts into place a new set of previously unstudied features that may alter meaning-making processes.

Lastly, on-demand work is a type of service work in which work is accomplished through interactions between workers, customers, and organizations. While the literature on the meaning of work has not specifically looked at this three-way dynamic, a central theme of labor process theory and service work literature is how workers make meaning of the service triangle. Framed as a dynamic contestation or struggle between workers, companies, and customers, a core question is whether workers experience their work as alienating or fulfilling—or, more accurately, to what extent workers are alienated from their work. In classic labor process theory, workers collude with co-workers to resist management's exploitation by shirking, sabotaging, and boycotting (Roy, 1952; Burawoy, 1979; Montgomery, 1979). Customer service work entails that workers manage their emotional displays towards customers for the benefit of the organization, whether through smiling (Hochshild, 1983), being joyful (VanMaanen, 1989) or irritated (Sutton, 1991), which alienates them from their true emotions and ultimately their work. In addition, workers may be unfairly evaluated by customers (McCammon & Griffon, 2000; Fornell, Johnson, Anderson, Cha, & Bryant, 1996; Parasuraman, Zeithaml, & Berry, 1988), which is exacerbated in online labor markets where customer ratings are the only form of evaluation (Curchod et al., 2019; Rosenblat & Stark 2016). Organizational routines offer some protection against customers, providing workers guidelines for how to respond to inappropriate behavior so workers can maintain a sense of dignity and self-worth (Leidner, 1993; Sherman, 2005; 2007). In sum, the service work literature suggests that gig work will be another work context that will exploit workers.

The literature on the meaning of work and on service work leaves unanswered questions about meaning-construction and on-demand work. What cues are prominent in such a distributed work environment, and how do these cues shape workers' attitudes, beliefs, and practices? To explore these questions I turn to the ride-hailing industry, the largest employer within the on-demand economy. Ride-hailing involves three-way interactions between workers, customers, and the technology (app) that assigns, routes, and evaluates rides. My findings show that drivers make two overarching interpretations of the work—seeing it as either an alliance or as an adversarial relationship—based on cues from the customer and the technology. To frame my findings, I review literatures on the meaning of work and service work with a focus on how these theories may or may not apply to on-demand work. After describing my data collection and analysis, the findings section begins by explaining the shared beliefs and work biographies of drivers. I then delve into the experience of work itself, documenting three sets of practices and beliefs—in relation to customers, technology, and the company—that shape how drivers make meaning of their work. Together, the configuration of practices and beliefs converge into two constellations—alliance or adversarial—that describe two different modes or relationships to the work arrangements. Taken together, this study unpacks the workers' experience of on-demand work, detailing how multiple sources of the work environment shape workers' meaning-making construction. Theoretically this study makes several important contributions to the literatures on the meaning of work and on service work.

Literature Review

Making Meaning at Work

How an individual makes meaning of work—interpreting what work signifies and the role it plays in their life—is a fundamental part of the human condition (Baumeister & Vohs, 2002; Brief & Nord, 1990; Hall & Mirvis, 2004). According to Pratt and Ashforth (2003), meaning is the output of having made sense of something, or what it signifies; as in an individual interpreting what role her work plays in the context of her life. As opposed to sensemaking (Weick, 1995; Weick, Sutcliffe & Obstfeld, 2005; Maitlis & Christianson, 2014), which occurs only after an unexpected event or challenge, meaning-making is on-going and pervasive and, unlike meaningfulness (Dubrow, 2012; Bunderson & Thompson, 2013; Schabram & Maitliss, 2018), may lack significance or importance.

Meaning can be constructed individually (from a person's own values and perceptions), socially (from norms or shared perceptions), or both (Pratt & Ashforth, 2003). Psychologists have long considered the self as a primary agent or determinant of many kinds of behaviors, attitudes, and beliefs (Bandura, 1989; Brief & Nord, 1990; Maslow, 1968; Rogers, 1961) that influence workers' perceptions of the meaning of work. For example, the belief of how central work should be in one's life is associated with one's parents attitudes toward work (Dekas & Baker, 2014) and maps onto three ways individuals orient to work, as either a job, a career, or a calling (Wrzesniewski et al., 1997). Social information processing theory (Salancik & Pfeffer, 1978) and its conceptual cousin, interpersonal sensemaking (Wrzesniewski, Dutton & Debebe, 2003), suggest that individuals scan for, read, and interpret cues that directly and indirectly inform how workers make meaning. Coworkers reinforce certain values and identities (Kahn, 2007), such as being a caring and considerate team member (Wrzesniewski, Dutton & Debebe, 2016), and provide opportunities for workers to express these identities. Managers guide organizational missions and goals in ways that influence workers' perceptions of the meaning of their work (Podolny, Khurana, & Hill-Popper, 2005), even neutralizing the stigma of socially undesirable jobs (Ashforth, Kreiner, Clark & Fugate, 2017). Job crafting poses workers as active meaning creators in that they can alter the task and relational boundaries for their work (Wrzesniewski & Dutton, 2001; Tims, Bakker, Derks, 2012; 2013). Further, workers can change their own or others' expectations of their behaviors (Berg, Dutton & Wrzesniewski, 2010) or pursue activities outside of their normal job duties (Berg, Grant & Johnson, 2010). Organizations also provide cultural raw materials or repertoires (Swidler, 1986) for individuals to draw upon, such as training opportunities that allow for the construction of self-narratives about growth (Sonenshein, Dutton, Grant, Spreitzer & Sutcliffe, 2006). Taken together, the meaning at work literature has evolved from looking at psychological to social mechanisms of meaning-making, such as interactions and cues with managers, co-workers, and the organization itself.

Yet, the changing nature of work, as evidenced by an increase in remote/virtual work and precarious work conditions, may alter how workers construct meaning (Standing, 2011; Katz & Krueger, 2016, 2019). Being physically separated from managers and peers can foster extreme emotions (Petrigileri, Ashford & Wrzesniewski, 2018) and feelings of social isolation (Bartel, Wrzesniewski & Wiesenfeld, 2012), often leading many remote workers to turn to alternative work spaces such as coworking communities (Garrett, Spretizer & Bacervice, 2016). Other dimensions of the work context, such as individuals' financial circumstances, shape how individuals determine the meaning of their work (DeVoe & Pfeffer, 2007; Pfeffer & DeVoe, 2009; Meuris & Leana, 2018). Research has shown that for those who are involuntarily unemployed or otherwise have inadequate incomes, the economic value of work becomes more salient (Brief et al., 1995; Brief & Nord, 1990; Jahoda, 1982; O'Brien, 1986) as opposed to the more latent value of work (e.g., self-fulfillment). In other words, workers with greater financial needs focus more on the economic value of work than its psychological significance. Existing research on meaning-making tends to identify a single source of meaning that may be crowded out in classic "strong" situations, such as poverty or financial insecurity (Leana, Miettal & Stiehl, 2012). This literature suggests that elements of the changing work context, such as more remote work and precarious financial circumstances, may challenge meaning-making for workers.

Looking across this literature identifies two unexplored questions. The more general question is, "How does meaning making occur in the everyday absence of triggers or work that is inherently significant?" Second, "How might theories of meaning-making be extended by exploring its construction in the 'strong situation' of a contemporary workplace with fewer social and organizational cues and more financial insecurity?" To more deeply explore these questions, I turn to the customer service industry, the fastest-growing sector in the US and global economy, and its associated literature.

Meaning Construction in Service Work

Job growth is concentrated in the fast-growing service sector, which, as of 1980, overtook manufacturing as the largest industry in the United States (Westcott and Bednarzik, 1980) and is still the largest industry world-wide, constituting 80% of US GDP and 60% of the global GDP (World Bank, 2019). Service work is defined as value that is created collaboratively through the exchange of intangible resources and competencies by one party for the benefit of another (Apte 2019; Vargo, Lusch, & Akaka, 2010). At the heart of service work is the triangle relationship between customers, workers, and organizations, dubbed the service triangle or the triangle of power. Two focuses of this literature are on the emotional labor of workers and the role of customers affecting the service triangle.

Customers introduce a level of uncertainty into any economic exchange. Emotional labor—the process through which interactive service workers align their emotional displays with managerially imposed "organizational feeling rules"—is meant to reduce that uncertainty, in essence turning work into a commodified service exchange (Hochschild, 1983/2013). Flight attendants must "go out there and smile…. really lay it on" (Hochschild 1983: 4), Disney park employees are told to project an image of being "friendly, young, and educated" (Van Maneen & Kunda, 1989: 59), and insurance agents were dared to "develop a winning personality" (Liedner, 1992: 104). Not forced to display only positive emotions, bill collectors are trained to convey a sense of urgency and irritation to debtors to induce prompt payments (Sutton, 1991) and doctors are taught to remain neutral even when delivering bad news to patients (Fineman, 1993). This acting—suppressing one's true emotions and expressing the "appropriate" emotions toward customers to enhance the exchange—estranges workers from their true emotions ultimately alienating them from their labor (Hochschild, 1983).

Relationships with customers can mitigate or amplify this estrangement. Customer relationships can be divided into two types: service and pseudo (Gutek, 1995; Bhappu & Schultze, 2006; Gutek & Welsh, 2000). Service relationships are characterized by the opportunity for repeated service exchanges between the same customer and worker with customers considering the worker in possessive terms such as "my doctor," "my hairdresser," or "my nanny." Over time, these relationships become interdependent based on shared history, trust, and repeated goodwill, leading to a greater sense of worker fulfillment (Gutek, 1995). In pseudo-relationships, customers have repeated service exchanges with a specific organization rather than the same provider, such as seeing doctors within an HMO or visiting a McDonald's. This service design assumes that workers are functionally equivalent and interchangeable. Pseudo-relationships are challenging conditions for meaning-making, given that workers have weaker relationships with customers and the organization. Further, given that workers are seen as interchangeable from the organization's viewpoint, it heightens feelings of estrangement.

Another line of research examines power dynamics within the service triangle. Classical labor process theorists argue that organizations and customers always have control over workers leading to their estrangement from work (Braverman, 1974; Burawoy, 1979; Edwards, 1979). Taking a situationist perspective, Leidner (1994, 1996) challenges this concept arguing that customers can be antagonists or allies of workers and organizations based on a shifting three-way interest alliance. In some situations the routines of service workers or scripts serve to align the interests of workers and customers against the organization, making it possible for workers to feel better about work (Leidner, 1994). Other research suggests that organizations structure worker-customer relationships in a way that predisposes whether interactions with customers are experienced by workers as alienating or fulfilling. In organizations with a market orientation, as opposed to relational, workers are more likely to find the work alienating (Korczynski, 2009). Race and class struggles are embedded within the job role, such that minority workers are given less visible jobs (Williams, 2006) or are subject to more extreme Taylorization (Sallaz, 2009), and used against workers to have them lower pay and status (Williams & Connell, 2009).

Data Analysis

Data Analysis

I analyzed data using a grounded theory approach (Charmaz, 2006; Locke, 2001; Strauss & Corbin, 1990) with field observations, interviews, and artifacts collected from drivers as my primary data sources.

Stage 1: Focused Coding. Whether or not drivers enjoyed their work was evident from my first weeks in the field. While I tried to come into the field as a "tabula rasa" or blank slate given all the public media and around ride-hailing, I initially thought that most drivers did not like their work. Yet, in my first day of driving, I noted both positive and negative things about my day. Befuddled by the app, I missed my first ride, dropping my phone under the seat, but in the subsequent ride I received my largest tip ever ($20) and had an amazing conversation with a nurse who had a daughter at my alma mater. My first two interviews confirmed these different perspectives. Nixon complained at length about how customers disrespected him and about his physical pain from driving, noting several PTSD-like incidents. In contrast, Sam enthusiastically shared about the friendships he developed with customers—indeed he became an informant and he gave me several rides off the app. Three subsequent interviews with drivers offered similar positive feedback about the work. Thus, I followed my data, probing on the aspects of the work drivers did and did not enjoy, making sure to ask every participant questions such as, "Tell me about a positive (negative) experience with a rider?" or "What has been your best (worst) day working?"

Based on my field work, I split the interviews into two categories according to how drivers evaluated their work (positive/negative), but it quickly became apparent that these categories were too coarse, as even people who were satisfied with the work had complaints and vice versa. I then tried two different coding schemes, first adding two different valence categories (neutral and both highly negative/highly positive) and then trying to recategorize the interviews on a continuum from highly negative to highly positive. Neither proved fruitful, as I still did not have enough theoretical leverage, being unable to find mechanisms to explain the difference or extrapolate and answer the question, "What is this a case of?" Thus, I stopped analyzing my data at the individual level and started searching for a new unit of analysis. Though drivers did not work in a traditional work setting, there were specific things they continually interacted with or frequently thought about in the course of their work activities. Thus, I decided to re-center my analysis around these touchpoints or salient features of the environment that were central to completing the work. In re-reading my fieldnotes and transcripts focusing on what features of the work environment were most salient, I came up with the following list: customers, car, app, algorithm, phone, pay, company (overall), the business model, the physical body, and the traffic.

Stage 1: Axial Coding. In the next stage of analysis, I began axial coding and iterating between the data and existing theory to begin building "a dense texture of relationships" around concepts (Charmaz, 2006: 60). I created a spreadsheet with all touchpoints and participant comments on each. I removed traffic because of insufficient data, as there were fewer than two-dozen pieces of data as compared to hundreds for the customer touchpoint. Drawing on Straus and Corbin's (2007) suggestions for early-stage coding schemas, I then coded whether each mention of a touchpoint was a thought, feeling, or action. By far data about the customers were richest, as they contained thoughts, feeling, and actions, so I began more detailed analysis comparing when references to customers also mentioned other touchpoints. From this I was able to further refine my analysis. Cars, for example, could be mentioned in two different ways: In the context of customers mentioning the car, comments were specifically about the driver's own car or the objects within; however, in the context of the business model, comments were more about their car as a depreciating asset. Similarly, body pain was mentioned only in the context of the business model and the business model was only mentioned in the context of thoughts about the company. This analysis allowed me to condense my touchpoints to customers, technology, and the company.

Stage 2: Theoretical Coding. In the final round of analysis, theoretical coding, I developed relationships between categories elicited in earlier stages in order to "weave the fractured story back together" (Charmaz, 2006: 63). At this point I had all of my data neatly laid out in front of me in a mass of index cards—the touchpoint, data for each touchpoint, and whether it was thoughts feeling or action. I then asked myself two questions "What is the fundamental assumption driving the thoughts, feelings, and behaviors relating to this touchpoint?" and "What is the larger story about the touchpoints?" I went back to a quote from Lincoln (which opens this paper) that had particularly haunted me as it highlighted the tension I was seeing in the data. "I have a double feeling about the company. It's a great way to survive.… We are all miserable. We kill to pay for the car, to pay for gas." After reading the quote several times, things began to click. This "double feeling" was why my first attempt of coding only on positive and negative perspectives about the work lacked analytical leverage, as workers were often feeling, thinking, and enacting both. And their interactions with the touchpoints showed the meaning-making process as workers knitted together a view of the work that was both engaging and estranging. I had experienced this tension firsthand—my glee in setting my own hours and delight in engaging conversations with customers, and my frustration every time the app matched me with a long-distance pick-up or annoyance every time a chatty passenger sat in the front seat uninvited. I went back to my data around touchpoints and coded again around positive and negative valence. Moving between analyzing data, drawing models, and writing memos, I further refined categories to better understand the mechanisms that participants credited as responsible for creating meaning. I mapped these mechanisms for each touchpoint and then abstracted these ideas to devise a theory that explains how workers construct meaning within a web of touchpoints in an organizationally sterile environment.

Findings

I present the empirical findings in three sections to address how workers construct meaning of gig work. First, I describe common experiences and beliefs among drivers. I then focus on the distinguishing practices and beliefs between drivers, particularly their interactions and interpretations of customers, technology, and the company itself. After presenting these findings, I present a nomological model showing how workers' practices, beliefs, and emotions mutually reinforce two predominant orientations towards the work: alliance or adversarial.

Shared Experiences and Beliefs

Drivers' shared prior job experiences and attitudes toward work. Most had prior experience in either production or customer service work. Drivers' most immediate past jobs included food services/retail, call center work, delivery driving, and sales, and nearly one-fifth had previously worked in the transportation industry. Drivers described their attitude to work in general as a means to an end in which they "do to get paid" (Joel) and "don't like doing, but it puts food on the table" (Sheldon)—with "the only part that I like about working are the paychecks" (Aaron).

Drivers expressed similar experiences that brought them into ride-hailing, describing various push and pull factors. Shocks, such as an illness or layoff, often pushed workers into the industry as they needed to find alternative work quickly. "I was working with Zipcar and the position I had got terminated. I wanted a car and thought Uber was the perfect way to pay for your own car. I could work whenever I needed to while looking" (Nixon). In contrast, pull factors were based on lifestyle and pay preferences. Describing his calculations between his regular work and ride-hailing, Kenny said, "I've been really contemplating on doing it full time because just doing the numbers, I know I can make at least what I'm making during my eight hour shift." All drivers except for one depended on driving income to pay portions of the household expenses. (See Table 4-1 for participant inventory of prior work held and expressed motivation for driving.)

Once in the ride-hailing industry, drivers encountered similar work environments across companies. Driving is distributed work in that workers are physically independent from the company, with little, if any, direct contact with managers, co-workers, or other organizational members. During my three years of driving, I did not meet a single member of either company I drove for. Instead, information and behavioral cues were transmitted through the app via algorithmic nudges and notifications. In such an organizationally sterile environment, drivers rely on customers, their only source of direct human interaction, and their own practices to make sense of their work and working environment.

Work Practices

In the next section of the findings, I describe how workers behave with their main source of human interactions, customers, through two sets of work practices: relational and transactional. In relational practices, drivers define their work as customer-service oriented, focusing work activities and deriving meaning through developing positive rapport with customers. In contrast, for transaction practices, workers define their work as getting a customer safely to their destination focusing their efforts and deriving meaning through making each ride as efficient as possible. In each of these practices drivers create more or less social distance with customers, setting looser or tighter emotional, mental, and physical boundaries.

Relational Practices

Going Above and Beyond the Call of Duty: Building Rapport and Caring for Customers. Relational practices are routine rider-focused work activities that are meant to facilitate the customer service experience such as by providing care, building rapport, and developing positive relationships with customers. Before a ride begins drivers attune for cues, watching customers as they are walking to the car, observing for possible conversation starters, such as a Redskins baseball cap or Macy's shopping bags. Sam keeps three phone chargers, water, an umbrella, two blankets, and gum among other snacks in his car "just in case." (See Image 1.)

> I was working football last Saturday and two guys got in the car late and we were sitting in a traffic jam and the guy was like, "I'm dying, my God, I'm so thirsty." I was like, "There's water in the back. Go grab one," and you would have thought they won a pot of gold. They each had a water in their hand. And they're like, "God, I'm starving," and I'm like, "Hey, here's some summer sausage, you guys should eat it," and they're like, "Oh my gosh, you're the best driver ever!" (Laughs.) You never know. It's a dollar water and a dollar sausage and it made their day...They're going to go back and remember me and talk about me for the rest of their lives. They won't even know who I am. (Sam)

Signaling that they genuinely care about customers' well-being, and customers return affirmation that they are valued, are indicators to drivers they are doing their job well. Offering emotional support is another relational practice. As popularized on the HBO show, Taxicab Confessions, the close quarters and limited relationship length can entice riders to share intimate life details, with drivers stepping into the role of counselor and confidant. "You know how Dr. Phil does 5-minute cures. I call mine 7-minute interventions. I let people vent. Your boyfriend broke up with you? I tell you to find another one! I make 'em laugh" (Karen). In extreme situations, drivers may even stop working to console riders.

> A young lady in the back, she started crying. I pulled over and got out the flashlight. She was crying because she was a lesbian and never told anyone. Her sorority, sister, family, friends would kick her out—and she came out to me. I had no experience. I just said "There. There. It'll be okay." So we sat there on Hill (St), until she calmed down. (Aaron)

These forms of emotional relational practice are labor intensive in that drivers must attune to a rider's emotions and search for the appropriate responses, which can lead to emotion, mental, and physical fatigue. Yet their offering of emotional support in response to a stranger's distress signals drivers' care and concern for customers.

Building friendship is another relational practice. Beliefs about customers—that they were "professional" (Kenny) and "high class people" (Jonathan)—facilitated drivers being friendly and open which led to cultivating relationships. Describing his overall attitude towards customers, Japan said, "Getting in a Lyft or Uber should always feel like you're getting a ride by your cousin's friend to the airport. Why would you try to do anything other than to make them feel like they're your buddy?" In the car's close quarters, drivers and customers swap stories and discover shared interests, with several drivers reporting later hanging out with customers at bars, casinos, and sporting events.

> I met this girl who was also in a band and she invited me to come to one of her shows. I did and their band is totally kick ass. I've gone to five of their shows now, I see her at other shows and stuff. I feel like I made a buddy—I see her at shows all the time and we always catch up. (Jared)

Discovering mutual interests and learning from one another strengthens rapport between drivers and customers, making work more pleasurable and meaningful. In addition to friendships, several drivers reported finding professional contacts (e.g., a termite inspector, a babysitter, a job lead) from riders and one driver even helped a customer find a summer internship. In sum, in relational practices, drivers cultivated rapport with customers through offering care, emotional support, and friendship.

Crafting a Shared Experience: Using the Car to Vibe with Customers. Using the car or props within the car to create a shared experience is another way drivers build rapport and signal care to riders. The car, especially the American car, is an extension of the self and a means of expressing personal and/or group identity (Berger, 2001). Popular media outlets such as MTV's Pimp My Ride, Lowrider Magazine, and Instagram feeds dedicated to "VanLife," showcase customized cars symbolizing one's self-expression and individualism. Within their car, drivers often create their own physical and social space, complete with tchotchkies and snacks for the customers. Music can also be a medium to create connections. I describe my interaction with a party car on a Friday night ride:

> The car was popping! Fairy lights on the floor. Tinsel garlands on the backseat. A globe and glow sticks on the dashboard. Top 40 music. I'd never seen anything like it. "It's a party car. I do it on Friday and Saturday - it's a hit on South campus [fraternity row]." Seems the car has quite a reputation. On the drive he told me several stories about how excited students were when they got inside and realize they got "*the*" party car. [Fieldnotes-Sept 2018. See Image 2.]

Not only are the artifacts potential conversation sparks, they are tangible signs that the driver has spent time, money, and effort to enhance the customer's experience. The car becomes a talking point for drivers and customers to talk about their social life, music, and weekend plans.

Music is a powerful tool for transcendence, making it possible for individuals to communicate across gender, race, class, national, and even language boundaries (Juslin & Sloboda, 2011). After noticing Jamal's rather eclectic choice of politically conscious hip-hop music—including Tupcac's "Brenda's Having a Baby," a song about a young girl's rape, followed by her pregnancy, homelessness, and attempts at selling drugs and her body before her murder—I started a conversation about Michelle Alexander's *The New Jim Crow.* At the end of the ride, Jamal thanked me, noting his frustration at not being able to have more real conversation, and his appreciation for our talk, calling it "refreshing." In a follow-on interview, I asked more about his music choice.

> Driving started getting easy after I figured out what music people liked to listen to, so we could all vibe together. Honestly, I didn't know what white people liked listening to (laughs). I figured black people love Drake, so white people might like Drake, so I played Drake's Views album. A lot of the black community is starting to wake up [become socially aware], so I'm going to play an artist that's a little woke. So I play Chance the Rapper and a lot of people started vibing and that's when I really started getting more comfortable.... [My favorite thing about this job is] teaching people about black people. A lot of white people need to learn, teaching—you can't do that at the [traditional] workplace because people get uncomfortable. (Jamal)

Music allows drivers to bypass the mundane and engage in deeper, more meaningful conversations. Other driver artifacts that sparked conversations included pamphlets, unprompted scripts, and products. Similar to Jamal's social awareness campaign, other drivers shared memorial cards of black victims of police shootings. (See Image 4.) During my time in the field, I met a gubernatorial candidate who handed and read me a copy of his stump speech, an author who tried to sell me a copy of his latest book on public speaking, a fundraiser who solicited donations for his after-school tutoring program, and an energy healer who explained to me the various crystals and Tarot cards that decorated their car. (See Image 3.) Music, print materials, and other artifacts were thus sparks for conversations that turned the car from being the driver's personal space that the customer was just passing through to a space where more meaningful conversations and deeper social interactions could take place.

Summary of Relational Practices: In relational practices, providing good customer service is a key component to how drivers define their work, thus expressing care toward and building rapport with customers. Attuning for customer cues, offering emotional support, cultivating friendships, and using audio, visual, and physical materials to spark conversation, drivers engage in these relational behaviors on their own accord unprompted by the organization. These practices suggest that drivers see customers as a positive and integral part of the work which, in turn, shapes how they view the overall work arrangement.

Transactional Practices

Customers as Fares. Transactional practices are routine money-focused work activities that are meant to facilitate drivers optimizing their earnings by minimizing interactions with customers and enforcing boundaries around additional, uncompensated rider requests. In transactional practices, workers define doing a good job as getting their customers safely to their destination and earning money. Describing her relationship with customers, Casside said "All I know is that I need to get you to your destination 'cause that's my mindset, get you to your destination in a fast, safe way so I can get my money and you can get out of my car." At best customers are faceless fares that need to be transported, or at worse self-centered monsters that drivers must continually defend against.

> Twenty to thirty percent of people are nice, but I'm not trying to establish a personal relationship. This is a taxi. I get you where you need to go and go about my business. I'll talk, but I'm not trying to get to know you. I don't do much if I'm not getting paid for it. Not going out of my way to help you. People will take advantage of you. It's the ones who do three-minute rides and try to take two or three treats. It's one treat or get the hell out of here! People get crazy, greedy, take more than they should. You're dealing with random people you don't even know and you're sharing your space with them (laughs)... after a while mentally you black it out. I'm not trying to develop a full-blown relationship, hang out with them on the weekend, pow wow, and all that stuff. It's just a ride and that's it. (Laughs.) Get the fuck out. (Ernest)

Given the belief that the majority of customers are unpleasant and try to take advantage of drivers' generosity, drivers merely tolerate customers. By avoiding emotional engagement through eye contact, eschewing conversation, and not offering help, drivers create psychological boundaries to protect themselves. Indeed, offering emotional support is seen as potentially dangerous, "I just be taking them where they want to go. I had about five or six ladies in my car crying. You think you're helping somebody and then you get an email from Uber saying you hurt them or you harassed them" (Jackson). Drivers describe compartmentalizing their behavior, "keeping it business, professional" (Kenny). Another way that drivers avoid emotional engagement with customers is by pretending they do not understand them when there are problems.

> If I see you're about to say that you are not happy, I pretend that I don't understand. I just try to change the subject or talk about something else or I'll pretend I didn't hear what you said or that I just don't understand. And once I pretend I don't understand, everything is okay. And when they get out, they're like "Okay, bye, have a nice day." (Porris)

By giving the illusion of not understanding customers and avoiding emotional labor, drivers are again demonstrating that providing superior customer service is not an integral way they define their work. Instead, all of their actions are directed towards minimizing interactions with customers so they can complete their rides as quickly and efficiently as possible.

Enforcing Boundaries. Along with cognitive and emotional boundaries, drivers enforce physical boundaries to protect their belongings and themselves. Placing a bag on the front seat to stop chatty passengers from sitting there was a commonly mentioned physical boundary. Driving is mentally and physically taxing, as one must stay alert to changing road conditions, and this is a strategy I used frequently as a driver to avoid emotionally draining small talk. (See Image 5.) More generally, drivers felt customers disrespected their vehicle, "People forget it's my vehicle. They put feet on seats, fart in car, do all this weird stuff. They mess up your door handles. You know they've got food on their hands. These people don't care!" (Ernest). Towels on the backseat, floor covers, and signs requesting customers to wipe their feet and refrain from eating and drinking or slamming serve as reminders for riders to behave.

> "What's that?" I asked pointing to a dry erase board in the back pocket. Kandace quickly went into a long rant, her voice getting louder and angrier. "I had to make it cause people were misbehaving. They trifling. This one woman spilled coffee all over my backseat – and didn't even say sorry!" [Swings arms open.] "So I made the sign. But then people started touching the sign. And messing it up. **No** [voice gets even louder]. You don't need to touch the sign to read it, so I had to make a new sign." [The first line on sign is "Don't touch the sign."] "Is it okay if I touch the sign?" I asked. "Yeah, but don't mess it up." (Fieldnotes - Sept 2019. See Image 6.)

Objects serve as material deterrents against inconsiderate customers by helping enforce physical boundaries of what is and is not acceptable in their cars. Drivers also protect their time and themselves from potential legal liabilities by not doing extra, unpaid work, such as carrying bags, or waiting for customers while they are running errands. Two drivers below describe the boundaries they enforce:

> I try not to overstep any boundaries. These people are strangers. If it wasn't for the app, your problem wouldn't be mine. I have people coming up to the car and

> they got real luggage and I say, "I'm sorry, I'd really like to help you but I can't touch your luggage. You want my help now, but the moment one of those straps breaks, you're gonna be writing a complaint and I'm gonna be responsible." So I got to respect myself. I gotta respect my boundaries. (Jackson)

> They want to go to McDonald's and get something to eat. If somebody gets in the car and says, "Hey, do you mind going through McDonald's?" I say, "Absolutely not. Why would I go through McDonald's?" And they say, "Well, I have other drivers that do it for me." I say, "Well, if other drivers like to wait 15, 20 minutes sitting in a drive-thru, that's on them." I don't want to make 17 cents a minute and drive you a mile down the road and have my car smell like McDonald's and have you sitting back, eating fries, making my car smell like fries. (Roger)

In refusing to take on any duties beyond driving to a destination, drivers reaffirm that that their primary purpose in working is to transport passengers. By reinforcing their boundaries about what behavior is and is not permissible for the customers, drivers define what type of work they are doing and emphasize what parts of the work are meaningful for them.

Technology Practices and Beliefs

In the next section, I describe the relationship between relational and transactional work practices that are associated with thoughts and feelings about the technology. Specifically, I show how relational practices are associated with seeing the technology as helpful and supporting drivers' interests, while transactional practices are associated with seeing the technology as adversarial and subverting drivers' interests.

Technology as a Friend: Divine Intervention and Relational Reminders

Algorithms as God. Algorithms are the scaffolding of the ride-hailing system in that they assign, structure, and evaluate work. Drivers acknowledged that algorithms underpinned their work, although they were unclear exactly how. Discussing the opacity of the ratings algorithm, Kenny said, “They say I made the top ten percent, but it doesn’t tell you in what. Maybe it’s the amount of hours you’re on the road. Maybe it’s the number of five star comments you get. I don’t know. I honest to God don’t know.” Another driver invokes God in describing the algorithm’s actions:

> I really believe it’s God and the algorithm. I don’t know how it works, not like that. There’s a lot of passengers that’ll say, “I wish there was a way I could pick you specifically as a driver.” I don't know. But at the end of the day, it just works out. It’s really weird, really weird. (Sebastian)

Though many drivers believe the algorithm is unknowable, there is a general belief that algorithms are benevolent in that they make sure drivers are treated fairly, receive accurate ratings, and are assigned profitable rides. Even when falling behind in their earnings, drivers believe the algorithm is assisting them.

> I don't know, I call it lucky or blessed, but it seems when I start late I’ll just get trips that are worth more money. I can’t say that I can aim for that, but it just seems to be I get lucky all the time. I catch a surge, a big surge halfway across town, and then I catch another surge back across town, and then I’ll be right back to the money where I would have been working that whole morning. I say it’s a groove because I keep getting that same luck. (Laughs.) I know what it takes to get my 200 bucks a day. (Chapman)

Although describing himself as knowing what it takes to earn $200 a day, Chapman is really attributing his ability to meet his income goals to the algorithm which he doesn’t fully understand, calling himself lucky and blessed. These positive believes contribute to the idea that they drivers will generally earn enough to meet their needs.

App as Relational Reminder. For those engaged in relational practices, the app became a physical memento of past positive conversations with customers. Workers describe touching the app while working and at home to revisit their compliments (qualitative comments from riders), badges (company non-monetary awards), and ratings. Two drivers describe their app interactions:

> I have all of the reviews to prove [I am a good driver]. I can go on there and [see], "I just loved the conversation. Thank you for the ride. You put me in a good mood." "Your car is so clean. Your car smells good, you're a sweet person." All of this stuff, it's wonderful. It makes you feel good and want to do better. I always look at everything because I play with my app a lot. I'll go in it and look at different things or look at my ratings, see if it's still a 4.86. I just go in the app and touch all over it. It gives you that motivation to continue. (Casside)

> It makes me really happy—no, really! When I read them I'm like, oh, great, this guy loved me. So those are awesome. I normally have great people. So yeah, we rate each other very well. I've had very good ratings on most. I check it all the time—I check it more than I drive. (Kristin)

Serving as a physical artifact of the work, the app for some drivers is a tangible reminder that they performed their jobs well by providing good customer service. It can be checked repeatedly, in or out of working hours, serving as an always-ready reminder of the positive human aspects of work.

Summary of Technology as Friend. In this perspective, drivers perceive aspects of the technology, namely the algorithms and the app, as helpful in making sure they earn enough money. Even though drivers don't actually understand what the algorithm is doing, there is a general sense that the algorithm is working in their favor by assigning the most lucrative rides and rating them well. Additionally, for those engaging in relational practices, the app reminds drivers of one of the most enjoyable aspects of their work, i.e., customers. Overall, a positive interpretation of the technology contributes to workers developing positive beliefs about their work.

Technology as Foe: Conspiracies and Misleading Information

The Algorithm is Out to Get Me. In transactional practices, drivers focused on efficiency, aiming to complete each ride transaction quickly with as little emotional and physical labor as possible. Evaluating the technology similarly, drivers assessed if the algorithm was matching them to the most optimal (lucrative) rides, with the algorithm consistently falling short. Indeed, drivers often interpreted the algorithm as "out to get them" by not assigning better rides.

> I swear there was a conspiracy because in the afternoons—I logged in every single day at 4:00—I would get a long ride that would take me out of the city in the opposite direction towards the airport. And then right after I get out of the city, the city would light up like a Christmas tree [on the heat map display]! I swore it was a conspiracy against me because I did very little, if any, prime-time rides. Because I'm always sent in the opposite direction. (Slim)

Are algorithms conspiring against drivers? The opaqueness and inscrutability of the algorithm makes it impossible to objectively know, yet subjectively Slim interprets the algorithm as conspiring based on the pattern of logging in and being assigned lower-earning rides. These Drivers feel sure about who is making the algorithm work and it's not God: "The machine and the software are set up by people, by humans. God?? No! Just humans made it" (Chad). Drivers report the algorithm manipulating wait times, making them wait longer and longer to drive down their hourly wage after a high-paying ride, or only matching rides right as they are signing off.[17] Here the algorithm is perceived as forcing drivers to stay on the road longer when nearing a bonus target:

> I've had that weird thing happen outside a building and didn't get rides. I know what they're doing. It's not rocket science. If a driver gets to 67 rides, and they've got three to go [to reach a incentive], why would you want them to get in the queue quicker than everyone else? So, if I need three more rides, it's 4:00 in the morning, I'll get a ride in Bethesda, which is 50 minutes [long], and then I'll get a ride that's another hour. Well, all that time, I'm looking at the clock going I almost don't want to take this ride because I need to get quick [short] trips, so I can just get the bonus. When you're two rides away from the bonus, you don't care about [the fare]. You just want to get the ride, so you can get that extra

[17] There may be an objective reason supporting drivers' interpretations, as some hailing companies have publicly claimed to keep driver hourly wages between $12 - $19 (Hall & Krueger, 2016; Mishel, 2018), although this does not seem to be common knowledge among drivers. Furthermore, for some companies in some cities (e.g., Uber in New York City), there is a guaranteed minimum hourly wage, which may affect how algorithms assign work.

> hundred bucks, or 80 bucks, whatever it is. But, I think Uber, they know what they're doing. I think they have it programmed to make it as hard as possible when a driver is pushing the edge of the envelope to [get the incentive]. (Roger)

In contrast to the unknowability of the algorithm, as evidenced by the belief of drivers engaging in more relational practices, these drivers are clear on what the algorithm is doing—making work less efficient by keeping them on the road for longer hours at lower rates of pay. Drivers' inability to access technical support cements for drivers that they are at the whim of an algorithm. Irritated after receiving only one ride an hour for the past week, Chad called support.

> "Oh, your rating is down. I'm sorry, we can't do anything. Thank you very much." If there's a judgment, if there's a consideration, if there is something, you would say, "Oh, I'm working really with a human." I'm not working with a human, I'm working with a machine.

Overall the algorithm was perceived as not being aligned with drivers' interests, instead thwarting them from earning the most money in the shortest period of time.

Misleading Information. Some drivers believed the app transmitted false messages about changing work conditions and pay. They complained that information about surges was misleading, as the surge frequently disappeared when the driver arrived in the area, leading to the popular catchphrases: "Don't chase the surge" (Sarah) and "I'm too smart to chase surges" (Sheldon). Drivers felt frustrated and sometimes bombarded by surge alerts, receiving up to three notifications per day. "Why is Uber sending me alerts for surge pricing? I never walked out of the house or jumped out of the bed because of the surge" (Zara). Ringing sounds when a ride was assigned, pop-ups, and priming cues, such as the word "money" in the color green, urged drivers to pay attention to information delivered through the app.

> I mean it's all so simple; humans are just animals at the end of the day. If you give the cat a shiny toy it will play with it for hours; with humans it's a little more nuanced, but at the end of the day it's the same. When you get a ride

> request, it's like Pavlov's dogs. The thing rings a bell—"Oh, new customer." And then you go to press the button to pick them up. If you have audio plugged in, it used to count down to make it more intense. That shit was insulting when I think about it. (Jared)

The frequency of the messaging and not so subtle priming cues coupled with the challenges of earning a buck led some drivers to question the veracity of the information and, at times, the entire business model. The work "is not as easy as they advertise" (Ernest) and the companies "do a lot of false advertising" (Leo) about pay. In reference to an in-app message about changing fares, one driver reported:

> Uber still lies to people. What's the latest one they did? They told people, when you get in a car, they charge you [a pick-up fee]—$2 and some change. Basically what they did is they raised it 30 cents. They told the customer is that it's for the drivers—well they don't give anything to the drivers. But yet they send us something that's actually still on my phone that states that the [pick-up] fee for a passenger went up, but nothing will change on your fare. So basically they're saying the fee is for administration. And they've done it twice in a year. Uber did over a billion rides last year. They gave themselves a $30 million raise twice. (Leo)

Seeing the disconnect between the fare information presented to customers and drivers, drivers interpreted that the app was providing misleading information, which then made them question the overall business model. In sum, many drivers believe the company had conflicting interests and its actions were not always aligned with their self-interests, and thus drivers needed to carefully evaluate any pricing information.

Summary of Technology as Foe. In this perspective, drivers perceive the algorithm and app as antagonistic in meeting their goals of being effective drivers. Drivers describe the algorithm as actively conspiring against them by not giving them the most lucrative rides, and purposefully giving them misleading information that then shapes their thoughts about the business model. Taken together, these perspectives may make drivers more critical towards their work.

Feelings and Beliefs about the Company

In the following section, I describe how workers think and feel about their work arrangements and the company as a whole. Drivers with more relational practices and positive beliefs about the technology tend to see the company and the work itself in a more positive light; they believe that the company was helping them earn more and have enjoyable experiences, as well as enabling them to serve society at-large. In contrast, those with more transactional perspectives and negative beliefs about the company tended to be more pessimistic about the work, finding it hard to earn enough money and describing the company as a bottom-feeder.

Company as Supporter, Helper, Community Builder

Cultivating rapport with customers and having positive perspectives about technology were associated with drivers having a more positive view of the company, as they experienced the different components of the work as complementary. Drivers often described the work as pleasurable, enjoying the act of driving and the companionship from customers. “I kind of like driving. This gets me out to see beautiful views of the city, to hear cool things and cool stories, and meet people from all around the world. This job is so much freedom.” This sense of freedom was due, in part, to the fact that drivers felt like the system was enabling them to meet new people, own their schedule, and earn money—in short, the system was working for them and adding value. Suffering from multiple chronic illnesses, Karen had not worked a steady job in more than fifteen years before driving; she reported that working helped her “build myself back up to a person within a year,” exclaiming, “if this car thing goes well I could actually be independent.” Similarly, Chapman felt empowered by driving, realizing he no longer had to work in a “Matrix type of situation.” Describing his relationship to ride-hailing, he said, “I think of what a great idea, what a great company. It’s a pleasure to work with them. To work *with* them, because we're partners, so I don't say work for them. It's a great partnership."

More generally, workers recognize the impact of ride-hailing on the larger community. After complaints about the city's expensive and ineffective taxi service, an elected official I interviewed championed and then drove for a ride-hailing company, reporting, "I had watched the fight to bring [company] to [my state] when it went through the legislature. I have experienced the very tough taxi market as it relates to the customer experience in [city]." Drivers were proud that their work provided transportation to those that most needed access.

> It's such a help to the person that's getting a ride, to the person that's giving the ride, and the community as a whole if the person is drunk. Or helping mothers get to work without having to call people to ask them to come take her to work. You got students that can be independent. Wives that can be independent of their husbands without the car. The family with one car now, with a budget, can become two cars with Uber's help. When I really realized the impact that Uber had in everybody's lives, especially when I drive the drunks, being that my son got killed by a drunk driver, I always tell them I appreciate that they're actually doing Uber and saving somebody's life. (Chapman)

There is an overarching sense that ride hailing is working well—not only for the drivers themselves, but in terms for the community at-large.

Company as Adversary and Community Destroyer

Focusing on efficiency, by minimizing interactions with the customers and viewing technology as misleading and a hindrance to said efficiency, was associated with drivers having an antagonistic view of ride-hailing. Drivers described their relationship with the company as adversarial, blaming it for damaging their bodies and cars. Two drivers describe their aches and pains:

> It wasn't what I thought. You really have to grind for the money and then when you think about the gas that you're spending, you ain't really making that much money. I heard people say, "Oh, I make $1,500 a week or $1,200 a week or whatever." I guess they might be working 14 hours … it messes up my body to

> sit in the car for so long. I had a friend who was making real good money on Uber—like $1000 week—and man he did not look too good. Like not healthy. (Nixon)

> [I: And when I say the word Lyft, what comes up?] Well, the first thing, back pain. (Laughs. Pause.) Maybe like tiredness. I don't know why I'm going this route, but I am. Gas. Money. And bottom feeder. It's mainly my side gig now, but when I was doing it as my only source of income it was keeping me busy, but I found that I didn't have the stamina to do it as much as I wanted to. I had these grandiose plans of driving 10 to 12 hours a day six days a week and it just doesn't work like that. Your body can't do that. I don't know how truckers do it. I really don't. (Jared)

Unable to afford a larger car to accommodate his 6'2" frame, Jared eventually stopped driving due to back pain. Similarly, Nixon left ride-hailing for the more regular hours and less physically-taxing work of a medic. The continuing physical pain of driving affects drivers' enjoyment of the work, highlighting the physical and financial costs of the work.

Even savvy drivers, who analyze traffic patterns to find the most efficient times and places to work, are uneasy about the business model.

> It's not necessarily something I like to talk about a lot. It's complicated, because … honestly being an Uber/Lyft driver is far more complicated than being a taxi driver. In terms of what I do for preparation, what I do to analyze areas that are busy, the hours that I schedule it around. It's not something I'm proud of either. A huge, huge part of the gig economy is they take advantage of people who don't know any better. A lot of people that drive aren't that smart at all and I don't want to be grouped in with the people that don't understand the difference. (Ralph)

Being taken advantage was a common refrain. Commenting on their increasing body pain and falling wages, drivers feel stuck in "a money game, making money for them. I'm just a cog in a money making machine... a cog in a non-profitable company" (Japan), and find themselves in an unsavory relationship where "Uber is the pimp, the riders are the johns and we just open our legs" (Leo).

Process of Meaning-Making in New Gig Work

Drivers come into ride-hailing with similar work histories, general attitudes about work and motivation, and encounter identical, organizationally sterile, work environments, yet their differing practices and beliefs radically shape the meaning they construct. In two different sets of practices, relational and transactional, drivers either cultivate connections or enforce boundaries with their customers, viewing them as a joy or a nuisance to be managed. Similarly, drivers develop contrasting views about technology, perceiving it as either supportive in meeting their income goals or actively working against them. From these contrasting practices and perspectives, drivers develop two different relationships towards their work arrangement, viewing it as either a complementary system, in that the work serves them and the community, or an exploitative system, in that the work destroys their body, property, and spirit. I call these relationships "modes" as they represent a preferred or prevalent orientation, but, at the same time, indicate that the orientation is not a permanent state. This process is outlined in Figure 6.1.

Alliance Mode. Drivers' work practices, beliefs, and associated feelings are mutually reinforcing, creating two modes: alliance and adversarial. When viewing themselves as in an alliance with their work, drivers see customers and technology as aligned with their interests. The belief that delivering good customer service is an integral part of their work and that customers are professional, high class people makes it natural for workers to extend care, offer emotional support, and build positive relationships. Technology serves as a repository of past customer interactions, storing compliments, badges, tips, and customer ratings that reinforce drivers as good at customer service. In other words, technology reminds drivers that they are good at their job, leading to a positive interpretation of the technology. Though the algorithm is inscrutable, drivers believe that the algorithm ensures things work out, in that they earn enough money to meet their goals. This belief, along with the thought that the company is serving society at-large by taking drunk drivers off the road and providing transportation for at-need populations, reinforces workers' beliefs that they are in an alliance. These practices, beliefs, and feelings are mutually reinforcing, leading workers to perceive that they are in a benevolent work system.

Adversarial Mode. When viewing themselves in opposition with their work arrangement, drivers view customers and technology as misaligned with their interests. The belief that getting customers safely and efficiently to their destination is their primary job and that customers are inconsiderate leads drivers to enact mental and physical boundaries, limiting their engagement with customers. Technology reinforces negative beliefs about customers, as it is seen as the object that brings customers' problems to drivers. As drivers must rely on the algorithm to assign and price rides, they are unable to tell if they are working as efficiently as possible. This lack of information is associated with mistrust in the algorithm and the perception that the app is providing misleading information. Though the algorithm is inscrutable, drivers believe that the algorithm has only the company's interests in mind and is actively conspiring against them by making it harder to meet their income goals. Bodily aches and pains remind drivers of the physical toil of the work for not enough pay. This belief that they are being harmed by the company along with the belief that the industry's reputation taints them reinforces workers' beliefs they are in an adversarial relationship with their work. Taken together, these practices, beliefs, and feelings are mutually reinforcing, leading workers to perceive that they are in a hostile work system.

Discussion and Contributions

Implications for Literature on Meaning-Making

The literature on meaning-making has generally constrained itself to looking at single, largely intrapsychic antecedents of meaning in each study, such as values (Baumeister & Vohs, 2002), beliefs (Wrzesniewski et al, 1997) or familial attitudes (Brief & Nord, 1990) that are largely intrapsychic, which limit our understanding of the many sources from which workers draw meaning. In this study, I propose a more integrated model of meaning-making composed of a complex interplay of social and material interactions. Specifically, this research explores meaning construction around two previously unexplored parts of the work context: customers and smartphone technology. The meaning of work literature has just begun to look at the role of social interactions in the workplace in shaping meaning and, to date, has largely focused on other organizational members who are physically present such as managers (Pododny, Khurana, & Hill-Popper, 2005) and co-workers (Salancik & Pfeffer,1978; Dutton, Debebe, Wrzesniewski ,2016). Though interactions with customers lack the duration and depth of exchanges with managers and co-workers, I find they are a crucial component of the meaning-making process. Indeed, these encounters with customers are powerful enough to shape and reinforce technology practices and beliefs in so far that technology is neither inherently perceived with malice or goodwill, but instead shaped by these encounters. Technology can remind workers of positive prior interactions or lead to the belief that they are being taken advantage of economically. These findings align with other scholars' assertions that meaning at work—and life—requires contributions from multiple sources (Baumeister, 1991; Chalofsky, 2003).

This study explores the process of meaning construction in lower-skilled service workers who are nearly all economically dependent on their work. Almost universally the meaning of work literature is framed around highly skilled workers (Dobrow, 2013; Petrilgeri, Ashforth & Wrzesniewski, 2018) or meaningful types of work (Bunderson & Thomspson, 2009; Schabram & Maitlis, 2017), which raises the question of whether workers for whom economic motives are more salient engage in similar meaning-making processes. While thoughts about whether or not the business model is economically sustainable for workers is part of the meaning-making process, other features of the work environment are also salient. Indeed, the strong economic situation may actually account for why workers express conflicting thoughts on the work arrangements, both appreciating the flexibility and being exploited by the business model. By seriously considering the meaning-making processes of this population, this paper addresses concerns that the meaning of work literature over-emphasizes positive motives for work, neglecting workers who must work to meet financial needs (Brief & Nord, 1990; Rosso, Dekas, & Wrzesniewski, 2010).

The ultimate meaning individuals made of their work arrangements is that they were either engaging or estranging. This bifurcated state has been seen in other literatures such as the promotion/prevention approach to goal-setting (Higgins, 1998; 2005), appetitive/aversive approaches toward interpersonal relationships (Gable, 2006; Gable & Gosnell, 2011), and labor's feeling of alienation/fulfillment toward management (Marx, 1847; Burawoy, 1976). This study explores some of the practices, beliefs, and emotions that underlie these end states of engagement and estrangement.

Implications for Literature on Service Work

Prior literature on the service triangle has primarily used a lens of power, conflict, and struggle (e.g., Leidner, 1993; Williams, 2006; Sallaz, 2009; Korczynski, 2009; Reich & Bearman, 2018); in contrast, this study focuses on how the elements of the triangle mutually reinforce one another to shape worker experiences and beliefs. By taking this alternative perspective, the present study makes at least three unique contributions to the literature in service work. First, it describes games on the service floor, both with customers and with technology. Second, it suggests that different customer-engagement strategies can exist within the same organization, and that they lead to two different subjective experiences of the work. More generally, this study adds to the literature on how materiality, namely technology, influences relationships within the service triangle.

The concept of shop-floor games assumed a central role in the analysis of conflict and consent studies of manufacturing work, but has been neglected in the study of service work (Lopez, 2010; see Williams (2006) and Sallaz (2009) for exceptions). This study shows how the customer takes the place of the manager as the "thing to be managed" and the algorithm takes the place of machines as the source of unpredictability in shop floor games. For those deploying relational practices, in addition to striving for material wins like tips, successful social interaction with the customer can itself be a kind of "win"—that is, a desired outcome that can constitute the object of the games. And these wins are multiplicative in that these successful interactions are forever shrined within the app's technology, as badges and compliments, or when drivers thank passengers for using a ride when drunk. Thus, an alliance mode is achieved. In contrast, those deploying transaction practices have much less clearly defined wins. The goal is in trying to complete a ride as quickly as possible, and thus this practice is based on minimizing losses as opposed to maximizing gains. Algorithms and customers are sources of unpredictability that must be actively managed or, in the case of algorithms, cannot be managed, and these losses are multiplicative. Thus, an adversarial relationship.

Another line of work argues that service work changes the nature of the organization to a "customer-orientated bureaucracy" (Korczynski; 2002; Filby, 1992; Ungerson, 1999). This line of research argues that the organizing practices of the firm—market or relational—shape whether workers experience customer interactions as more or less alienating. In contrast, this study shows that alienation and fulfillment can exist within the same organization. At its core, the platforms rely on markets, aiming to efficiently match drivers with riders as quickly as possible for the lowest cost. Yet, with drivers' performance evaluation being tied to the customer rating, the firm's organizing practice appears to be more relational. Drivers who are efficiency-focused "lose" in that they tend to be more alienated from the work while those with a more relational mindset tend to feel less alienated. This finding is surprising since one would expect the first group—whose actions are most aligned with the organization's—to express more satisfaction and harmony with their working environment, yet it is the inverse.

More generally, this study offers insight into the role of materiality in service work, something that has been understudied. Most research focuses on service workers who create products as desirable objects for consumption, such as retail displays (Pettinger, 2004; 2006; Warhurst et al., 2009), or workers themselves who are the product of consumption, such as "pretty girls" at nightclubs (Mears, 2011; 2015). In contrast, this study looks at the material object as being a key component of the service triangle—indeed, one may think of this context as like the traditional service triangle, with technology taking the place of the organization as its mouthpiece. Although the algorithm's code is inscrutable, drivers always ascribe intent, viewing the algorithm as either helping or harming them. However, the technology is not always evaluated with suspicion (Marx, 1847; Brown & Korczynski, 2010) or as an autonomy enabler (Mazmanian, Orlikowski & Yates, 2013; Shevchuk, Strebkov, & Davis, 2018), but instead is always evaluated in light of its surrounding context, an evaluation that reinforced workers' assessment of the work arrangement.

Limitations and Future Research

Several of this study's limitations provide opportunities for future research. First, the sample was chosen to answer the research question and, though it was diverse in age, prior work experience, and length of time driving, participants were predominantly men and were all living in North America. Also, for the most part, these drivers had decided to continue driving for some time—i.e., now workers who had driven for only two days and then quit. Although the model may help explain the meaning-making experience of those in a variety of male-dominated occupations (such as construction, manufacturing, or banking), future research could explore the transferability of the model to contexts with different gender and or cultural compositions.

This study looks at one variation of service work and future research could test and expand on these findings in other service configurations. Other intermediaries that are part of the digital service system include mystery shoppers, payment systems, data services, etc. Hospitality, education, and health systems are other examples of service systems that could be examined. For example, hospital social workers may act as buffers for the organization, treating the patients as "humans" and thus permitting physicians and other health care workers to concentrate on the technical parts of health care (Heimer & Stevens, 1997). Additional research is needed to understand how these findings may apply in other service systems.

One limitation of this paper is that it cannot answer why workers undertake a specific work practice. A reasonable assumption would be that workers who were 'forced" or pushed into driving by a shock event, for example, may be more likely to enact transactional practices while those who were more "attracted" or pulled into driving may be more likely to enact relational practices. However, my analysis of comparing push versus pull factors showed no differences between groups. Similarly, I found no relationship between work history or amount of economic dependency and either kind of work practice. A larger, more diverse sample size and other research methods, such as longitudinal surveys, may provide additional insights. The process portrayed in the paper shows engagement and estrangement as "end states," but, in fact, these two states are fluctuating and can change over time or even exist simultaneously, such as in the case of Lincoln's "double feeling." However, there could be times in a driver's work life where one mode is more salient than the other or, alternatively, certain events may trigger a driver to switch to another mode (e.g., a driver switching from alliance to adversarial mode after an unfair termination). Following workers over several years would provide greater insight to these questions.

Similarly, one criticism of this paper is that workers who enact relational practices did not encounter disrespectful customers, and those in transactional practices did not encounter friendly, open customers. Given my broad sampling and how customers were assigned to riders (by the algorithms), this is likely not the case; it is more likely that workers interpreted their customers differently. Labeling theory argues that deviance is not a quality in behavior itself, but in the interaction between the person who commits an act and those who respond to it (Becker, 1991). As previously described, differences in beliefs about elements of the work ("the work is about providing good service and customers are friendly" vs "the work is about being efficient and most customers are greedy") predisposed drivers to have varying beliefs about customers.

Another lens to examine in these worker-customer interactions is through boundary work (Lamont, 2009) or normalizing the interactions across class differences. In relational practices, no boundary work is needed—drivers see themselves as wanting to provide a positive customer experience and see customers as good people. Conversely, in transactional practices, much boundary work is needed—drivers see customers as having lower morals and being less professional. However, in contrast to prior research (Lamont, 2009; Sherman, 2005, 2007), the boundary work associated with transactional practices did not neutralize, but instead exacerbated, the differences between the two groups—as drivers remained aloof and hostile towards customers. This is due, in part, to other elements of the service triangle (technology, algorithm, beliefs about the company) that reinforce the original negative beliefs about the customers.

Conclusion

I began this research project with a simple question about how meaning is constructed in the contemporary workplace, the gig economy. Though drivers share common experiences and beliefs about work, I find workers developing two opposing relationships to their work arrangements. Specifically, I document a set of mutually reinforcing practices, beliefs, and emotions, in relation to the customers, technology, and the company itself, that shape workers' relationship to their work arrangement. These two modes—alliance or adversary—indicate whether workers believe the work system is working for or against them. This paper contributes to our understanding of how workers construct meaning in the changing contemporary workplace.

Image 5-1: Snacks and Drinks for Customers

Image 5-2: Party Car on a Friday Night for Customers to Enjoy

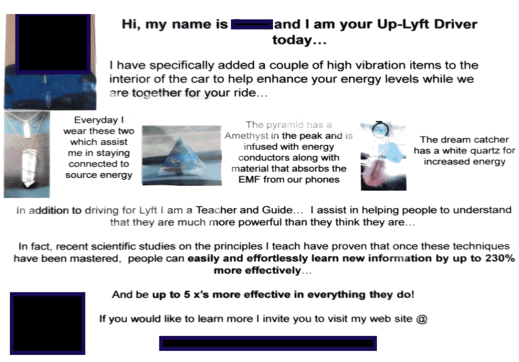


Image 5-3: Shared Media about Driver's Metaphysical Work and Artifacts to Spark a Conversation

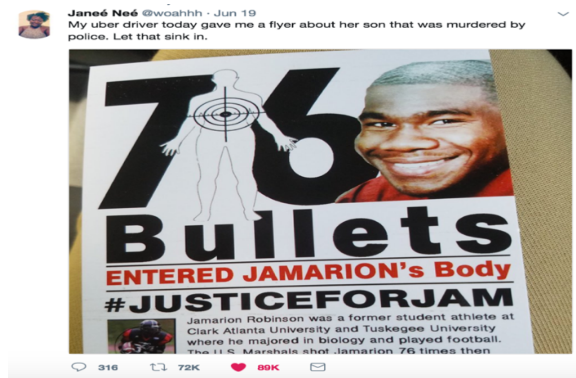


Image 5-4: Shared Media to Spark Conversation around Social Justice Issues

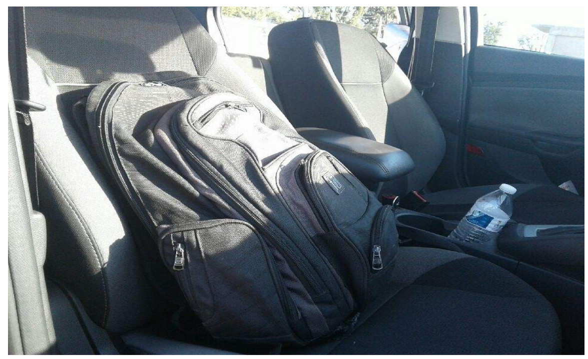
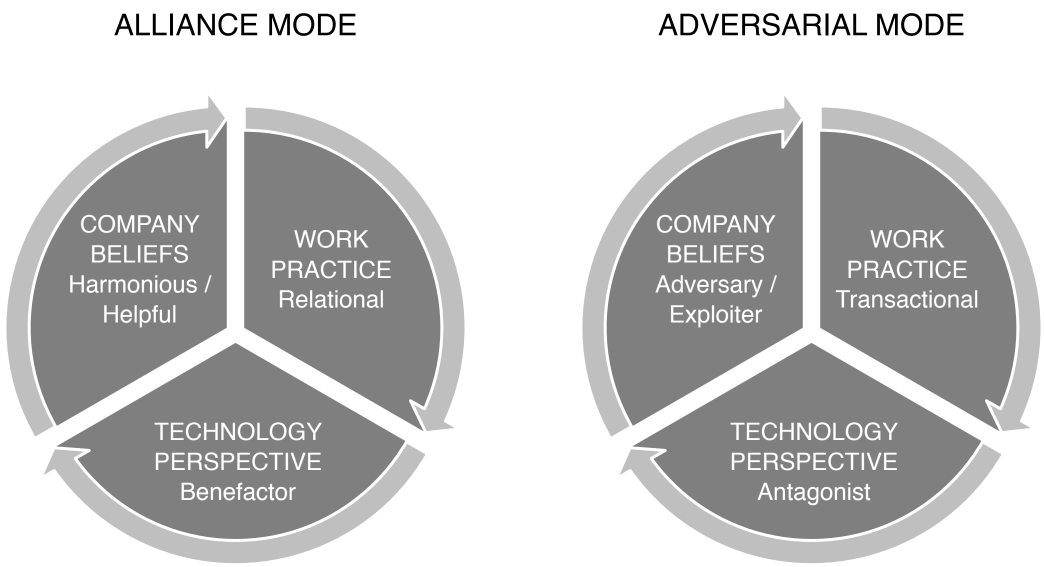


Image 5-5 Backpack as Object to Enforce Physical Distance between Drivers and Customers

Image 5-6: Sign Reminding Customers of Boundaries in Backseat Pocket

Figure 5-1: Alliance and Adversarial Modes toward Work Arrangements



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CHAPTER 6

Choice without Freedom: Autonomy and Control in the Algorithmic Workplace

The unknown future rolls toward us. I face it, for the first time, with a sense of hope. Because if a machine, a Terminator, can learn the value of human life, maybe we can too.

- Sarah O'Conner

Algorithms—computer-programmed procedures for transforming input data into a desired output (Gillespie, 2014: 167)—are transforming how work is controlled and coordinated by allocating, optimizing, and evaluating the work tasks of millions of employees, from Starbuck baristas to Wal-Mart clerks to Uber drivers. By 2020 more than 70% of jobs and 90% of service work will require interaction with digital technology (Muro et al., 2017). Yet, work that is controlled and coordinated by algorithms, in which algorithms substitute for human managers, presents fundamentally different challenges for organizations and workers that have not yet been explored. In this article, I consider the behaviors of workers employed in an algorithmic workplace in order to examine how they navigate the tension between algorithmic control and the individual need for autonomy. Given the rapidly evolving contemporary workplace, understanding the experience and implications of algorithmic work is crucial to developing updated theories of organizational control and worker autonomy.

Organizations control and coordinate what workers do. Ever since firm owner-operators lost the ability to oversee workers directly (Edwards, 1979), organizations have strived to regain control through controlling pacing (Taylor, 1911, 1949), formalizing policies and procedures (Weber, 1947; Gouldner, 1954), and enforcing social pressure through co-workers (Barker, 1993; Mazmanian, Orlikowski, & Yates, 2013) and customers (Liedner, 1996; Lopez, 2010). Algorithms—a new mechanism of control and coordination—promise to tighten control, further reducing inefficiencies by transferring managerial oversight to software code. Algorithms allow work to be dynamically assigned, sliced, monitored, priced, and evaluated. In some contemporary work settings, such as the on-demand economy, algorithms are embedded throughout the entire human resource cycle, selecting applicants, creating schedules, and evaluating performance. When matching workers with firms needing a particular expertise, for example, algorithms have augmented or replaced referral-based hiring practices in companies as diverse as Amazon, LinkedIn, and Nippon Airlines. Deliveroo, a food delivery service, eschews human managers by having algorithms compare workers' delivery times to create performance ranks. The increasing reliance on algorithms and the effect of algorithms on work coordination raise significant questions about how organizations will maintain control and, correspondingly, how workers will respond.

Autonomy—the ability to exercise a degree of control over the content, timing, location, and performance of work activities—is a core human need (Maslow, 1968; Ryan & Deci, 2003; Wageman, 1995) and a defining feature of jobs (Hackman & Oldman, 1976). Indeed, autonomy is associated with higher levels of job satisfaction, motivation, and job performance (Oldman & Hackman, 2010; Langfred & Moye, 2004; Langfred & Rockmann, 2016). However, from the standpoint of organizations and their agents (managers, owners, and principals), the temptation has long been to squelch autonomy and exert total control over workers—with the goal of maximizing efficiency and optimizing output. Compared to higher-skilled work, lower-skilled work is especially vulnerable to autonomy restrictions as tasks are more discrete and less complex (Burawoy, 1976, Edwards, 1980). Algorithms further threaten lower-skilled workers' autonomy as they lessen the need for managers—who can offer autonomy by granting leniency (Anteby, 2008) and brokering idiosyncratic deals (Rousseau, 1995)—and can reduce the scope of work activities by formalizing tasks and procedures. On the online labor market MTurk, for example, larger work assignments are sliced into micro-tasks: for a translation job, workers might be asked to translate a single sentence as opposed to an entire document, and are then evaluated and paid by the sentence. Autonomy is such a defining feature of work that Kalleberg (2009, 2011) describes it as the distinguishing characteristic between higher-skilled "good jobs" and lower-skilled "bad jobs."

Overall, emerging research argues that algorithms will tighten the "iron cage," squelching workers' autonomy for the sake of algorithmic efficiency (Faraj, Pachidi & Sayegh, 2018; Kellogg, Valentine & Christin, 2019; Rahman, 2019). Yet, from my extensive qualitative field study of the ride-hailing industry—the largest employer in the on-demand economy—I found that ride-hailing drivers express a sense of autonomy in response to algorithmic controls. Here, I define and explore the concept of algorithmic work—work that is constituted, to some extent, by an algorithm or a set of instructions programmed by a computer—and consider how long-standing theories on organizational control and worker autonomy need to be reconceptualized in this new context of the algorithmic workplace. I found that drivers choose between three tactics—compliance, engagement, and deviance—in response to the algorithm's demands, each tactic reinforcing their sense of autonomy as they strive to maximize income. This study puts algorithmic work on the map by identifying its structural elements and analyzing how workers actively navigate the algorithmic workplace. Challenging the emerging assumption that algorithms cripple worker autonomy, I conclude with the idea of a "good bad" job, arguing that autonomy is not solely a function of job design and that a sense of autonomy may actually be enabled by algorithmic controls.

Control and Autonomy in the Algorithmic Workplace

By their very nature, organizations are intended to provide some level of control and coordination. Indeed, if an activity had no need for centralized control and coordination, there would be no need for an organization (Blau & Scott, 1962; Gouldner, 1954; Thompson, 1967). According to March and Simon (1958), one of the defining characteristics of an organization is a central coordinative system that links work activities to a shared goal. Much of the research on organizational control builds on labor process theory (Braverman, 1974; Buroway, 1979; Edwards, 1979; Thompson & Vincent, 2010), which describes how managers, driven by capitalism and a desire to maximize profits, continually deploy new technologies and control mechanisms to extract more value from workers. In Adam Smith's hypothetical pin factory, foremen coordinated specialized roles (metal cutter, pin drawer, roller, finisher, etc.) to increase productivity under the foreman's watchful eyes (Smith, 1827). As firms grew in size, control structures evolved to compensate for the lack of direct control or observation and monitor more complex production processes. With the development of technical control, organizational technologies became a substitute for direct supervision—assembly lines at a machine-like pace to make it harder for workers to loaf, for example, or cash registers to monitor transactions and make it more difficult for workers to steal. Developing his theory of scientific management, Frederick Taylor set out to control workers' behaviors by directly linking wages to effort and specifying the exact physical movements needed to perform a task most efficiently (Taylor, 1911, 1947). Following the Second World War, organizations continued to become more complex, giving way to new models of control, such as bureaucratic controls that relied on formal and informal rules and procedures to guide workers' behaviors. The organizational structure of the firm establishes company policies as the basis for how to accomplish tasks, set wage tables, and guide advancements (Selznick, 1943; Blau, 1955). Job descriptions (Weber, 1947; Gouldner, 1954), checklists (Pronovost & Wohr, 2010), advancement guidelines (Gouldner, 1954), and scripts (Moreo, 1980) direct workers' behaviors, which are then evaluated by supervisors (Vancil, 1982) and metrics (Govindarajan, 1988). In practice, direct, technical, and bureaucratic control are multi-layered in that they frequently combine and overlap creating reinforcing levels of controls (e.g., Barley & Kunda, 1992; Cardinal, Kreutzer & Miller, 2017; Sitkin, Cardinal & Bijlsma-Frankema, 2010). Together, these control mechanisms can make workers feel like they are in an iron cage—a technologically structured, rigid, and dehumanized workplace (Barker, 1993; Weber, 1968).

As we enter the twenty-first century, technology is again reshaping work—this time through algorithms—prompting another evolution of control models. More and more organizations are deploying algorithms—computer-programmed procedures for transforming input data into a desired output (Gillespie, 2014: 167)—as a central coordination system for assigning, pricing, monitoring, and evaluating work. Algorithms were first widely introduced in workplaces in the 1980s, with the development of micro-computers and information technology that allowed work to be infomated and automated (Zuboff, 1988). Over time, they became associated with data-mining and machine-learning, as algorithms came to discern patterns from large amounts of heterogeneous "big" data (Danaher, 2016; Kitchin, 2017). More recent research, oddly enough in fields outside of management, documents the birth of algorithmic management or the practice where software algorithms and the surrounding devices that support them assume managerial functions. Accounts describe algorithms selecting work (O'Neil, 2017), scheduling shifts (Hodson, 2014; Kantor 2014), assigning tasks (Lee et al., 2015; Rosenblat, 2018), prioritizing tasks (Gupta, 2018), setting wages (Borgs, Candogan, Chayes, Lobel, Nazerzadeh, 2014; Chen et al., 2016, 2017), nudging behaviors (Burbano, 2016), surveilling activities (Viscelli, 2016; Levy & Barocas, 2018), and evaluating performance (Edelman, Luca, & Svirsky, 2017; Kirilenko et al., 2017). These reports of today's information and communication technologies (ICT) suggest a resurgence of Tayloresque control practices, with workers being subjected to high levels of monitoring, detailed measurement of work productivity, and statistical analyses of performance (Taylor & Bain, 2005; Kristiansen et al., 2018). Such accounts equate the work environment to an "assembly line in the head" (Bain & Taylor, 2000) or an "electronic sweatshop" (Fernie & Metcalf, 1998).

Algorithms differ from prior control models in that they are more comprehensive and opaque. Algorithms enhance already in-place monitoring technologies, such as cameras, sensors, and biometrics trackers, by comparing inputs to expected outputs such as physical features (O'Neill, 2017; Wang & Kosinski, 2018), speech patterns (Leonardi & Contractor, 2018; Lix, Goldberg, Srivastava & Valentine, 2019), production speed (Landay, 2019; Xu, He & Li, 2014), and movement patterns (Clemes, O'Connell & Edwardson, 2014; Thorp et al., 2012; Levy, 2014). Truck drivers receive admonishments from their driving app if they deviate from prescribed routes or speed limits (Levy, 2015); a machine-learning tool notifies managers when their employees' projects appear to be moving too slowly (Schweyer, 2018). Algorithms provide instantaneous feedback that can be immediately entered into the production process, continuously updating control mechanisms (Crowston & Bolici, 2019). Upwork, for example, sends algorithmically-powered chatbot warnings that remind workers of their agreement to not work outside of the platform when they include personal information such as phone or email addresses in their communications with clients (Jarrahi, Sutherland, Nelson & Sawyer, 2019). Algorithms can further control work activities through task formalization, prescribing how, when, and by whom a task is performed (Hall, 1977; Adler & Borys, 1996). Through formalization, a large task—say, building a massive open online course (MOOC)—can be broken into smaller chunks: building a webpage, designing quizzes, and creating a syllabus. Each task is then distributed among workers and independently monitored and evaluated by algorithms (Valentine et al., 2017). The inner workings of such algorithms are opaque, due to intentional secrecy, required technical literacy, and machine-learning opacity (Burrell, 2016). The codes that produce algorithms are often propriety and, even if disclosed, are usually not interpretable to the average user (Boling, Anderson & Schwarz, 2015). The expansion of algorithms into work has largely eroded people's capacity and psychological motivation to take meaningful action against them; workers rationalize their potential harm believing that privacy loss is inevitable (Fast & Jago, 2019). Lastly, machine learning is unintelligible to humans as algorithms make forecasts and predictions based solely on learned patterns and inferences in short periods of time (Borch, 2017; Dietvorst, Simmons & Massey, 2015; Karppi & Crawford, 2016; Weld & Bansal, 2018). Taken together, this research suggests that the rise of algorithms as a coordinating mechanism within organizations will further tighten the iron cage by restricting worker autonomy and furthering alienation and estrangement from work. Yet, at the same time, we know the need for autonomy and self-determination is innate (Orpen, 1985; Wageman, 1995; Ryan & Deci, 2000; Manslow, 1968) and that workers often defend their autonomy in the face of tighter organizational control.

Scholars have generally understood autonomy in the workplace as the ability to exercise a degree of control over the content, timing, location, and performance of work activities. Autonomy is considered crucial to work, as it is positively linked to well-being, engagement, motivation, job satisfaction, and retention (Annink & den Dulk, 2012; Vera, Martínez, Lorente, & Chambel, 2016; Wu, Griffin, & Parker, 2015), and it is seen as the defining feature between "good" and "bad" work (Kalleberg, 2009, 2011). Autonomy can be operationalized structurally and psychologically. Structurally, in the employment relationship, workers may have choice in when, where, how, and what work to complete (Cappelli & Keller, 2013), for example the ability to set their own schedules and set their wages. It can also be prioritized as a function of organizational and job design. For example, a traveling salesman or R&D scientist may have more discretion in their daily work arrangements and tasks than a call center worker or lab technician. Managers may also create idiosyncratic arrangements with individual workers, or i-deals that allow for increased flexibility (Rousseau, 1995), for example, or grant leniency in the face of questionable behavior (Anteby, 2008). Co-workers can grant one another autonomy through encouraging loafing, machine sabotage, or unprofessional behavior, or by prioritizing one task over another. Often seen as in direct conflict with the management's interest, these behaviors have been labeled as resistance by practitioners and scholars alike (Vallas, 2016). Psychologically, autonomy can be experienced when workers believe they have control over their work activities—I refer to this as having a sense of autonomy. Workers may passively internalize organizational norms and rules such that they believe they are making their own choices (Van Maneen, 1979; Kunda, 1992) or, more actively, craft meaningfulness and purpose (Wrzesniewski & Dutton, 2001) through changing their perspectives and behaviors (Bakker, Tims & Derkas, 2012; Berg, Wrzesniewski & Dutton, 2010) and interpreting cues from their environment (Dutton, Debebe & Wrzesniewski, 2016; Sonenshein, et al; 2013).

Lower-skilled workers are generally assumed—by virtue of their lack of occupational status, undifferentiated skills, repetitive work tasks, and lower social position—to require more control. Subsequently, work is designed to eliminate autonomy through deskilling (Burawoy, 1976), fixed scheduling (Reich & Bearman, 2018), fixed piece-rate pay systems and wage schedules (Gouldner, 1954; Shaw, 2014), scripts for routine customer interactions (Liedner 1996, 1999), and continual pressure exercised through organizational norms (Barker, 1993; Mazmanian, Orlikowski & Yates, 2013; Michel, 2011; Van Maneen, 1979; Kunda, 1992). In spite of these constraints, workers regularly undertake acts of autonomy (e.g., Anteby, 2008; Haraszti, 1978; Juravich, 1985; Ramsay 1966; Bensman & Gerver, 1963; Pollert, 1981; Hodgson, 2004; Gouldner, 1954) and management responds with attempts to squelch them (Edwards, 1979; Ezzamel & Willmott, 1998; Gouldner, 1954; McLoughlin, Badham & Palmer, 2005; Reich & Bearman, 2018; Vallas, 2016). Organizations view these acts of autonomy, at best, as attempts to undermine productivity and, at worse, as threats to extinguish the organization. Algorithms provide a new, powerful tool to further redesign jobs and limit autonomy.

In contrast, lower-skilled workers who have a psychological sense of autonomy over their work activities often appear less threatening to organizations and management. A sense of autonomy is positively associated with job satisfaction, motivation, and performance (Bunderson & Thompson, 2009; Kristof-Brown, Zimmerman, & Johnson, 2005; Rosso, Dekas, & Wrzesniewski, 2010; Tims, Derks, & Bakker, 2016). Being able to craft one's jobs and design meaningful work (Wrzesniewski & Dutton, 2001) is especially important for lower-skilled workers who often find themselves in physically demanding and stigmatizing work (Leana, Miettal & Stiehl, 2012). Meaningfulness is often constructed through interpersonal sensemaking and interpreting the cues workers receive from their supervisors and co-workers (Wrzesniewski, Dutton & Debebe, 2003). Those in lower-skilled work, for example, may experience meaningfulness from managers normalizing stigmatized activities (Ashforth, Kreiner, Clark & Fugate, 2017), job titles (Grant, Berg & Cable 2014), reminders from peers about their values (Dutton, Debebe & Wrzesniewski, 2016), or connections to a broader purpose such as animal welfare (Schabram & Maitlis, 2017). Compared to those in higher-skilled positions, lower-skilled workers often find it harder to craft a sense of autonomy in their work activities as they must change the expectations of others as opposed to only altering their own thoughts and behaviors (Berg, Wrzesniewski & Dutton, 2010). Further, features of the algorithmic work environment may limit the ways lower-skilled workers seek and experience autonomy. Often physically isolated, these workers have limited exposure to interpersonal cues from managers or co-workers that could enforce their sense of autonomy. The isolation also makes it harder for workers to engage in conversation with one another, discuss concerns, and coordinate collective action in response to shared grievances.

The literature on control and autonomy in the workplace thus offers conflicting assessments on how control and autonomy might be experienced by workers in an algorithmic workplace. On the one hand, algorithms can be seen as constraining autonomy by monitoring, structuring, and formalizing work activities with more comprehensive and invasive methods than prior control models. Algorithms can lead to more distributed and remote work with workers no longer co-located with supervisors whom they can coax and cajole to change rules or with co-workers with whom they can organize and conspire. This then further tightens the amount of unchecked control that organizations can exert. On the other hand, algorithms also create a space where workers can have greater control over their work activities. As work is spliced into smaller, independent segments, it can be distributed among independent contractors. In this employment arrangement, workers choose whether, when, and where to complete each task and often operate away from the prying eyes of managers and co-workers. As the mechanisms of socialization are faint, workers may be less likely to internalize organizational culture and rules, hence increasing their autonomy.

The tensions between control and autonomy raise critical questions on whether bedrock theories of organizational control from decades of research are still relevant for the contemporary, algorithmic workplace. If not, what are new mechanisms of organizational control and their relationship to worker autonomy? Focusing on workers' experience working and interacting with algorithms, this research aims to explore how workers navigate the tension between algorithmic control and their needs for individual autonomy. I found that many drivers working for the ride-hailing industry experienced a sense of autonomy even at times when the algorithm was most constraining, because they interpreted their responses to the algorithms as helping them meet their goals of earning money. Unpacking the dynamics of these workers' experiences allowed me to make sense of these contradictions and to develop an understanding of the relationship between work, control, autonomy, and algorithms.

Research Setting and Data Analysis

The Ride-hailing Industry

First launched in 2011, ride-hailing services such as Uber, Lyft, Evercar, and Juno have disrupted the taxicab industry. Algorithms, which serve to coordinate the work, are the core innovations that enable these services: Algorithms match independent, distributed drivers (working from their own cars) with customers within seconds, giving block-by-block directions. Fares dynamically adjust based on consumer demand, and driver performance is evaluated by customer ratings and driver acceptance and cancellation rates. Drivers have little direct contact with company representatives; even hiring and firing, euphemistically called activation or deactivation, is conducted online. Work requirements may vary, with most companies requiring clean driving records, no moving violations in the previous three years, state vehicle inspections and, increasingly, despite industry protests in some cities, criminal background checks. Once hired, which can take from three days to three weeks, workers can go "online" and begin driving.

A Typical Ride: The Work Task

Completing rides, or a work cycle, is based on a coordinated three-way interaction between the driver, the rider, and the app. Drivers begin a shift by choosing a location to open their app, then they swipe right to go "on-line," signaling to the platform that they are ready. A complete ride consists of 1) the app matching the driver and rider; 2) the driver getting to the rider's location and waiting for rider to enter vehicle; 4) the driver swiping "start ride" on the app; 5) the driver and rider interacting; 6) the driver dropping the rider off at their destination; 7) the driver swiping "end ride" and rating the rider. (See Figure 1.) Work cycles may end prematurely, such as when a rider fails to show up or the app malfunctions. After the end of a work cycle, employees may stay "on-line" and wait to be matched again or go "off-line" and stop working altogether. In smaller cities, where trips tend to be shorter, drivers can complete as many as six or seven rides in an hour while, in larger markets, a driver may only complete two or three. Rates for each ride are determined locally and based on a pick-up fee, distance, time, and surge (if any). Drivers may also be offered bonuses for completing a certain number of rides within a designated time period, but this is not required and is not offered in all markets. Gross reports of earnings range from $12 to $30 per hour.[18] (See Chapter 4 for a more complete description of the ride-hailing industry.)

Data Analysis

I analyzed data using a grounded theory approach (Charmaz, 2006; Locke, 2001; Glaser & Strauss, 1997) with field observations, interviews, and forum postings as my primary data sources. Please see chapter 4 for more details about my setting and data sources.

Stage 0: Iterative Collection and Analysis. Data was collected in four two-month waves, with each collective wave followed by two months of preliminary analysis and reflection. For example, after my first round of data collection (roughly 10 hours of driving and 20 interviews), I refined my research questions, interview schedule, and the structure of my field notes. I noticed that drivers often discussed pricing incentives (surges and bonuses for completing a certain number of rides) and setting daily/weekly earning goals.[19] This issue and similar themes appeared often in my field notes, and thus in subsequent interviews, I probed to understand if and how drivers' activities were shaped by incentives (e.g., ignoring bonuses that were too challenging to achieve, choosing to drive around projected surge times). I also paid attention to this in my own behavior as a driver. I continued to identify new themes as my research progressed, thus coming to ask about pricing incentives and how changes in policies (e.g., Uber's

[18] Calculating drivers' true net pay is difficult as earnings vary based on mileage rates (which vary by city), incentives offered (which vary by person as determined by the app), hours worked, the cost of operating the car (gas, insurance, depreciation, maintenance), and tax rates. Further, some cities, such as New York City, have implemented hourly minimum wages.

[19] Similar to cab drivers, ride-hailing drivers set daily or weekly earning goals; however, unlike taxi drivers (Camerer, Babcock, Loewenstein & Thaler, 1997), drivers will stay out longer during periods of high demand, such as in inclement weather, earning above their initial goals (Cramer & Krueger, 2016).

addition of tipping in 2017) influenced work activities as well as drivers' concerns about the ratings evaluation system.

Stage 1: Open and Focused Coding. Towards the end of my field work, I began focused data analysis. While my preliminary analysis informed my way of thinking, I put these early observations aside in order to see my data with fresh eyes as I began coding, or as Charmaz (1996:45) calls it, "generating the bones of analysis." First, I read over my field notes to familiarize myself with their content and then turned to the interviews for more in-depth coding. Interviews and field notes were coded over five rounds. I began by open coding one-fifth of my transcripts selected on maximum variation of the following: gender, number of hours worked, length of time driving, and geographic location. From the initial codes three major themes emerged: narratives about the work experience (emphasis on general (dis)like of the work itself and the app), income (emphasis on maximizing income), and ratings (emphasis on grievances about the ratings system). In the next two coding rounds, I started to focus on identified themes while also continuing open coding, through which two additional themes emerged: interactions with the app (i.e., accepting a ride request) and strategies to create a good work day. No new themes emerged in the last two rounds of coding. Throughout the process, I wrote memos, discussed ideas with colleagues, and presented early findings at workshops.

Stage 2: Axial Coding. In the next stage of analysis, I began axial coding and iterating between the data and existing theory to build "a dense texture of relationships" around concepts (Charmaz, 2006: 60). Based on my lived experience, I knew there was a rhythm to driving so I began by constructing a model of a routine day and a routine ride. I quickly noticed work repetitions depending on the time I worked, driving the same streets (e.g., North Capitol Street on weekday mornings, Wisconsin Avenue on weekend evenings), with similar people (e.g., professionals in the morning, partiers on weekend evenings), having identical conversations (i.e., silence in the morning, drunken conversations on Saturday night). Work tasks were also repetitive in that each ride required the same interactions with the app (e.g., accepting a ride, rating the rider). Informants across cities used near-identical language to describe their days and rides, which confirmed my hunch. Using stacks of index cards, I laid out the five thematic codes on top of the routine day and routine ride models and, as I had more data for typical rides than typical days, I focused my analysis on the former. As rides were coordinated through the app, I turned to the literature on mobile devices, platform work, and algorithms. One thing that puzzled me in the literature was that algorithms were often described as a discrete unit (e.g., Orlikowski and Scott, 2013; Seavers, 2017; Curchod et al., 2019) as opposed to a system of distinct yet interlocking controls, as both I and my informants had experienced. Declining a ride, for example, affects ratings and ratings can affect the following week's bonus offering. Building on this insight, I re-coded my data around each mention of an algorithm-like function.[20] I identified five types of algorithms: work matching, work instructions, surge pricing, bonus pricing, and ratings. Further coding clarified the following for each algorithm: its purpose, how it communicated to drivers, how it was linked to other algorithms, and whether it influenced drivers through rewards or sanctions. With the temporal work cycle and function of each of the five types of algorithms, clear coding for the second half of my findings was relatively straightforward. I identified and coded human-algorithm interactions, paying close attention to the conditions surrounding each interaction, as well as consequences and drivers' responses.

[20] As my informants rarely used the word algorithm, instead choosing to obscure the algorithms' functions, I relied on my own experiences to determine whether an informant's responses referenced an algorithm.

Originally, I had only two tactics (compliance and deviance) that were associated with two algorithmic controls (rewards and sanctions). Conversations with colleagues pushed me to consider cases where the drivers were making choices that the algorithm didn't reward or punish, eventually leading to the labeling of engagement tactics.

Stage 2: Theoretical Coding. In the final round of analysis, theoretical coding, I developed relationships between categories elicited in earlier stages in order to "weave the fractured story back together" (Charmaz, 2006: 63). At this point I had all of my data neatly laid out in front of me in a mass of index cards—the tactics linked to each algorithm and each algorithm linked to a different stage in the temporal work cycle. I repeatedly asked myself, "What is the company trying to do?" and "What are the workers trying to do?" In re-reading transcripts, I found that one of my informants had already answered these questions: "The company is trying to make drivers take as many rides as possible. The driver is trying to make as much money as possible." Suddenly everything clicked. The company was trying to structure work in such a way that drivers would find it easy—even compelling—to give as many rides as possible. Tasks were simple and discrete, so they could be monitored and doled out by an algorithm, yet they were also designed to be motivating, hence the pricing incentives. Advertisements emphasized the personal freedom of driving one's own car, and workers were drawn to the idea of being free to work and earn whenever and whatever they wanted. From my first day in the field, I saw drivers, including myself, taking advantage of the flexibility in the schedule while trying to maximize earnings. I went back to my data and re-coded around themes of choice, discretion, and freedom. Identifying autonomy as a key theme in how workers viewed the work overall and in each algorithmic encounter gave me more confidence in autonomy as a key finding. Moving between analyzing data, drawing models, and writing memos, I further refined categories to better understand the mechanisms that participants credited as responsible for shaping their autonomy. I mapped these mechanisms for each tactic and then abstracted these ideas to devise a theory that explains how workers construct a sense of autonomy in light of algorithmic constraints.

Coordination and Autonomy in the Algorithmic Work Environment

I present the empirical findings in three sections to address how workers navigate the inherent conflict between algorithmic control and individual needs for autonomy. In the first two sections, I describe how this tension is present in the work arrangement. First, I describe how algorithms scaffold and coordinate work, through rewards, sanctions, and pacing, which, in turn, create the algorithmic work environment. I then discuss how two features of the work arrangement—schedule flexibility and the compensation structure—create a set of expectations in which drivers perceive ride-hailing as enabling freedom, especially as compared to standard work. In the final section and heart of the paper, I explore the lived tensions between algorithmic control and autonomy. I investigate how drivers navigate their day-to-day work environment using three sets of tactics: compliance, engagement, and deviance. I then explain how these tactics and the inferences that undergird them reinforce workers' perceptions of autonomy even though the work is tightly coordinated by algorithms. After presenting these findings, I conclude that while this type of work promises freedom in terms of flexibility, it actually only provides choices; yet, these choices are sufficient enough to foster a sense of autonomy. Thus, the term "good bad job"—good in that this work offers a sense of autonomy, which is often lacking in lower-skilled work, yet bad in that this work is inherently precarious and bounded by algorithmic controls.

Structural Context for Work Coordination in the Ride-hailing Industry

Algorithms Scaffold Work Coordination. Algorithms scaffold the ride-hailing system by coordinating the work cycle and controlling behaviors through rewarding, penalizing, and timing drivers. Five algorithms coordinate the work cycle by: 1) matching drivers and riders, or assigning work; 2) instructing drivers on how to do the work (e.g., giving directions, setting timers, suggesting acceleration speeds); 3) adjusting ride prices dynamically during busy times (surge pricing); 4) offering bonuses ("Do 50 rides in the next 5 days for an extra $50."); and 5) evaluating performance through customer service metrics. (See Table 1 for descriptions of all five algorithms.) [Insert Table 1 about here.] Together these control and coordination mechanisms create a workplace where the algorithms are the focal feature—for example, in a four-hour shift a driver may only complete a dozen rides but will have more than a hundred unique interactions with the algorithm.

Rewards. Algorithms coordinate work through rewarding, sanctioning, and pacing drivers' behavior to guide workers to behave as desired. The pricing algorithms—surges and bonuses—reward drivers if they coordinate their schedules in response to demand. Surges can be predictable, such as commuting hours, or sporadic based on local events, traffic patterns, and weather. Texts or in-app notes alert drivers that: "Demand is higher than usual in Center City. Take advantage of higher than normal fares!", "1.2 - 1.8x boost - 4.30PM-7PM in downtown DC!" and "Adele is playing at the Convention Center tonight! The streets will be full of people!!" (See Image 5-1.) Heat maps pop-up when drivers first sign on and after every ride, displaying real-time demand, with darker colors indicating higher surge areas. (See Image 2.) Checking and following heat maps become a routine part of the workday, so that one "turn[s] on

[the] app and then you see that very orange, bright color" (Sarah, Chicago) and rush to "try to go where the heat maps are surging" (Nancy, San Francisco) for the rewards of higher pay. "I got three pool rides in a row—sweet!" (Field notes, February 2017).

Weekly bonuses offer extra pay for completing a ride quota that is algorithmically determined. How bonuses are set are proprietary and at times seem arbitrary; for example, a driver who meets the quota one week may receive an easier or harder quota the following. Bonuses and quotas are clearly and continuously communicated to drivers though texts and in-app alerts—indeed, while taking a three-month hiatus I still received biweekly texts. (See Image 3.) Bonuses also induce commitment by offering larger rewards for staying on the app for longer periods. After driving with a competitor, a Boston driver, Porris, received a bonus offer from his prior company: "They will pay me up to $500 on top of the money that I make for [regular rides]. And if I stay without logging out for one hour they will pay me $40. (Laughs) That's how they just got me back easily." In sum, pricing algorithms reward drivers, and these payments influence commitment to a particular company.

Sanctions. The matching and evaluation algorithms sanction workers who do not comply with company policies. When the algorithm matches a driver to a rider, the driver's phone buzzes, presenting approximate distance to pick-up locations, details about the rider (rating), and surge amount (if any); drivers have fifteen-seconds to accept. If drivers do not accept and complete a certain percentage of rides, they are sanctioned. "We use acceptance rates to determine driver eligibility for certain incentives and help keep rider wait times short," one policy notes. Escalating repercussions for declining rides include warnings, temporary blocks, and permanent deactivation; consequently, most drivers reported accepting all requests. (See Image 4.) When asked if she declines any rides, Jay, in D.C., replied, “Not really, because like I mentioned, I’m out here to work.” Laughing, she added, “You can decline—how are you going to decline?” and reported that she had accepted every ride request in the past year.

Riders’ ratings serve as a proxy for managers’ performance evaluations, as high ratings (>4.6) are required to continue driving. In short, riders can fire drivers. While instances of deactivation due to ratings are low, with leaked internal reports suggesting only 2-3% drivers are at risk (Cook, 2015), the threat of low ratings looms large. Drivers hang signs over backseats reminding riders that anything less than five stars is harmful. (See Images 5, 6, and 7.) At the end of one ride, a driver cheerily said to me, “You’ve been a five-star customer! I hope you rate me the same!!” while making sure I was watching him rate me. Drivers with high ratings receive compliments, badges, and congratulatory notes from headquarters. (See Images 8 and 9.) In the case of a ratings drop, some drivers receive warnings, with information about how to improve customer service or an order to attend a class, while others are deactivated with no means of recourse. (See Images 10 and 11.) In cities with only one ride-hailing company, deactivation is the equivalent of an industry shut-out.[21]

Timing. Lastly, the work instruction algorithm coordinates work through navigation and timing. After a driver accepts a ride, these algorithms provide directions, create queues, and set timers. Instructional material describes the process as follows: “After you accept a request, tap ‘Navigate.’ The app automatically opens your selected navigation app to guide you to the rider. The rider will see your car icon approaching on their app and your ETA. When you’re getting close, we’ll send them a text message.” (See Image 12.) Once the driver arrives, a countdown

[21] While drivers also rate riders, these ratings do not have the same consequences. If a driver rates a three or below, they are not matched with the rider again, thus reducing their number of potential riders; however, given the larger ridership pool, this is not a reported concern.

timer appears dictating how long drivers must wait (sixty seconds to ten minutes based on ride type) before marking the rider as a no-show and being matched with the next. In shared rides work instructions are critical as multiple individuals with different destinations share the same vehicle and drivers depend on the navigation systems to indicate the route. Instructions urge drivers to "Always follow the app's instructions. The route is built on efficiency, so the order of who is picked up and dropped off first varies from ride to ride." (See Image 13.) In another example of timing, in high-traffic areas such as airports and sporting events, drivers are assigned to virtual queues.

Nudges or algorithmically-informed suggestions influence work coordination by suggesting behaviors. Texts—such as, "You haven't driven in three days. Go out there and make some money!" or "Summer weekends are busy! Head to your promo hub [in app] for weekend incentives and surge pricing"—encourage drivers to sign on. Other notifications push longer hours, such as pop-ups that appear only when logging off: "You've only driven 11 hours today!" or "Only $18 to go until you meet yesterday's pay-out." (See Image 14.) Drivers must click "OK" to acknowledge the message before they can log off. Telemetrics monitor speed, acceleration, and deceleration, offering encouragements such as: "Good job keeping your breaking smooth!" (See Image 15.) In sum, through rewarding, sanctioning, timing work activities, and nudging behaviors, the algorithms create the structural environment or algorithmic workplace within which drivers navigate.

Drivers' Image of Work

The Air of Freedom. Two features of the work arrangements—schedule flexibility and the compensation system—create a psychological lens through which drivers view the work as enabling freedom.

S*chedule Flexibility:* Freedom from the tyranny of the 9-5 workplace is the most-touted promise of ride-hailing. "I'm my own boss" is a common refrain drivers use to describe their work, largely based on the ability to set their own work schedule in their own car, without managerial interference. Advertisements urge potential drivers to "Drive into the Future and Ditch the 9-5." (See Image 8.) Viewing traditional 9-5 workers "as almost being in a Matrix type of situation, stuck to their jobs, stuck to their time and all that," Chapman, in D.C., credits driving with opening his eyes so he doesn't "see work as something that you got to go fill out an application and be somebody's employee." Comparing ride-hailing to his prior union job, Jackson, in Philadelphia, said, "I don't have to do eight hours. On my [prior] job, you show up for four hours and then you want to leave for two, that's not an option. Uber, I can do it for four hours. Stop for three hours, then start for four hours. I control the shift. I don't have a boss." Drivers scheduled work around professional and personal obligations. Seth, a D.C. driver, said the flexibility made him a more available parent: "I'm a man with kids and I didn't want to miss my kids' school appointments. I'll be able to be home with them and I don't have to call no bosses and lie and give an excuse that I'm sick." Schedule flexibility also allows drivers to take extended breaks. Sheldon, in Ann Arbor, takes four to five months off every year to run another business. It took more than two months to schedule a follow-up call with Nathan, in Charlottesville, as he often traveled. "Nobody told me that you can go or you can't. I turn off my application, I go home [to Pakistan]. I come back and I start again. At other companies, you have to give notice months [before] and sometimes it is impossible. If you find [another] job for a month or two, you get your job, and come back. Nobody asks you why you are not here." Schedule flexibility allowed workers to juggle multiple priorities and obligations without having to interact with a manager, supporting their belief that employment in the ride-hailing industry enables freedom.

Drivers report that being able to work unencumbered by management and co-workers was another perk that enhanced flexibility. Tabitha, in Detroit, wanted to continue driving as she did not "want to have another bad boss and be miserable." Describing his prior job at a nursing home, Aaron, in D.C., said, "The working environment stressed me out a lot and my coworkers. [And I just had to do something.] I interviewed a few drivers and they tell me they like the flexibility. So Uber is the right choice, it was a smooth transition." Driving in personal cars allowed drivers flexibility in designing their work environment with bobbleheads, floor lights, signs, play lists, and snacks. Some drivers guide conversation to topics of interest such as social justice. This flexibility can make driving work feel freeing, especially compared to traditional work.

> Uber doesn't feel like real work to me. The time goes fast. Today I been [driving] since 6 AM. It's 9:41 in the morning now. I'm at Starbucks getting my coffee. I ordered a mocha with whip cream earlier. I listen to my own music. I control where I'm going. It doesn't feel like work. Not asking someone else for permission—now that separates it from work. I don't have to stay a certain time. (Jackson, Philadelphia)

In sum, the flexibility the work arrangement provides, through scheduling and being away from managerial oversight, sets drivers' expectations that this type of work will enable freedom.

Unlimited Earning Potential: The compensation system also contributed to drivers' sense of freedom; given the scheduling flexibility, drivers could literally work non-stop.[22] Drivers reported they could "basically write their own check" (Polly, Philadelphia) and "there's a lot of money to be made" (Jamal, Detroit) if you "put in the time" (Tabitha, Detroit) by "getting up early, being out there [and] not going in for stupid reasons" (Kristen, New Haven). Chapman, a former union worker reflected the sentiments of most participants:

> If I need $1,000 in one week, I can get it. If I need $2,000 in one week, I can get it. At a job I couldn't do that without tons of overtime and approvals and whatnot. I can do that with Uber, I can make as much money as I can possibly, basically just put[ting] myself to [it], I can make it. It's very refreshing.

Expected and unexpected bills kept drivers on the road. Winnie, in D.C., reported driving on her day off to pay for the water bill her daughter ran up when home for the holidays. One winter week I noticed I was taking longer and longer breaks, once taking a three-hour break to feed ducks at a park. The next day, looking at an upcoming bill, I decided to make a change:

> Well, it's before 7 a.m. and I'm on the road. That's much earlier than any time this week. I'm a bit nervous because it's my first big [long] day and I don't think there's any way I can cover the rental [car] cost unless I get the promotion [incentive]. Here I go—I gotta get out there and get my paper!! Ain't nobody going to pay me unless it's me. (Field notes, February 2017)

Through self-talk I propelled myself into action, reminding myself I was responsible for my earnings. Like many drivers, Kentucky in Philadelphia set earning goals to ensure he makes what he wants: "Usually I like to make $150 or more. That's a nice number to get. If I'm getting a lot of short rides the whole night, I'll settle for 120 or 30 and then I'll go home—nothing less." Overall, schedule flexibility was valued by drivers as it allowed them to dictate both their working hours and money earned.

[22] The majority of interviews were conducted before ride-hailing companies started capping how many consecutive hours drivers could work. Starting in mid-2018, drivers were forced to take a 6-hour break after 12 hours on the road. The few drivers who complained about the cap have circumvented it by splitting their shift or working on more than one app.

Worker Experiences in Response to Coordination by Algorithms

The control and coordination of work by algorithms and workers' needs of autonomy create a continual tension that are played out at the site of each human-algorithm encounter. In the following section, I describe the lived experience of this tension by exploring the practices individuals use to navigate their algorithmic work environment and the consequences of those practices. Ultimately, I find that the responses to each tactic (compliance, engagement, deviance) reinforce drivers' sense of autonomy in spite of the constraints imposed by the algorithms.

Compliance Tactics: Algorithms as Rules.

Driving is often routine. How often do we check the side mirror before signaling and changing lanes? Or stop upon hearing the sirens of an ambulance? These small, routine actions are part of the rules of the road and, similarly, drivers follow rules when encountering algorithms. Following the algorithms' rules such as accepting rides or heeding routing directions are built into the work system—if drivers fail to comply, they are not able to work and thus are not able to earn money. Other times, following the algorithms' nudges (such as driving to an area indicated as surging by a text message) is financially rewarded. Jay, in D.C., described the work environment as a system of rules meant to be followed:

> The system is: [you] do the work or you don't. There's no in-between. You got to be out here. If you are out here during the surge hours in the morning then you're going to be ahead of the game within those two hours, you can make $50 to $60—as the day goes on you make $200. If you work during the surge in the afternoon that adds up. So that's the only thing you can really do. You can't go around the system. The system is foolproof. You can't cheat it [laughs]. There's no way. Yeah. No. The app determines the distance and determines how long you're in the car and how much you're going to get paid—so there is no way you can mess with it.

In order to meet their income goals, following the algorithms' rules becomes standard behavior. When asked, "How do you use the app?" or "Do you have any special techniques you use driving?" the most common responses were: "Like you're supposed to," and "No." Drivers know to accept most trips because if they decline, that means no work, and they ultimately want to work.

Hard Compliance: Hitting Incentives. In hard compliance, drivers are rewarded by following the algorithm's nudges. Common nudges are text notifications of hourly wage guarantees, surge pricing, and bonuses for completing a certain number of rides. Choosing to stay on the road to meet a bonus is a way for drivers to express autonomy. Polly, in Philadelphia, said, "I try to be in the areas where the incentives are. That's more money for me." Flexing her schedule around the bonuses, Tabitha, in Detroit, said, "You know what you need up front in the beginning of the week. It's a 20 percent bonus and that's basically what I'm trying to hit. If I hit this, then I'm good, I'll go home [laughs]." Chapman, a Detroit driver, said,

> It's an opt-in thing they make you do—so by opting in that's my way of saying, "I'm taking the perks and I'm working the system." Last week I made 35 extra dollars off some perks and I did it by doing what I'm supposed to do. That's all I continue to do. In any job do what you're supposed to and everything else will work itself out. It's just staying on the road, cause you gotta do the hours to make it work out. You can't cheat, you know what I mean?

Opting in, or following the algorithm, is seen as the only way to increase earnings; thus, drivers stay on the road to meet their goals of maximizing income. Nervous laughter and references to the futility of cheating suggest drivers believe they have less control than the algorithms. Even though it is clear who is creating the rules (the algorithms) and who is following them (the drivers), drivers are still able to exercise some discretion by choosing to drive long enough to meet the ride quotas. By keeping themselves moving, drivers feel they are accomplishing their work and exerting their best effort to meet their goals.

Soft Compliance: Giving Riders Five Stars. In soft compliance there are no rewards or punishments associated with following the algorithm's rules, although drivers are aware of its preferences. Drivers are encouraged, for example, to rate riders five stars. After completing a ride, drivers are directed to a screen that is prefilled with a five-star rating and it is easiest just to accept that rating. Jackson, in Philadelphia, said, "I give everybody five stars. It's just not that deep, mentally, to me to be giving somebody three stars instead of five. As long as you stay back there, don't mess up my car, and don't bother me, you're five stars." Likewise, Casside, in Houston, said,

> I don't have a problem with the rating system because everybody that I bring, I give five stars. You could've been ugly. You could've been mean. You could've been everything. I'm gonna still give you five stars because of the fact that—guess what?—you paid me. I brought you to your destination and you paid me. I don't have no shade about why you mad today. I didn't do it. All I know is that I need to get you to your destination in a fast, safe way so I can get my money and you can get out of my car. Gotta keep it moving.

By choosing to accept a pre-filled five-star rating regardless of riders' behavior, drivers are saving themselves the time and mental effort of evaluating every ride. By extension, drivers report not considering riders' ratings when deciding whether or not to accept rides. Joel, in Detroit, never declines rides based on ratings, explaining: "I want to work. I'm not here to see what you're rated." Drivers follow the rating-system suggestions in part because they can get back to their primary task, making money, as soon as possible—simply put, it is easier to give five stars than not.

Compliance Tactics Summary: Autonomy as Mobility. In compliance tactics, drivers interpret the algorithm as a set of rules, and believe they need to follow the rules in order to reach their earning potential. Instead of drawing on schedule flexibility as a source of autonomy, these drivers associate physical mobility with autonomy. They view being on the road and earning rewards from the algorithm as the only path to success: “You gotta be out there” (Jay). “It’s just staying on the road, cause you gotta do the hours” (Chapman). “Keep it moving” (Casside). “Keep on moving and pick up the next one” (Roger). “If your car is not moving you cannot earn money. That’s what the driving job is all about” (Jonathan, D.C.). Overall, this tactic suggests that though some drivers see themselves as working for the algorithm, being able to physically navigate their environment in a way that is rewarded by the algorithm gives them an overall sense of autonomy.

Engagement Tactics: Algorithms as Tools

Driving often requires strategizing. On a road trip, for instance, a driver might use a navigation system, cruise control, and a toll pass to reach the destination faster. Similarly, drivers engage with algorithms to navigate their environment and earn money more efficiently. Using the algorithm to make strategic decisions is neither rewarded nor penalized.

Chasing, Ignoring, and Avoiding Surges. Taking into account surge pricing is the most common way drivers report engaging with algorithms. Ernest, in Los Angeles, described the importance of surges:

> [They] play a critical role in whether or not you’re going to go out, because you’re dealing with economics—one thing about [driving] is you don’t want to waste your time or your gas. I use it to my advantage. They give you the information via the satellite and when it comes into your app, you want to be in those areas. [The company] pays flat rates and obviously the flat rate is not as attractive as surges.

Surges can often make the difference between breaking even and making a profit, especially as base-mileage pay declined over the years. To chase a surge, drivers check heat maps, text messages, or in-app notifications before driving to in-demand areas. Porris, in Boston, uses the heat map to determine the most profitable areas. “I’m just waiting for the surge price to go up. When the surge price is starting to go up, that’s when I put the system on. I know where to be, when, what time—every single day.” Forum posts offer complex suggestions to monitor surge pricing through time-lapse screenshots or using “one phone to drive for Uber or Lyft, and the other phone to zoom out to your entire market to watch the surge areas.”

Not all drivers chase surges. SueEllen, in Denver, ignores them. “I don't pay much attention to the surge. I start up where I start off and just go wherever I get my ping. Driving towards the surge, it’s just not worth it. It’s just too much thinking.” Due to their real-time nature, surges change frequently. Drivers often mistrust surges because they disappear quickly or attract too many drivers. Jared, in Seattle, said,

> [The surge] is a little annoying because it’s often times misleading or by the time you get there it’s gone. They’ll send out a text message that says, “Adele is playing tonight, the streets will be filled with people.” But I’m still going to be taking one person at a time. There’s going to be a lot of traffic and I’m going to be driving one person. They just exaggerate—maybe that’s a better word—you’ll make crazy cash this weekend. It’s almost like they’re insulting your intelligence [laughs].

Tempering expectations and carefully choosing routes are important strategies, as following the surge does not necessarily lead to more money. Others go a step further, examining the heat map and then going in the opposite direction. Seth, in D.C., said,

> I don’t hang around where the surge is because there are a lot of cars around. You go a little farther to get more passengers than to go where the surge is and get less passengers. For example, get one passenger in 30 minutes and make $20, but go outside the surge and get four passengers and make $50.

By monitoring surge notifications and making estimates to determine if a ride is worth their time, drivers exercise autonomy. Irrespective of their actions—Porris, for example, only turns on his app when there is a surge while Seth drives in the opposite direction—each driver is monitoring the app, filtering information, and responding in a way they believe maximizes pay.

Screening Rides. Another engagement tactic is when drivers screen for rides after being paired by the matching algorithm. Forum posts urge drivers to "Screen your rides and only take the ones that make sense for you. Learn to say no to long rides during rush hour. It will absolutely enhance your driving experience and add several thousand dollars per year in your pocket." Drivers filter rides by distance, ratings, and surge, often declining rides that are more than ten minutes away or that will pull them from preferred areas. Ralph, in Detroit, said,

> I screen out riders by their name, rating, and location. These people are more problematic than average. I won't even pick up because it's not worth it. They just harass me. I'm traveling from 10-15 minutes away to take them to a liquor store and wait for them with their kids.

Before each pick-up, a driver does a mental calculation using the output of the matching algorithm as input to calculate potential income versus time spent. Rejecting more distant pickups allows drivers to be available for shorter, more profitable rides. By screening, drivers are able to strategically use the algorithm's information in a way that supports their own interest to earn money.

The "Get Rides to Destination" feature allows drivers to request the matching algorithm to pair them with rides in a chosen direction (limited to two per day). Nancy, a San Francisco driver, uses it to pick up riders while commuting to her primary job. Forum drivers report putting in distant destinations, states away, to get longer rides. Like many drivers I entered my home address towards the end of a shift to get another fare before stopping for the day.

> I needed to be home by 3:15, so I put on the "Get Rides to a Destination" feature. Ping … [shared ride], too much hassle, plus it's an 8-minute drive away. Decline! Ping. Another [shared ride]… Decline! Can these people not give me a good ride? [Shared] rides take too long and there's no way I'll get home in time. Another decline and I'll be blocked [30 seconds] from the app. Whatever. Ping. Oh good, it's a [private] ride. Accept! I drop the lady off only a few blocks away from my house and I'm home at 3:08! (Field notes, July 2018)

This example illustrates the multiple ways drivers can engage with the algorithm while staying within the boundaries. Even after requesting rides in a certain direction, I exercise another level of choice by calculating which rides are more likely to get me home in time and am indifferent to the penalties for rejecting multiple rides.

Selective Work Entry and Exit. Another engagement tactic is to strategically log in and out of the app to earn more. Many drivers prefer starting work in busier areas, even if it means commuting thirty to ninety minutes. Chase, in D.C., said, "I try to stay away from the inner cities, because it's a lot more traffic, so I normally cut it on when I'm on the Beltway [or] when I get almost to the airport." Kentucky drives forty-five minutes from the suburbs to downtown Philadelphia.

> Usually what I do is I get to the Manayunk-Roxborough exit. Two miles before I get to the exit I turn it on to try and get the algorithm working because the algorithm factors in how much time you've been waiting to receive a ride. The longer I'm online, the more chance I have to get a ping and go pick somebody up. The first couple days I did that I got a ping right as I got off the exit. That's where I start and then I keep going on from there.

In the hopes of influencing the matching algorithm, Kentucky turns on the app before he arrives at where he actually wants to start working. In a similar tactic, called going fishing on some forums, drivers scope out other drivers on the passenger app and either position their car between or far away from other cars to optimize chances of being paired with a ride.

Lastly, workers may turn off the app in one area before turning it back on in another more lucrative area. In college towns most rides are short and thoughts differ on whether or not these are profitable. Two drivers describe their opposing beliefs.

> I told my buddy this. Sometimes you just got to turn on the app and go wherever the riders take you. If you go to Ypsilanti, just leave it on. If the Ypsilanti person takes you to Detroit, leave it on. If the Detroit person takes you to Royal Oak, leave it on. Do that once and see where you go and how much you make, because you'll see that it doesn't pay to do that. They'll see that staying in Ann Arbor is the best thing you can do as opposed to going outside. At the end of the day you look and see how much money you made, and you realize that, hey, I didn't make a lot of money at all. (Sheldon, Ann Arbor)

> I get out of Ann Arbor as fast as I can. They charge about 20 cents more a mile, which is good. They charge more of a base rate, which is good. But your rides are much shorter. So if you're going two miles in Ann Arbor, it could take you 10 to 12 minutes to get there. You can't make any money. Between the hills and people walking, you can't get anywhere fast. I'd rather take someone 20 miles on a highway, because I can get there in 20 minutes and make some money, than take someone three miles around Ann Arbor making an extra 20 cents a mile. (Leo, Detroit)

Although drivers differ in their opinions about what types of rides are more profitable, their responses are the same—engaging with the app to stay in their preferred areas. Blind compliance will not result in more money; only strategic interaction does. Switching the app on and off gives drivers a sense of autonomy in that they are able to circumvent the matching algorithm and stay in preferred areas.

Engagement Tactics Summary: Autonomy as Strategizing. In engagement tactics, drivers interpret the algorithm as a tool using its output to inform their decisions. These tactics reinforce drivers' sense of autonomy in that they enable drivers to strategically navigate their work environment in order to meet their earnings potential. Each encounter with the algorithm presents drivers with another opportunity to exercise their discretion, such as analyzing a heat map before deciding whether or not to drive towards a surge area. Additionally, the tactic of choosing when to begin and end work further reinforces a sense of autonomy as it is linked to schedule flexibility. Unlike compliance and deviance tactics, drivers are not rewarded or sanctioned because they are interacting with the algorithm as intended or in a way that is not explicitly against company policy. In other words, while drivers' responses to the algorithm may not be what the algorithm is suggesting (i.e., drivers ignoring surge nudges), all their responses are within the boundaries of the company's rules and regulations.[23] Drivers thus see themselves as working in conjunction with the algorithm. In sum, strategizing reinforces drivers' sense of autonomy as it enables them to align their responses to the algorithm with their interests of meeting their earnings goals.

Deviance Tactics: Algorithms as Clay

Drivers skirt the rules. Late to work, a driver may roll through a stop sign or dart into the HOV lane and, while these maneuvers can shorten trips, they are ticketable offenses if caught. Similarly, drivers manipulate the algorithms to earn more, which can result in punishments if detected by the work system.

Pre-Selecting Riders. One of the most prevalent deviance tactics is when drivers attempt to circumvent the blind matching algorithm by trying to have the algorithm match them with someone already in their car. When I first began data collection, drivers in several cities recounted this tactic and my field notes describe such an incident in D.C. in which I was the rider:

> [She] seemed unphased as we navigated bumper-to-bumper rush hour traffic, but I was nauseated and frustrated with all the out-of-the way stops and complained after we dropped off the Georgetown frat boys."Wanna switch to a private ride?" she asked. "Sure, as long as it doesn't hurt you." "Naw, it's cool." She ended my ride and then went

[23] While drivers using the passenger app is not the intended function of the app, this tactic is well-advertised on ridehailing web communities and has not been blocked by the company, though it would technically be possible to do so.

> off-line. As soon as she went back on-line, she told me to request a new ride and—ta-da!—we were matched. As we continued to Ballston, she confessed she didn't like shared rides as she'll drive for half an hour and realize she's only made $5. (Field notes. August 2016)

Though against the rule, switching to a private ride was in the driver's interest as it paid more and pleased the rider (me). In late 2015, when ride-hailing first launched in my city, I became friendly with a driver who soon became my designated airport driver. I would text him my travel plans and once in his car I would request a ride and we would be matched immediately. As a rider, I appreciated the convenience of having a ride at a specific time and my driver appreciated a guaranteed large fare. By late 2016/early 2017, it took multiple attempts to be matched even though we were in the same car, and I often resorted to paying in cash. By mid 2017, I was back to using the app in its intended fashion for airport rides; around the same time across the country, drivers reported similar events. In late 2017, Pound, in Detroit, describes:

> [A friend asked] "I've got to go to the airport at 4:30 p.m. on Friday, can you take me?" Sure. It used to be that you would get in the car and they'd request a ride and automatically goes to you. It's changed dramatically. It takes maybe three or four times that [the rider] has to request a ride, cancel it, request a ride, cancel it, request a ride, cancel it. It gets to me.

Though the code underlying the algorithm is proprietary, it is clear to drivers that the matching algorithm has changed in that proximity is no longer the most heavily weighted variable. If drivers continue trying to bypass the matching algorithm by rejecting multiple rides, they can be charged a penalty or temporarily blocked. These penalties make it less attractive to preselect riders, thus further constraining workers' behavior.

Blanket Ride Rejection. Blanket rejection of specific rides is another deviance tactic. Shared rides, where the algorithm coordinates multiple riders who are traveling in the same direction, were introduced in late 2015. For the company, shared rides reduce road congestion (allowing drivers on the road to travel more quickly) and offer rides at a lower cost point, which may potentially bring in new customers. When the D.C. metro system was undergoing major repairs, ride-hailing companies launched massive advertising campaigns and I paid less for shared rides than a metro ticket. Most drivers, however, dislike shared rides due to the low fares, circuitous routes, and querulous riders confused by the service and frustrated by longer travel times. Two drivers shared similar sentiments about shared rides.

> I never did like [shared rides] cause it's too damn cheap—it's almost cheaper than a metro bus ($1.90). If you reject, it makes your rating go down and then they'll try to block you! I rejected a few until I got a notification, "Hey, we notice that you haven't been accepting your [shared rides]." Basically you gonna have to start accepting them or you gonna get blocked out of the system. (Winnie, D.C.)

> In the beginning they used to say [shared rides] were optional, but after a month they said it was mandatory and were sending messages saying they were going to cut me off the app if I kept [rejecting shared rides]. I wrote two messages saying all the reasons I don't like doing it. If I force straight decline the ride the app turns off, but I can take a break and turn it back on. I really don't like having five people in the car. (Jackson, Philadelphia)

Though drivers attempt to deviate by rejecting shared rides, their attempts are countered. The warnings were severe enough for Winnie to change her behavior, however Jackson continued to reject and be blocked. Serial offenders report harsher penalties such as being blocked for longer periods or deactivation. In late 2017, new incentives linked bonuses to ride quotas making shared rides more attractive. Two drivers described the changing sentiments.

> It was a good day yesterday—had a few [shared rides] so it was nice. [Shared rides are] good, especially if you want to get incentives for that promotion. It's easier and faster to get. (Sean, San Francisco)

> I love incentives—it helps when I'm trying to get multiple rides. If I'm trying to get 60 rides and I get a [shared ride], it takes 40 minutes, but I get three rides. It's a great deal and I don't have to worry about driving around looking for another ride. (Kentucky, Philadelphia)

With this new incentive, a deviance tactic—blanket ride rejection—is transformed into a compliance tactic—bonus opt-in. In doing so, expressing autonomy through deviant behavior is curtailed and, instead, drivers are encouraged to express autonomy in a way that is both lucrative and aligned with company policies.

Inflating Surges. In the next two deviance tactics, drivers are not penalized, as their deviance is not (yet) detected by the work system. Drawing on supply and demand theory, drivers try to inflate surge pricing by driving to areas that are about to surge, log off, and then monitor the ride app for prices to rise before logging back on. Describing a $180 fare to the airport, more than four times the regular fare, Ralph, in Detroit, said,

> What does [the company] want me to do? They want me to take as many rides as possible. What do I want to do? I want to make as much money as possible. They punish me for it; however I profit more than I hurt. [Describes declining several rides waiting for a surge increase.] They were trying to get me to work for a cheaper rate and I didn't want that, but if I [don't accept] three rides, I get punished and can't log in for half an hour. I figured out ways around it. I just request myself. [Laughs] I use a separate e-mail for my passenger and my driver account and I'll go back online. There is a bit of an opportunity cost, but it's better than being locked out for 30 minutes.

By circumventing the algorithm's countermeasure (blocking), drivers exercise choice and manipulate the algorithm to get the ride at the rate they want. As described earlier in this section, trying to be matched with a preselected rider has costs both in terms of time and money, yet Ralph is so determined he is willing to pay to earn a higher fare. This escalating cycle of "driver deviance-system countermeasure-driver work around-driver deviance" ultimately reinforces a sense of autonomy in that the algorithm is eventually "beaten" and a higher fare obtained.

Protecting Ratings. Drivers can be deactivated or deemed not eligible for incentives if their rating falls below a threshold. Fearing a poor rating, drivers act preemptively by cancelling potentially negatively-rated rides. Porris, in Boston, said, “If I make a mistake I cancel the trip and give it to you for free, doesn’t matter where you are going. [That way] people don’t really have the chance to give me any bad rating.” Likewise Roger, in D.C., described:

> I’m 4.90 and before I was a 4.93. I had just turned 4.93 and I picked up a woman and her kid. The app took me to the back of where she lived and she was in the front and it was really cold. She was holding the kid in her hands, she called me, she was all pissed off at me. I said, ma’am, I'm just going where the app sent me. She ran in the back, got in the car, destroyed me on the ratings, and I went from a 4.93 to a 4.90 just like that. And if you lose points it’s real hard to get them back, so what I’ve learned is that if you want to make sure that the person can’t rate you, close out the ride right before you let them off. The ride will cancel—it will still pay you up until that point, but it’s impossible for them to rate you. I tell them straight up too. I tell them so that they understand, I’m canceling you because I don’t want you to rate me.

Prematurely cancelling a ride allows drivers to shape the working environment before the rider and rating system can. In Roger’s situation, three interdependent factors beyond his control—a malfunctioning work-instruction algorithm, the rider’s sour reaction, and the rider’s negative rating—affected his rating. Similar to Ralph, Roger exercised choice and canceled the ride early, shortchanging himself in order to protect his ratings.[24] Drivers also manipulate other ratings systems, such as accepting rides they have no intention of completing in the hopes that the rider will cancel and their acceptance rate will remain high.

Deviance Tactics Summary: Autonomy as Manipulating. In deviance tactics, drivers interpret the algorithm as malleable clay that they can manipulate in order to increase their earnings. These tactics reinforce drivers’ sense of autonomy in that they enable drivers to select the rides they most want even when that means going against company policies. Each encounter with the algorithm presents an opportunity to manipulate it, such as turning off the app to reduce supply

[24] While it is statistically impossible for one ride out of the 5,000 that Roger has completed to affect his overall score so significantly, drivers report that a single negative rating can have a disproportionate effect on ratings. Further, company websites state that ratings are not always calculated by a straight average of the last 500 rides, but give no further information on how averages are calculated.

and inflate surges. This autonomy comes at a price in that even when these tactics are not detected, drivers sometimes sacrifice earnings to manipulate the system. Yet, the very possibility of manipulation reinforces drivers' sense of autonomy as it enables drivers to counter the algorithm repeatedly. Taken together, this suggests that drivers see themselves as working against the algorithm in that they have greater power over it.

Inferences and Responses to Algorithms that Reinforce a Sense of Autonomy

Attempting to succeed in a working environment with opaque rules and scripted work activities, drivers engaged with the algorithm in ways that supported their aspirations to earn money and reinforced their sense of autonomy. Industry standards and norms—such as advertising rhetoric, the contracting employment relationship, and the absence of human managers—supported drivers' sense of autonomy by enabling drivers to feel in control of their work activities around scheduling and earnings. In contrast, the most prominent feature of the industry, algorithms, served as a structural constraint controlling and coordinating work activities through assigning rides, dictating wait times, and dynamically setting and adjusting fares. However, somewhat paradoxically, drivers interpreted their interactions with the algorithms as reinforcing their sense of autonomy. In response to each encounter with an algorithm, drivers deployed a tactic, either complying, engaging, or deviating with the algorithm, based on their thoughts about what the algorithm was doing, how much autonomy the algorithm was allowing, and their own interests. Ultimately, each tactic reinforced drivers' sense of autonomy in that they were indeed their own boss. This process is outlined in Figure 1.

Although algorithms are a structural feature of the work environment, drivers interpret them and interact with them in ways that reinforce their sense of autonomy. Upon encountering an algorithm, drivers make a mental calculation based on their goals, the current working conditions, and prior experiences with the algorithm before deciding how to respond in a way that will align with their interests. As the inner workings of the algorithms are inherently obscure, drivers have to fill in the gaps or make inferences about how the algorithm coordinated the work so far and how it would continue to do so. Interpretations of the algorithm fell into three broad categories (rule, tool, clay), which allowed a certain amount of autonomy and were associated with a corresponding tactic that, in turn, helped drivers maximize their income goals.

Every interaction with an algorithm or an associated nudge (e.g., heat map, ride assignment) set off a chain of interpretations and behaviors that ultimately reinforced drivers' beliefs that they could maximize their earnings. If drivers complied with the algorithm, they were inferring the algorithm was rigid, like a rule, so they needed to follow or work for the algorithm to meet their goals. Compliance was observed and often rewarded by the company, such as extra pay for hitting a ride quota, and the extra pay could help drivers feel autonomous in that they had done something (following the rules) to help meet their financial goals. Another type of compliance, accepting rides, kept the drivers on the road, enabling them to be matched with more rides and thus to meet their income goals. In sum, for compliance tactics, accepting the algorithm's nudges is the most apt way for drivers to meet their financial goals, thus the algorithms are seen positively and aligned with drivers' interests.

If drivers engaged with the algorithm, they were inferring the algorithm was providing information, like a tool, and thus they needed to work with the algorithm to meet their goals. For example, a driver could selectively decide when to start and could suspend driving in order to remain in more lucrative areas. In this way, drivers strategize and exercise choices about what to do. These actions are within the standard practices of work so drivers are neither rewarded nor punished by the company (as long as the behavior is not excessive). In sum, for engagement tactics, each algorithm's nudge provides information that must be evaluated for drivers to meet their financial goals, thus the algorithms are seen as neutral, because, depending on the situation, the algorithm can be in (mis)alignment with the drivers' interest.

Lastly, if drivers deviated from the algorithm, they inferred the algorithm was malleable, like clay, and they needed to work against the algorithm to get what they wanted. Drivers, for example, might turn off the app in an area they thought would be busy in order to increase surge pricing. When these actions are detected by the system, drivers can either be directly sanctioned or collectively curtailed by being "programmed away" by the company, keeping drivers from doing this action in the future. In sum, for deviance tactics, algorithmic nudges are, at best, to be negotiated and, more often, actively countered in order for drivers to meet their earnings goals, and therefore the algorithms are seen negatively and at odds with drivers' interest.

Tactics enforce drivers' sense of autonomy in two different ways. For each tactic, drivers responded to algorithms in ways that support their interests, such as maximizing earnings or getting home at a certain time. Meeting their goals gives drivers a sense of autonomy in that they are making choices that directly affect what they deeply care about. Even in the cases where two drivers engaged in completely opposite behaviors to maximize income, such as one staying in a certain area while another avoided it altogether, each driver believed they were taking the optimal course of action. That drivers make these decisions independently, without the input of managers and co-workers, heightens a sense of autonomy.

Second, each tactic is associated with a micro-expression of autonomy that highlights a specific element of control a driver had over their work activities. In compliance tactics, drivers keep their car moving and are quickly matched with rides, thus earning more. When deploying deviance tactics, drivers are sanctioned (if caught) with lower ratings and lock-outs and, in return, report deploying counter-measures against the algorithm. This cycle of deviating from the algorithm, being countered, and then deviating again can give drivers a sense of autonomy as they are negotiating with the algorithm to meet their goals. When deploying engagement tactics, drivers are neither rewarded nor punished but instead strategize about how to make the best use of the information provided to maximize their earnings. By using information from the algorithm to make decisions, drivers exhibit a sense of autonomy over their work activities, while still operating within the boundaries of the algorithm to meet their goals.

Strikingly, the algorithm, a feature of the work environment that constrains behavior, is interpreted by drivers as enabling autonomy. In part this is due to drivers having a broad conceptualization of autonomy and being unaware of how the algorithm actually makes decisions. This gap creates a space where drivers are able to interpret the algorithm and their responses to it in a way that supports their interests and ideas about autonomy. No matter if a driver deems the algorithm as constructive, obstructive, or neutral with respect to their goals, they can always interpret their responses to the algorithms as supporting their interests. Shaped by the industry's narrative of freedom and their own experience of schedule flexibility, drivers frame all of their responses to the algorithm as indicators of autonomy. Drivers have dozens of interactions with the algorithm, and each interaction reinforces a sense of autonomy. In a single ride a driver, for example, could use the passenger app to locate the most lucrative area to wait for a ride (engagement tactic), then accept the first ride request (compliance tactic) and cancel the ride early so the passenger cannot rate the ride (deviance tactic). In sum, although drivers make different inferences about the algorithms, all the inferences and the corresponding tactics reinforce drivers' sense of autonomy.

Discussion

Venturing into the "contested terrain" (Kellogg, Valentine & Christin, 2019) of algorithms, control, and autonomy, this study offers insights into the nascent field of algorithmic control and how workers navigate within these systems, thus answering calls to develop grounded models that reflect the changing realities of work (Barley, Bechky, & Milliken, 2017). Specifically, I shed light on how workers navigate the tensions between algorithmic controls and workers' needs for autonomy, ultimately explaining how these workers are able to maintain a sense of autonomy within a constrained environment. The identification and articulation of this phenomenon offers a number of insights to the literature of autonomy and algorithms in the workplace.

Implications for Algorithmic Control

Existing research argues that algorithmic control facilitates a new form of rational control that is more invasive than technical and bureaucratic control because it is more comprehensive, instantaneous, and opaque (Aneesh, 2009; Couchon et al., 2019; Faraj, Pachidi & Sayegh, 2018; Kellogg, Valentine & Christin, 2019; Rahman, 2019). Yet, in spite of its constraining nature, I find several distinct features of algorithmic control systems that facilitate autonomy. Algorithms allow for work to be distributed across individuals so that the organization's goals are accomplished by each worker's independent effort. This pooled interdependence allows workers to have a greater sense of control, mastery, and autonomy over their work activities (Thompson, 1967), which counteracts the alienation and estrangement that commonly arise in lower-skilled work (Vallas, 2016). In addition, the macro-employment conditions of schedule flexibility and less structured relationships with management and customers can "enchant" workers (Endrissat, Islam & Noppeney, 2015), despite the harsh material realities of long hours, precarious work status, low pay, and dangerous work conditions. The remoteness and physical isolation that is often found in conjunction with algorithmic work can also heighten a sense of autonomy. In the absence of organizational and managerial cues to guide workers' interpretations (Jackson & Dutton, 1988; Sonenshein, et al., 2013), workers may have attributed their responses to the algorithms as self-directed. Further, the large information asymmetry between what the algorithm and the worker know may allow workers more cognitive space from which to draw their own conclusions which, in the absence of conflicting information, will support their already held beliefs that they are making their own choices (Festinger, 1954).

These insights about how autonomy is produced provide greater understanding about how algorithmic control models incentivize workers beyond the carrot and stick employed by other rational control systems (Adler & Borys, 1996; Blau, 1955; Edwards, 1979; Gouldner, 1954; Zuboff, 1988). I find that this system "manufactures consent" (Burawoy, 1979; Roy, 1952) by giving workers the choice to opt-in at every phase during the work cycle. Workers thus have more buy-in into the entire process, which is critical in a context where they can stop anytime. Similar to escalating commitment (Staw, 1976; 1981), repetitive requests and subsequent buy-ins engender commitment to the system while preserving a sense of autonomy. Within a six-hour driving shift, an individual may give consent hundreds of time with each act of consent further cementing psychological commitment. These micro-consent choices both reinforce a psychological sense of autonomy and autonomous behaviors in that workers are able to respond and interact with the algorithm by physically moving and strategizing and manipulating the algorithm. Though these actions of autonomy are embedded within a larger work system, drivers can enter and exit the system at will. Thus, in contrast to recent research on the "algorithmic cage" (Rahman, 2019; Faraj, Pachidi & Sayegh, 2019; Kellogg, Valentine, & Christin, 2019), I find that workers have real autonomy in algorithmic work.

Implications for Workers' Autonomy

Classic research on autonomy suggests autonomy is a stable, embedded feature of designing jobs and group structures (Hackman, 1976; Hackman & Oldman, 1976; Langfred, 2000; Wageman, 1995). These formulations assume that employee's aspirations for choice, dignity, and expression compete with the organization's implicit need for control and hence must be carefully doled out so that any workers' autonomy is in alignment with organizational goals (Blau, 1955; Osterman, 1999). Indeed, this quest for autonomy is so salient it is considered the defining feature between "good jobs" and "bad jobs" (Kalleberg, 2009). Management and team structures also enable autonomy. Managers grant autonomy through leniencies (Anteby, 2008) and idiosyncratic arrangements (Rousseau, 1995), while collusion among co-workers influence workers to take unscheduled breaks (Roy, 1952) or shortcuts (Bernstein, 2012). In line with this research, algorithms are theorized to further circumscribe work autonomy, designing jobs that are even more structured and more isolating. Yet, surprisingly, I found workers have a strong sense of autonomy.

These findings problematize general assumptions that autonomy is a stable job characteristic embedded only in "good jobs" and reinforced by interactions with managers and peers. No one would describe a ride-hailing job as "good," as it is inherently precarious with long hours, little pay, and no possibility of career advancement. Yet, these workers experience autonomy while engaging in work. In a recent review considering the future of job design, the founders of job design theory noted that they had "under-recognized the importance for work redesign in the broader context … [of] the organization's formal properties" such as "technology and control systems" (Oldham & Hackman, 2010: 472). These findings counter the assumption that only "good jobs" are characterized by high autonomy. Indeed, one of the fruits of the on-demand economy is the birth of the "good bad job."

Similar to Blauner's (1964) expansion of Marx's (1840) theory of alienation, this research broadens Hackman and Oldman's (1976) conceptualization of autonomy by explicating the linkage between work conditions, structures, and autonomy. This research details how different types of autonomy (mobility, strategizing, manipulating) interacted with one another in a short period of time to reinforce a sense of autonomy. In a single ride a driver could use the passenger app to position between other cars (autonomy as strategizing), reject all the shared rides (autonomy as manipulating) before accepting a private ride, and quickly rate the rider to get back on the road quickly (autonomy as mobility). Each of these tactics was interpreted as supporting drivers in meeting their ultimate goal of earning income, and together they mutually reinforced workers' sense of autonomy.

While the autonomy this work offers is not the promised freedom touted by the industry, it is also not an act of self-duplicity. Games on the shop floor are real choices, however narrowly conceived (Burawoy, 1976), and, in the same vein, tactics in response to algorithmic control are voluntary though circumscribed. These choices allow workers real discretion in accomplishing their work tasks. Nor, however, is the autonomy an act of defiance (Roy, 1952; Montgomery, 1979) or an attempt to find meaningfulness out of a "bad" job (Bunderson & Thompson, 2009; Wrzesniewski & Dutton, 2001); instead, it is the simple yet not insignificant act of trying to earn a living. Unlike other organizational ethnographies of lower-skilled work, this research seriously considers workers' accounts of autonomy, not discounting workers as victims of false consciousness (Marx, 1840) who are unwittingly reproducing systems of self-oppression

(Burawoy, 1976; Barker, 1993; Mazmanian, Orlikowski, & Yates, 2013). The heroes of those accounts are the workers who do not allow the "time study man" to observe them (Montgomery, 1979: 115), refuse to smile (Hoschilds, 1983), and do the "seatbelt squeeze" on unruly Disneyland riders (Van Maanen, 1991). My findings suggest an alternative, unsung hero: those who go to work each day to earn a living, enabling their own sense of autonomy in spite of organizational and algorithmic constraints.

Limitations and Future Research

My findings can foster naturalistic generalization, as parallels may be drawn between the description of a case and one's own experience in similar contexts (Stake, 1995). The ride-hailing case highlights workers' experiences in contexts in which the entire human resource cycle is managed by algorithms and subject to monitoring, evaluation, and control. As algorithms are becoming more integrated in the workplace, influencing hiring, evaluation, and compensation practices, more and more workers are being subjected to management by algorithms. What was previously under the discretion of a manager is now measured, quantified, categorized, and monitored under an algorithm's control and oversight. Surprisingly, I find that algorithms give rise to more opportunities for worker autonomy in that workers have another structure they can interpret, strategize about, and deviate from. In sum, individual discretion is not simply "programmed away," although this is an intention of algorithmic management and does not lessen the inherent control algorithms impose on the work itself.

This study is a first response to calls for research on how algorithms are being embedded into occupations (Kellogg, Valentine & Christin, 2019). My finding of a "good bad" job—in that work can be experienced as positive while structurally precarious—suggests that algorithmic work is not as alienating as previously forecasted. An Amazon warehouse worker may have some autonomy, in terms of physical movement, but less opportunity for strategizing or manipulating due to electronic tracking; a worker engaged in the "ghost work" (Gray & Suri, 2019) of algorithmic curation may have even less. In contrast, on-demand work for TaskRabbit and Upwork might be better "good bad" jobs, as workers have more possible ways to interact with the algorithm, clients, and platform. In pursuing the study of algorithmic work, researchers must be careful not to typecast the integration of algorithms as always estranging workers.

These findings can be also analytically generalized by moving beyond the empirical phenomenon to consider the conceptual implications of the case study (Stake, 1995). With the rise of online platforms, gig work has achieved the status of a household name, with more than 90% percent of Americans aware of the service, if not consumers or workers themselves. Recent discussions of contemporary life suggest that the experiences of these workers are consistent with broader shifts in the move toward post-traditional society (Gray & Suri, 2019; Standing, 2013; Vallas, 2016). Discontent at the rise of neo-liberalism and "surveillance capitalism" (Zuboff, 2019) fuels inquiries on finding meaning, value, and fulfillment at work. Industry and popular media discourses construe gig employment as emancipatory where freedom and self-fulfillment can be won.[25] Further, firms are encouraging workers to develop their personal brand (Vallas & Christin, 2018) and take ownership of their careers and skill development (Hall, 1996), leading to a "radical responsibilization" of the workforce (Fleming, 2017). These factors

[25] This is a dangerous assumption. Hatton (2011) described that from its inception, the temp industry has contributed to the degradation of work—from the "Kelly Girls" exploiting 1950s gender stereotypes to justify low wages, minimal benefits, and chronic insecurity, to the 2000s "permatemps" who painted workers as financial liabilities. Further, both Hacker (2006) and Fleming (2017) argue that the radical responsibilization is linked to growing economic insecurity and worrying levels of personal debt as more risk is being transferred from firms to workers through restructurings, reduced benefits, and limited internal mobility options.

help illuminate why the ride-hailing industry's claims of freedom are so popular and why workers are apt to interpret their interactions with the algorithm as reinforcing their autonomy.

Further, this case provides an empirical example of how control systems are layered over one another, or are a pampliset. Algorithmic control relies on traditional methods of technical and bureaucratic control (i.e., determining the rule and pacing the speed of work), but also introduces new methods, such as adjusting wages in real-time and using algorithmically-determined ratings. A unique feature of algorithmic control models is that mechanisms of control can be interdependent—the output of one type of control may be the input of another type of control. In ride-hailing, for instance, drivers' algorithmic ratings influence what rides they are matched with; meeting a prior week's bonus quotas affect what quotas you are offered the following week. Additionally, this case provides insight on how algorithmic control models can be adopted across multiple industries. In ride-hailing work, human-algorithmic interactions are part of an "algorithmic labor triangle" (Cameron, 2019), a three-way interaction between workers, management, and customers, in that customer evaluations affect how the algorithm assigns tasks to the worker, and the worker's task-acceptance rate affects evaluations. Each member of the triangle both controls and is controlled by different members in the labor process. Thus, algorithmic control can be seen less as a path-dependent model and more as an interweave of different types of control exercised by varying actors. Future work should continue to explore how this overlapping affects the ways in which control is actually implemented, especially with respect to managers and customers.

While this is an extensive study of the ride-hailing industry, it is limited to workers within one industry, and the sampling strategy did not allow me to identify clear variations across participants in terms of dimensions such as industry, gender, race/ethnicity, immigration status, tenure, hours worked per week, prior and/or co-current employment, or location. I also selected drivers who chose to continue to drive (the median time driving was a little over a year), as opposed to those who quit after a few weeks. Based on my sampling technique (I recruited most participants after meeting them in-person as a rider), these workers drove more often and were not representative of the overall population of ride-hailing drivers, many who drove less than 10 hours a week (Katz & Krueger, 2016).[26] This was a conservative sample as one would expect that the longer a driver worked, the less likely they would be to have a sense of autonomy, since the business model presents challenges to schedule flexibility (wages are synched to morning and evening high-demand periods, such that those who want to earn the most must work consistent time blocks). Over the course of my study, the continual downwards pressure on wages forced many drivers across the country to work even longer hours for the same or less pay. Furthermore, I studied drivers in the ride-hailing industry from 2016 to 2019 and algorithmic technologies have continued to evolve. These factors necessarily qualify my insights. However, as algorithms are becoming more and more embedded into work across a range of skill levels, these results offer important insights into the implications of autonomy within algorithmic workplaces. Future research should continue to examine whether and how individual experiences and algorithmic controls articulated here apply in the case of different types of work. Second, as this research focused on the employment relationship, drivers, and their experiences of the work, future research in algorithmic work should continue to explore its implications for customers, managers, and teams.

[26] Similarly, Gray & Suri (2019) and others convincingly argue that the majority (80%) of the work on digital platforms is done by the minority (20%) of workers.

Conclusion

I began this research project with a simple question about how work is navigated in an algorithmic work environment. My research describes a two-part framework where algorithms structure the work process through the use of rewards, sanctions, and timing. Drivers, in turn, make inferences about the algorithm and then respond with a set of tactics—compliance, engagement, or deviance—that give them a sense of autonomy within the constraints of their work environment. Taken together, this paper contributes to the understanding of autonomy in the algorithmic workplace. More importantly, this study gives hope—hope that the rise of algorithms being embedded into contemporary work will not condemn lower-skilled workers to an ever-tightening iron cage.

Figure 6-1: Algorithms and the Work Cycle

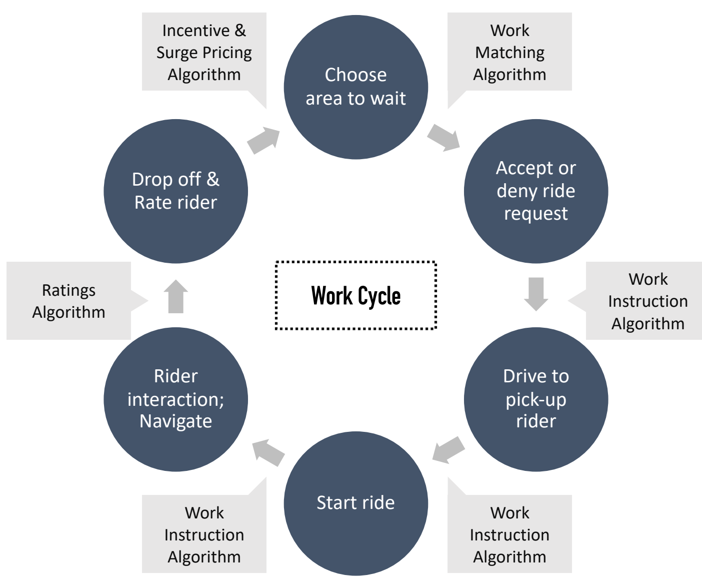


Table 6-1: Algorithmic Tactics

Tactics	Sub-Tactics	Data
Compliance	Hard	Last weekend it was 50 rides and you get $150 bonus. If you give 75 rides you get a $250 bonus. If you give 90 rides you get a $350 bonus. I was trying to work towards the 90 rides, but on Saturday it didn't work out because I got longer rides. I didn't get as many rides. I only got 21 rides. The first day I got 30. I was on track, but the second day screwed me. Then I got 80. This past weekend that just occurred, it was 60 rides for $175 bonus. 90 rides for $300 bonus and 105 rides for $375 bonus. That's [105] way too many rides. You could probably do it if you're out 13, 14 hours. [laughs] That's crazy. That's a lot of rides. First day [I was out] eight or eight and a half [hours]. The second day was five and a half. Then yesterday was 10 and a half. So, I was out probably combined in driver mode, 24 hours this weekend… With commuting, that was 30 hours total. (Kentucky, Philadelphia)
Compliance	Soft	Basically everyone gets a five unless they do something to annoy you, and then they get a four, and four out of five stars is supposed to be really good, but it's not…. if you get anything less than a five, it's kind of a problem. A three or less is, you'll never be paired with that person again. The scale of what the stars mean has really shifted and are really weighted on one end. So I give pretty much everyone a five—I've never had to give anyone less than a five. They actually started auto-filling it now, so when you complete a ride, it just pops up five stars and you just hit go, hit complete, so it just assumes you're going to give them five stars. (Charlotte, Ann Arbor)
Engagement	Catching Surges	Go to the big events at the height of a surge (i.e. when the event ended). What I found was that I lost a lot of time looking for riders, and then I would have to cancel. By that time, the surge was over and now I just lost time and money at this big event. A better strategy is to go a little before the event is over and after the big crowd is gone. It is easier to move in and out of the area and you can get multiple rides as opposed to one big ride. (RideHailng Blogger)
Engagement	Avoiding Surges	Lyft only displays Prime Time levels in two colors: pink and magenta. To complicate that, the amount of Prime Time on a given pink or dark pink tile varies. This means you don't even really know what these stupid pink squares mean! They are unpredictable. I have received 0% Prime Time after getting a request in a magenta square many times. I have also received 100% Prime Time when there were no pink Prime Time Squares on Lyft's heat map. It just appeared out of nowhere. I often feel like Prime Time is determined by a Random Number Generator (Harry, ride-hailing blogger)
Engagement	Avoiding Surges	You turn on your app and then you see that very orange, bright color around downtown area… you rush to that area, when you're five minutes [from] the area, the color just disappears or it becomes very light instead of that deep red or deep orange color that you saw at first, so that's the thing I don't understand. So I tried it. I did it a few times. I went to the spot and the color changed, so now I don't trust that color anymore. (Sarah, Chicago)
Engagement	Accept/Reject Rides	I only accept rides five minutes [away] and below. I'm not going to accept anything out of five minutes—especially if it's not a surge, okay? …Often times they're 15 minute rides, 14 minute rides [away]…And I'm not going to do it, because often times it's going to cost me more time and gas to get there for a three minute ride for the rider. That is totally not worth it to me. So going back to… how I utilize my app, you took a question directly from the methodology that I use in order to make my money. That's one of the methods that I use. (Ernest, Los Angeles)
Engagement	Accept/Reject Rides	If you live a long way from the concert venue, put on a destination filter with the concert venue as the target and sit and wait for your long run to the concert. Given that concerts are in the evening, when there is a whole lot of other traffic, it won't be as reliable as the airport runs on Monday morning. But it's a good way to try to

		get a really long run right out of the gate. Destination filters are also a great way to do “opportunity driving.” Going somewhere more than 10 miles away? Leave early and put on a destination filter for where you’re going. Maybe you’ll make a few bucks along the way!” (Ride-hailing blogger)
Engagement	Selective Work Entry/Exit	As a passenger, you can see all the cars around. That’s also another good indicator when you’re working too. If it’s a ton of Ubers around, don’t even bother. Don’t go out…. Before I get in my car I like to see if it’s even worth getting in. (Carlson, Maine)
Engagement	Selective Work Entry/Exit	You open the passenger app and it will show you the eight closest drivers and then you just go where they’re not. You could count all the other drivers on any given moment. It would be the 200 block of Ryman, but there were too many cars—it was too stressful…it wasn’t always a sure thing. So I would go four blocks away where there were less people but more bars. And it would work out for me. (Myrtle, Montana)
Deviance	Predeisgnating Riders	I had a woman who wanted me to take her home. Her friend canceled it, and she wanted me to take her home, so I said just make the request. No matter how many times she requested me, she never got me. It was always another driver. I canceled on two people while she was in the car and she had to cancel on three drivers before I just said you got to get out, it’s not working for some reason. So it wasn’t necessarily who was closer. You’ve got to realize [the company] is doing something, and whatever they’re doing is not necessarily whoever is closer, because if she’s sitting in the car with me, how are all these other drivers that are two blocks away getting the request? (Roger, Washington, DC)
Deviance	Blanket Ride Rejection	Well, actually I never did like [shared ride service] ‘cause it, it’s too damn cheap. Really. I mean it’s almost cheaper than a metro bus. If you reject, it makes your rating go down and then they’ll try to block you out the system! One time I rejected a few until I got a notification that basically, “Hey, we notice that you haven’t been accepting your [shared rides].” So basically you gonna have to start accepting them or you gonna get blocked out of the system. (Winnie, Washington, DC)
Deviance	Inflating Surge Pricing	There was a bigger concert and I kept denying rides, waiting for the higher surge charge because I knew there was going to be one. And they blocked me for like a minute or two, which I was fine with because that’s what I wanted to do. [Laughs.] I didn’t know if I was going to be able to turn back on, which I was irritated about, so I did a hard shut of the app a few times and it let me back in. (Tyrone, Montana)
Deviance	Protecting Ratings	So now it was Sunday night and I had completed my required trips but was just short of the required acceptance rate. I didn’t want to continue giving rides because it was late, requests were slow to come in and I really wanted to get home and sleep. But I also didn’t want to miss out on the $80 that I was so close to earning. So I figured out a way to get the $80 WITHOUT giving any additional rides. I decided that I’d remain online and accept the next request I received. A few minutes later a request came in and I tapped the screen to accept it. But instead of completing the ride, I cancelled it. Wait, what?? Yep, because I had accepted the request, my acceptance rate now jumped above the 80% threshold and unlocked the $80 bonus for me. BOOM! And because I then cancelled the trip, my completion rating dropped, but not enough to disqualify me from the bonus. I got my bonus and didn’t even have to complete an additional trip. (Also see picture) (Blogger)

Table 6-2: Algorithms Coordinating the Work Process

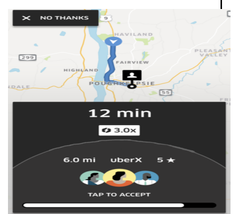
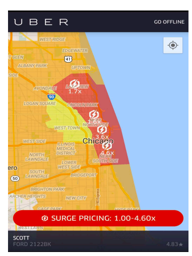
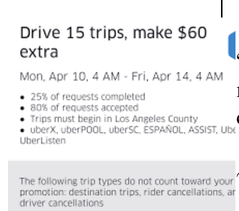
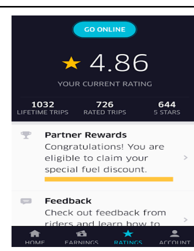
Type of Algorithm	Purpose	Method to Communicate	How it Structures	In-app Depiction	Example
Work Matching	Assigns the work task to workers	In the background, pop-up notice to accept/decline ride after match has been made	Sanction		"First day. I'm sitting on a shady street two blocks from my house, nervously checking my phone every twenty seconds so I don't miss a ping. My phone… suddenly starts buzzing. Yay – a ride! I see a flashing circle with a timer, counting down. My hands are sweaty, the phone is vibrating, and while trying to swipe I drop the phone under the passenger seat. Darn! After a few seconds the phone goes quiet. I've lost my first ride." ~ Field Notes, 29 July 2016
Work Instructions (Navigations, Timers)	Task instructions, such as how long to wait for customers and directions	Appears when navigating to/from destinations and when waiting at designated pick-up spots	Timing		Always follow the app's instructions. Keep a close eye on your app for shared rides. The route is built on efficiency, so the order of who is picked up and dropped off first varies from ride to ride." ~ Ride-hailing website FAQ document
Pricing - Surges	Sets task pay above the base rate, based on customer demands	Nudges through in-app notifications and text messages. Heat map of area surges appears after every trip	Reward		"Demand is higher than usual in Center City. Take advantage of higher than normal fares!" ~ Text message, from Web forums "You turn on your app, and then you see that very orange, bright color around downtown area, that means there is a surge there. There is a high demand…so you rush into that area." ~ Sarah, Chicago
Pricing - Bonuses	Sets payment for a "task bundle" at a rate that encourages longer-term commitment to the organization	Nudges through in-app notifications, text messages, and Emails	Reward		"For the weekend of 15 March 2018, my incentive was, 'an extra $90 for completing 24 trips.'" ~ Field Notes, March 2018
Ratings	Evaluations/ quality control for tasks, with actual evaluation at the customer level	Driver's rating appears on home screen and must-rate customer appears at the end of every ride	Sanction		"If you're ever paired with somebody who is a bad rider, if you give them a 1, 2, or 3, you're not matched with them anymore. If somebody is a bad passenger, I give them a one star and I don't have to worry about ever seeing them again. Ratings are good for drivers and the passengers. ~ Joel, Detroit

Figure 6-2: Inferences and Responses to Algorithms that Reinforce a Sense of Autonomy

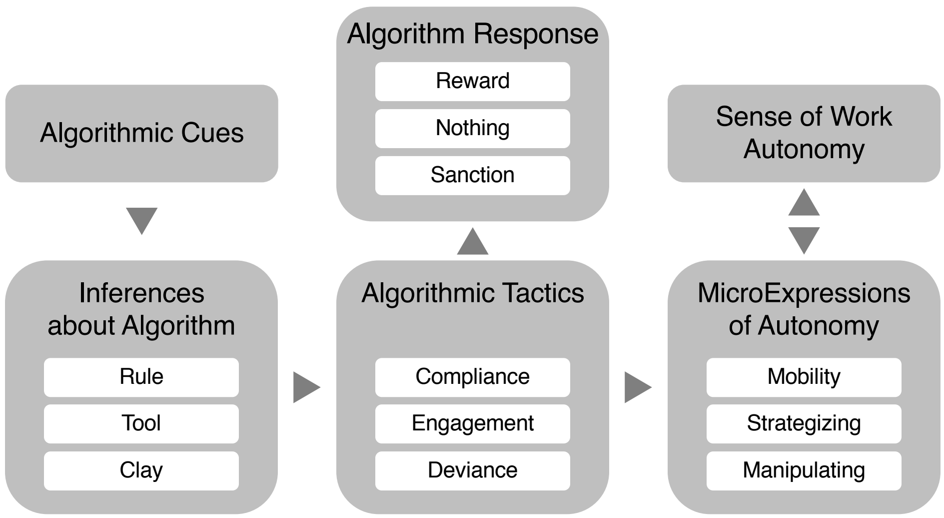


Table 6-3: Summary of Algorithmic Work Tactics

	Compliance Tactics	Engagement Tactics	Deviance Tactics
Algorithms are to be	Followed	Used	Manipulated
Metaphor for Algorithm	Rule	Tool	Clary
Drivers Get the Most Profitable Rides By	Following the nudges	Strategizing the best-paying fares	Subverting the algorithm nudges
How Work System Responds to Workers	Rewards	Does nothing to driver, punishes if excessive	Sanctions if caught
Drivers Feel Autonomous Because	They are moving and earning money	Exercising choice/discretion	Outsmarting the algorithm

Image 6-1: Surge Alert to Driver's Phone

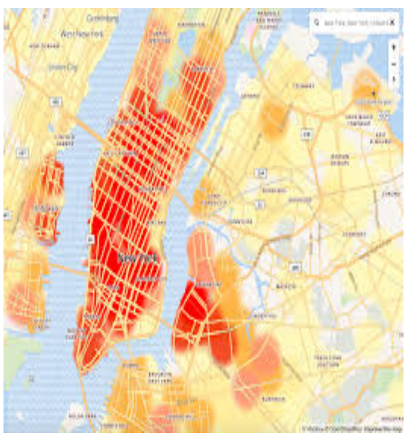


Image 6-2: Heat Map for New York City

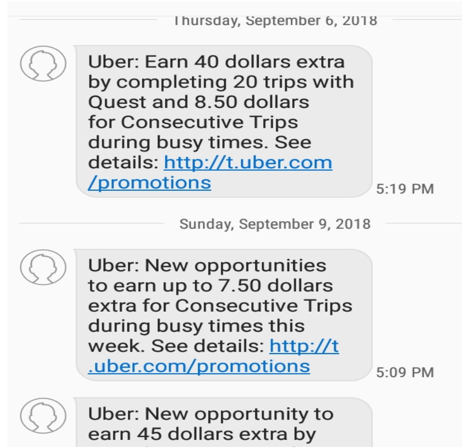


Image 6-3: Text Notification of Bonus Offers

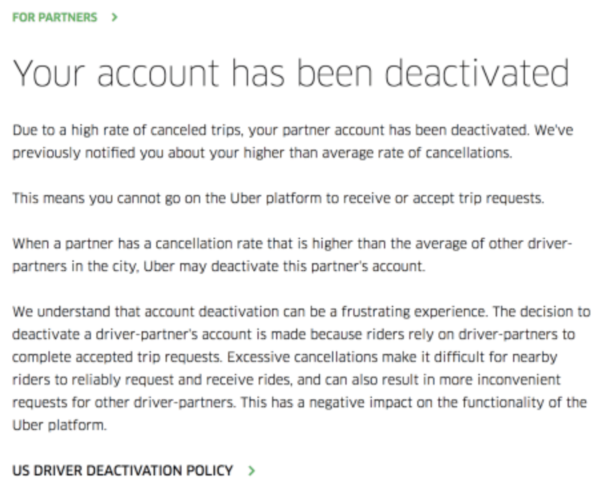


Image 6-4: Deactivation Notice (Accessed via Link in Email) for Declining Too Many Rides

Image 6-5: Sign on Driver's Backseat Encouraging Riders to Rate Five Stars

Image 6-6: Sign on Driver's Backseat Encouraging Drivers to Rate

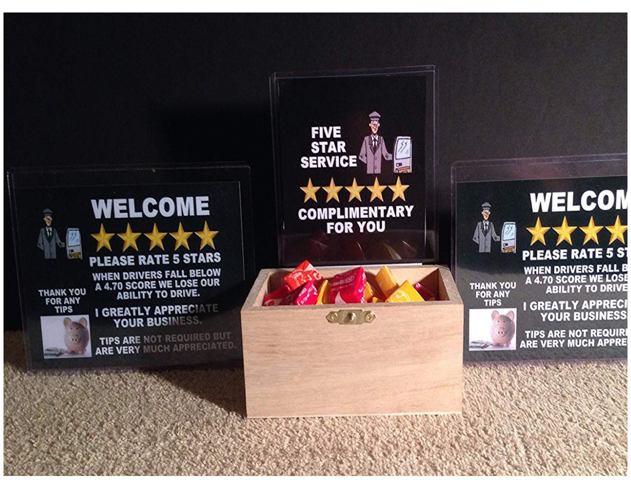


Image 6-7: Signs Available for Purchase on Website to Encourage Riders to Rate Five Stars

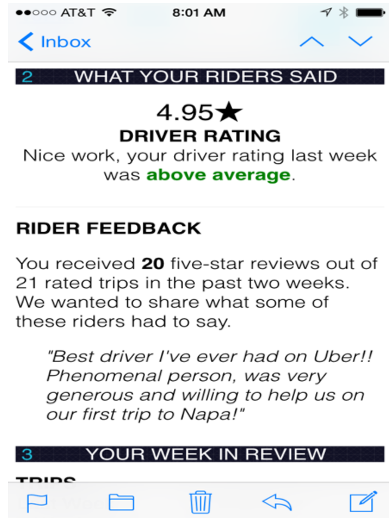


Image 6-8: Notification from Ride-hailing Company about Driver's Ratings

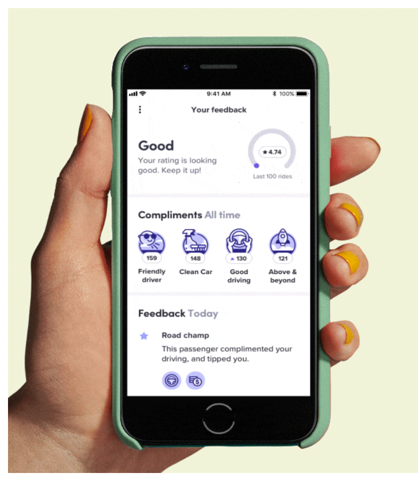


Image 6-9: Compliments and Badges Are Always Available to Be Viewed on App

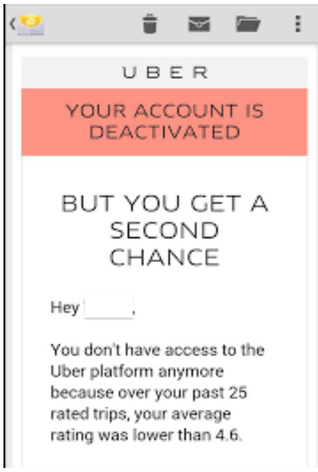


Image 6-10: Driver's Account Deactivated for Low Ratings with Potential for Reinstatement

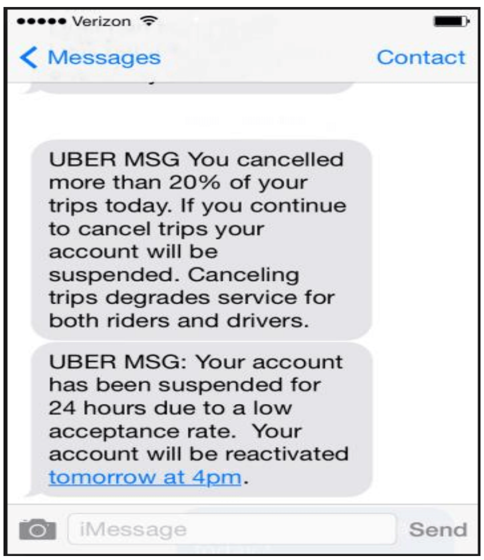


Image 6-11: Driver's Account Temporarily Suspended for Cancelling too Many Rides

Image 6-12: On-Screen Navigation Instructions

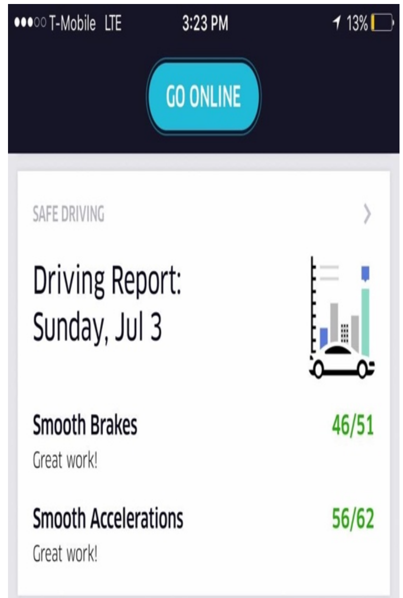


Image 6-15: Telemetrics Report on Driving Metrics

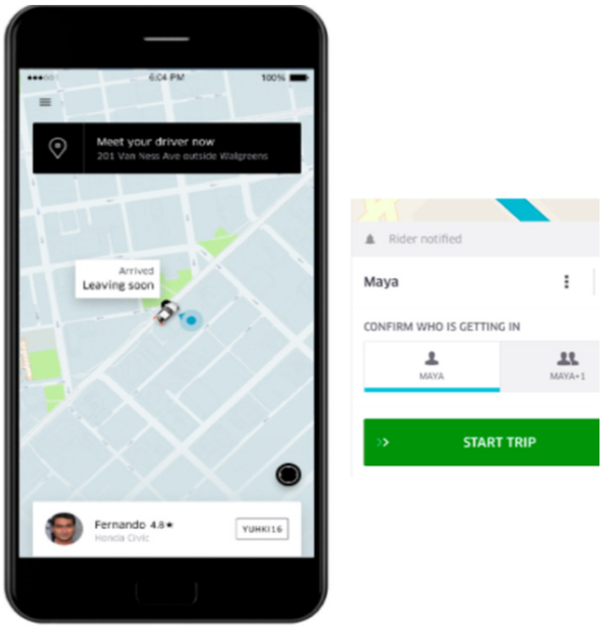


Image 6-13: Instructions for a Shared Ride, Showing Driver has arrived and the Timer Counting Down

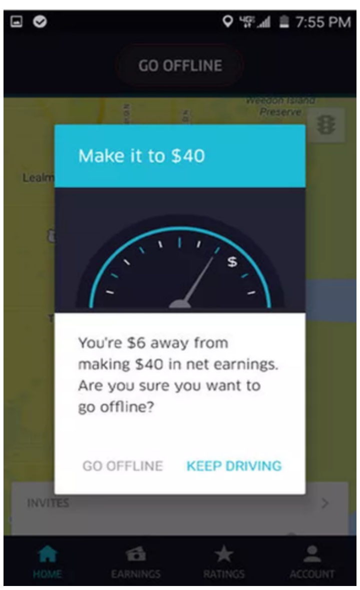


Image 6-14: Nudge to Keep Driving When Trying to Sign Off

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CHAPTER 7

Conclusion and Future Directions

In this dissertation, I have examined human-algorithm interactions, describing how workers accomplish their work tasks within an algorithmic workplace, and how they interpret the interactions with the algorithm.

In my first empirical findings, presented in Chapter 5, I consider how workers interpret and make meaning of work in an organizationally sterile environment, in which the organization provides few cues. Focusing on the practices and perspectives of the two most salient features of this work environment—customers and technology—I explore how these interactions lead drivers in the ride-hailing industry to understand their relationship to their work as an alliance or as adversarial. Over time, these work practices and perspectives culminate in different expected psychological, emotional, and behavioral outcomes.

In my second set of empirical findings, presented in Chapter 6, I find that workers navigate the tensions between organizational control and individual needs for autonomy by crafting a set of tactics—compliance, engagement, or deviance—in response to the algorithms' nudges. Although these tactics appear to be at odds, drivers describe their responses as evidence of their personal autonomy, in that they allow them to maximize earnings and create a continuous stream of work from a discontinuous set of tasks. This autonomy, which is conditional on time and the work, demonstrates that although algorithms may be seen as an unforgiving taskmaster, workers perceive otherwise. Further, by continually offering choice and requesting consent from workers at each stage of the work process, algorithmic systems enact control without authority.

Key Contributions to Long-standing Questions

Organizational-Level Questions. This dissertation addresses many important theories in organizational studies, in particular, theories on control, one of the most-studied and fundamental theories within the field. One could say that studies of bureaucracy and its effect on control actually founded the field of organizational studies (Marx, 1847; Gouldner, 1954; Blau 1956). Specifically, this dissertation answers the question of how control operates and is interpreted in the context of new technology algorithms. In doing so, I find that organizational control is maintained through a reconciliation of centralization and decentralization, or what Sloan (1956) calls decentralization with coordinated control. One aspect of decentralization is schedule flexibility—drivers can choose when and where they want to work, in a car that is also of their choosing, as opposed to for an organization that sets fixed schedules. But without adequate organizational control, work could not be accomplished, leading to the constant tension between decentralization (autonomy) and centralization (control and coordination). Algorithms coordinate work through setting pay rates, assigning rides, and maintaining the evaluation system. Unlike Sloan's examples of centralized decentralization on the production floor of General Motors, my findings are not a clear variation of the principal-agent problem, as the principal is not clearly defined, as the algorithm takes on different properties depending on the context. In their multivocality, algorithms can take on the form of a contract (e.g., the terms of agreements when drivers sign on, the pay rate), a suggestion (e.g., heat maps, incentive alerts), or a promise (e.g., of providing wide, instant pay). Thus, these findings can be taken as a case of a system that is coordinated through centralized decentralization with a multivocal principal.

Work in the ride-hailing industry is an example of a pooled interdependence system (Thompson, 1967/2017) in that algorithms allow for work to be distributed across individuals, so that the organization's goals are accomplished by each worker's independent effort. One benefit of pooled interdependence is that it allows workers to have greater feelings of control, mastery, and autonomy over their work activities. At the same time, the organization has less need for any particular individual worker and, correspondingly, less need for workers to exert autonomy on behalf of the organization, as workers are interchangeable. In contrast to the assembly line—where one worker could stop production entirely—ultimate control and authority rest in the hands of the organization and the algorithm which are coordinating the work. Thus, while pooled interdependence can foster an individual worker's sense of autonomy, it may actually inhibit group-level autonomy expressed in collective action, such as petitions, demonstrations, organizing, and strikes, that could facilitate actual change.

As this study is worker-centric, focusing on algorithms and work, it is intriguing to consider how these findings speak to the reverse: algorithms and an organization's control system. In a process called sedimentation, Edwards (1980) theorizes that when new control systems come into form, they layer over and change prior control systems. In the algorithm workplace, I observed all three layers of control: direct observation by electronic surveillance and telemetric tracking, technical control by the timers and routing directions, and bureaucratic control in the specification of labor and driver support systems (namely who drivers can and cannot easily communicate with). Some elements of the algorithm exert multiple types of control, such as the ratings system, which includes both bureaucratic and direct (by the customer) control. Other parts of the algorithmic system, which rely on the interactions between drivers and customers (e.g., adjusting ride prices, customizing incentive quotas, and escalating sanctions), suggest that algorithms may be a new form of control. This study provides the first piece of empirical evidence that hints at these possibilities, which may allow us to address whether a new era of control is upon us. Further research could continue to develop this idea by comparing potential algorithmic control systems with prior control systems.

Individual-Level Questions. Understanding autonomy within the confines of a tightly coordinated work environment is always a paradox. Originally coined "false consciousness" by Marx (1847), Burawoy (1976) advanced the conversation, recognizing that workers did, in fact, have some autonomy (though, presumably, in the wrong direction, as it was supporting a capitalist system), calling the process "manufacturing consent." This belief that even though workers feel autonomous, they are, by the very act of working, being duped and, at times, exploited, remains the rule (e.g., Barker, 1993; Burawoy, 1976; Mazmanian et al., 2013; Michel, 2011; Reich & Bearman, 2018; Vallas, 2016) rather than the exception. This study aims to bridge these two perspectives, understanding autonomy not as a mental trick to keep the hamster running on the wheel and the worker compliant within a system, but as something that is experienced mentally, emotionally, and physically in the body, and has positive benefits, while also keeping the work machine turning.

Future Research Directions - Emerging Questions to Consider

It is my sincerest desire that this dissertation contributes to the current discussion about algorithms in the workplace (e.g. Christin, 2018; Curchod et al., 2019; Gray & Suri, 2019; Lee et al., 2016; Rahman, 2019; Rosenblat, 2018; Shestakofsky, 2018; Ticona, 2015), opening new lines of research and ways of thinking about the world of human-algorithm interactions and their collective consequences. Paraphrasing Neil Armstrong's famous quote (1969), I find this line of research "one small step" for organizational researchers, and "one giant leap" for interdisciplinary social sciences, and a stepping stone toward many fruitful and impactful lines of research.

This study examines not only how algorithmic systems work, but what happens when they don't? Algorithms can misfunction in anticipated and unanticipated ways that may or may not be noticed by organizations or workers. Non-routine interactions offer unique opportunities to explore assumptions and to consider how repairs are undertaken (Feldman, 2000; Rerup & Feldman, 2011; Heaphy, 2013). This line of study could address questions such as: Who noticed the algorithmic misfunction and how does the information traverse to other organizational stakeholders? What did the misfunction cause to happen and what assumptions about the algorithm are revealed in light of a misfunction? How are algorithm misfunctions repaired? How is trust in the algorithm regained and what does this look like?

While this study examines how algorithms are embedded into the everyday nature of work, whole systems of algorithms are increasingly being inserted holistically into organizational design and work processes. In the healthcare system, for example, algorithms are used throughout, assigning patients to physicians, diagnosing illness, suggesting treatments and follow-ups, and scheduling and monitoring (Burt & Volucenbaum, 2018), with similar changes reported in education (O'Neil, 2016). Similarly, at Stitchfix, an algorithm curates a weekly box of clothes for customers based on an assessment of the preferences, sizes, and buying patterns. Questions that this line of study could address include: How do algorithms shape organizational design choices? How do designers decide where in the work process to implement an algorithm versus a human-overseen processes? What manifest and latent functions does the algorithm serve at each juncture in the work? What oversight systems are deployed? And, at the individual level, how do workers and customer experience and respond to these new systems?

Compared to traditional work on a shop floor or office space, algorithmic work has the potential to be socially isolating. Platforms like MTurk, Upwork, and HourlyNerd offer (worker-maintained) online forums, but digital intimacy is fragile (Salehi et al., 2015). Lack of social contact with other organization members and limited physical organizational scaffolding make it more difficult for workers to learn organizational norms, rules, customs, and procedures. Questions this line of study could address include: How does socialization occur in primarily asocial environments? What routines, connections, and material objects do individuals draw on and how do these relationships change over time? How does one know if workers are socialized "enough?"

Critics suggest that on-demand work and algorithms, in particular, can exert downward pressure on wages at the expense of human dignity (Kalleberg, 2009; 2011; O'Neil, 2016; Eubanks, 2018). Undoubtingly, we would expect workers to resist the erosion of their humanness—perhaps through taking unscheduled breaks (Roy, 1952), rate-busting (Burawoy, 1979), making homers (Anteby, 2008), subverting standard operation procedures (Bernstein, 2012) or, unconsciously, through physical breakdowns (Michel, 2011). Questions this line of study could address include: Given that work is highly atomized, do workers need to engage in collective action in order to resist? What are the lines between deviance, collective action, resistance, and a social movement? What does it mean to resist in a job that one can quit anytime with no penalty? Can resistance be directed to groups beyond managers (e.g., customers, the algorithm itself, coworkers) and if, so, what does this look like? How do we assess the effectiveness of resistance tactics?

I began this dissertation by noting that investigating how emerging technologies shape organizations, while not a new endeavor, is surely worthwhile. In the end, I do not offer a clear conclusion about the positive and negative aspects of the algorithmic workplace, but rather, I agree with Kranzberg's (1985) first law of technology, that "technology is neither good nor bad; nor is it neutral." The good news is that lower-skilled workers, who typically face the most precarity, abuse, and uncertainty in the workplace (Standing, 2011; Kalleberg, 2009, 2011), have unparalleled levels of autonomy. At the same time, control remains firmly within the hands of organizations, with the challenges of opacity and interpretability inherent to algorithms increasing the chances they will be used to exploit workers (Eubanks, 2018; Gray & Suri, 2019; O'Neil, 2016; Pasquale, 2015). Ever the realistic optimistic, I concur with Dr. Martin Luther King (1955) that "the arc of history [technology] is long yet it bends towards justice." Governments, universities, and advocacy groups continue to call for greater transparency into algorithmic work, in ways that augment and support workers (Brynjolfsson & McAfee, 2015; Diakopoulos, 2015; Dwoskin, 2018; Rostain, 2019). By describing some of the conditions in whcih workers interpreted and made sense of their work, I hope this dissertation advances the conversation about how to build a more just and equitable world with algorithms in the forefront.

And with that I wish you a fond farewell.[27]

[27] "And with that, I wish you a fond farewell" was the last line of my grandmother's 8th grade valedictorian speech, in 1922, which was the last year of school she completed. She repeated this line, ending with a curtsy, until a week before her death seventy years later from complications with Alzheimer's.

Chapter 7 References

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