Hands on the wheel: Navigating algorithmic management and Uber drivers' autonomy

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Abstract

With the rise of big data and networking capabilities, information systems can now automate management practices and perform complex tasks that were previously the responsibility of middle or upper management. These new practices, known as "algorithmic management," have been applied by ride-hailing platforms such as Uber, whose business model is dependent on overseeing, managing, and controlling myriads of self-employed workers. This study seeks to understand this phenomenon from an information systems management perspective, highlighting the inherent paradox between workers' sense of autonomy and these systems' need of control. The paper offers a conceptualization of algorithmic management and employs interviews with Uber drivers and forum data to identify a series of mechanisms that drivers use to regain their autonomy under algorithmic management, including guessing, resisting, switching, and gaming the Uber system.

Keywords: Algorithmic Management, Uber, Sharing Economy, Autonomy, Control

Introduction

Since the birth of the information systems (IS) discipline, the role played by information technology in the relationships between management and workers has received significant attention. Over the last few decades, modern organizations have implemented IS to introduce innovative work management processes, replace or augment existing human labor, change work procedures, and challenge traditional management practices (e.g., Barrett et al. 2012; Davis and Hufnagel 2007; Mazmanian et al. 2013).

The rise of fast networking at the end of the last millennium brought new capabilities that have allowed many work-related procedures to be remotely carried out in a distributed manner. This has led to increased offshoring and outsourcing of key organizational functions (Levina and Vaast 2008) and given birth to internet-based crowdsourcing (Fayard et al. 2016; Irani 2015; Orlikowski and Scott 2015; Xuegei and Joshi 2016). More recently, with the rise of big data collection and machine learning techniques, algorithms have garnered the ability to "learn" and adapt efficiently to given environments. This has allowed them not simply to provide decision support, but to take charge of management practices, replacing various jobs and performing complex tasks previously the responsibility of middle (and even upper) management (Autor 2015; Brynjolfsson and McAfee 2014; Constantiou and Kallinikos 2015; Lee et al. 2015). The combination of increased networking and improved algorithmic capabilities has given rise to business models like the ride-hailing apps Uber and Lyft, wherein hundreds of thousands of drivers are supervised and controlled by a mobile platform.

IS scholars have stressed the importance of studying the socio-technical aspects of algorithms on managerial practices (Orlikowski and Scott 2015); and early work in human-computer interaction (HCI) and computer science literature coined the term "algorithmic management" (Lee et al. 2015). However, this paper is the first to conceptualize algorithmic management from an IS research perspective and focus on the relationship between algorithmic management and workers' autonomy.

We believe this relationship is crucial, because algorithmic management practices are often applied in the context of freelancing or "quasi-employment" on digital platforms (Chen and Horton 2016; Orlikowski and Scott 2015; Lee et al. 2015; Rosenblat and Stark 2016). In the case of Uber, for example, drivers are freelancers who work flexibly and possess potentially high work autonomy (Greenwood and Wattal 2017; Rosenblat and Stark 2016). Uber drivers exercise autonomy over several work variables, including work hours, vacations and time off, the areas in which they want to work on a given day, and the cars that they lease or own. In some cases, the freedoms exercised by drivers conflict with the reliance of Uber's business model on drivers behaving as expected. To mitigate this challenge, ride-hailing services have implemented IT-enabled management practices designed to govern and enforce their policies by controlling drivers (Lee et al. 2015; Rosenblat and Stark 2016). Lately, these initiatives have been a focus of public concern, with mass media coverage of the behavioral manipulation and control mechanisms used by ride-hailing platforms to coerce drivers into compliance (Schreiber 2017).

In this paper, we fill a gap in current literature by researching the interplay between algorithmic management practices and worker autonomy.

First, we offer a conceptualization of algorithmic management in the context of IS management. We argue that the former does not posit incremental change to technology-supported management practices, but in fact constitutes a different managerial logic. Specifically, algorithmic management has the unique ability to track worker behavior, constantly evaluate performance with rewards and penalties and automatically implement decisions. Algorithm management provide the feeling of working with a "system" rather than humans, and is characterized by lower transparency (in most cases). Based on our conceptualization of algorithmic management, we seek to answer the following research question:

What emergent tensions arise between autonomous workers and algorithmic management systems and how do drivers react to them?

To answer this question, we utilize data collected from Uber driver interviews and forums to analyze their experiences with the system. We highlight the conflict between algorithmic management practices and worker autonomy in the case of Uber, one of the world's most highly valued companies. We identify tensions between freelance drivers' need for autonomy, who often chose the job for the freedom they hoped it would provide, and a platform programmed to always be in control. Lastly, we analyze collected data to investigate how drivers experience and resolve conflict between their need for autonomy and the algorithmic management practices that hinder it. We report four observed behaviors by drivers. Drivers guess and make sense of the system's intentions, and may then choose to resist, switch, or game the system to regain control and autonomy.

Overall, this paper posits that enhanced understanding of such behaviors may help frame questions regarding the future of work and workers' autonomy and inform the design of future algorithmic management platforms to improve worker treatment and satisfaction (Constantiou and Kallinikos 2015; Lee et al. 2015).

Literature Survey

In this section, we survey IS and management literature that informs our research question. Relevant research topics explored include autonomy in the workplace, quasi-employment on digital platforms, and the social study of algorithms in the age of big data.

Autonomy in the Workplace

Broadly speaking, autonomy is the ability to exercise control or freedom over aspects of work, including its content and boundaries, location, timing, and performance standards (Langfred 2007; Mazmanian et al. 2013). While previous studies generally concur that low autonomy in the workplace makes workers feel frustrated (Barley and Kunda 2004), the opposite is not always true. Specifically, high levels of autonomy as a result of digital technology-mediated work environments possess both advantages and disadvantages for the worker (Mazmanian et al. 2013). In many cases, autonomy may actually result in less control over work practices. Mazmanian et al. (2013), for instance, identified an "autonomy paradox" in how professionals use mobile technology to access their emails: while constant access to emails may increase their personal autonomy to affect work practices, it may also increase their commitment toward clients and colleagues to the detriment of their work/life balance (Mazmanian et al. 2013). Mobile technologies also help monitor worker performance more closely, which can negatively impact employees' mental health and cause stress and burnout (Murray and Rostis 2007). Similarly, while teleworking has been shown to give employees a greater sense of autonomy, it also imposes new constraints on employees required to constantly signal their availability and presence (Sewell and Taskin 2015).

Closer to our research context, Rosenblat and Stark (2016) analyze a similar tension among Uber drivers. Despite Uber's statements advertising driver autonomy and time flexibility, high information asymmetry between the Uber platform and drivers decreases drivers' sense of control over their work environment, resulting in negative feelings toward the company (Rosenblat and Stark 2016).

Freelancing and "Quasi-Employment" on Digital Platforms

Tension between autonomy and control has often been raised in discussions of freelancing and other self-managed work (Langfred 2007; Mazmanian et al. 2013). Moreover, the recent rise in the use of digital platforms to manage freelance work has sparked the interest of the IS academic community (Orlikowski and Scott 2015; Xuegei and Joshi 2016). Literature has emphasized that these platforms differ from traditional forms of employment. For example, Chen and Horton (2016) found that such digital platforms "look like true spot markets for tasks rather than markets for employment" (p. 403). Similarly, Xuegei and Joshi (2016) noted that "micro-tasks" conducted by individual workers on online platforms such as Mechanical Turk may be decomposed or self-contained, or may form small pieces of a more complex task. Thus, such online labor sites should be labeled as a form of "quasi-employment" (Chen and Horton 2016).

Like offline freelancing, these environments are characterized by workers' autonomy over their task choice and work schedule. Workers are typically not officially employed by the platform - but instead work as independent freelancers or contractors. The platform acts as an intermediary by matching two parties with each other – for instance, task requesters and workers in Mechanical Turk, or drivers and passengers through Uber (see Hagiu and Spulber, 2013; Parker and Van Alstyne, 2005, Möhlmann, 2016). The move to such platforms has transformed interactions between the freelance worker, the customer and the platform, rendering them short, virtual, mediated and more "task" oriented.

The work relationship between "micro-tasks" workers and the platform differs from the traditional employer-employee, "principal-agent" relationship in many aspects. First, it is not clear who acts as the agent in this relationship, because the traditional responsibilities of this role are divided between the platform and the worker, who are both "hired" for the task. Second, in these formed relationships, workers are free to defect (between micro-tasks) without being subjected to fines or risking breaches of contract customary to freelancing agreements. If the level of financial compensation drops, workers might also drop out, leading to high worker turnover rates. Third, traditional methods for assessing the quality or performance of workers and predicting their success are not applicable. Real-life interactions and word-of-mouth reputation are being replaced by review systems, which become a crucial indicator of a worker's performance. Research on the role of reputation in freelancing in online marketplaces (Yoganarasimhan 2013) suggests that reputation systems are crucial to overcoming the freelancer quality information gap; they are a key aspect of the process of matching supply and demand. Specifically, reviews are a crucial performance indicator on online platforms and are vital to the success of the algorithms (Orlikowski and Scott 2015). However, while reviews may be used as a control and quality assurance mechanism, users can attempt to "game" them to gain a competitive advantage (Luca and Zervas 2015), damaging their overall reliability.

The Social Study of Algorithms

Algorithms have always been a focus of computer science and IS research. However, with the rise of big data and the ubiquity of algorithm-based decision making, societal implications of algorithms, as well as their social construction, have been a topic of both academic and public debate (Dourish 2016). In the last decade, studies have discussed the cultural and socio-material aspects of algorithms. One early example can be found in Mackenzie (2006), who stressed that software algorithms provoke the re-thinking of production, consumption and distribution as entwined cultural processes. Only through practice can computerized algorithms come to life and their consequences be activated. More recently, Orlikowski and Scott (2015) emphasized the socio-technical aspects of algorithms. In particular, they stressed the necessity to recognize that algorithmic rating and ranking mechanisms materialize in practice. "A sociomaterial perspective helps us see the performance of algorithms as configuring online services through the material-discursive practices" (Orlikowski and Scott, 2015: 211). Closer to our research topic, Rosenblat and Stark (2016) studied how the implementation of algorithms unfolds in social contexts, specifically in the management of Uber's labor force. They found that information asymmetries arise due to the way these algorithms are constructed and used - and these create asymmetries in power that favor the corporation.

Previous research has also addressed the effects of algorithms on transparency. Hansen and Flyverbom (2015) posited that big data analysis via algorithms may increase transparency due to the systematic use of a defined set of rules. However, they also highlighted that "the algorithms of big data analysis are rarely accessible to anyone outside the super-crunching organization" (p. 14). Thus, corporate or state agents can also easily use them as a vehicle of surveillance and manipulation. Dourish (2016) identified challenges related to transparency. He discusses the challenge of identifying and pinpointing constantly evolving algorithms and the need to form an "algorithmic identity" as a means to audit and increase transparency, and accountability.

Algorithmic Management: A Conceptual Framework

Even though previous literature has discussed the nature and the implications of algorithms, "algorithmic management" is a new concept in IS management studies. Early work in HCI and computer science literature coined the term algorithmic management (Lee et al. 2015). However, no generally accepted definition of the term exists in IS management sciences. In this section, we address the topic by combining current knowledge from IS and management literature to form a conceptual basis. We emphasize how algorithmic management transforms the relationship between management and autonomous workers and how it differs from traditional management practices.

We define algorithmic management as oversight, governance and control practices conducted by software algorithms over many remote workers. These workers conduct tasks on online platforms but might be freelancers and not be officially employed by the company. We argue that algorithmic management is characterized by continuously tracking and evaluating worker behavior and performance, as well as automatic implementation of algorithmic decisions. In algorithmic management practices, workers interact with a "system" rather than with humans. In many cases, the system has less transparency, and workers have no knowledge of the set of rules governing the algorithms.

The first characteristic of algorithmic management refers to the constant tracking of workers' behavior. Access to reliable and valid data is a precondition for effective algorithmic management: "algorithms are inert, meaningless machines until paired with databases upon which to function" (Gillespie 2014, p. 169). While human managers are traditionally able to form close, trust-based, and long-lasting relationships with employees, this is impossible when overseeing thousands of employees mediated by a digital platform. In contrast to traditional management contexts, algorithmic management is built on a constant stream of information regarding individual workers' behavior in any given situation (Rosenblat and Stark 2016). Only by obtaining this information can algorithms be developed to exact personalized management decisions adjusted to each individual worker. In most cases, tracking is conducted through a digital device that connects the worker to the platform (e.g., browser, cellphone app or other device). Similar issues have been discussed in the literature focusing on work autonomy. Tracking of behavior using digital devices may diminish workers' autonomy (Mazmanian et al. 2013; Murray and Rostis 2007; Sewell and Taskin 2015) and can potentially create a constant feeling of surveillance and control (Lee et al. 2015; Rosenblat and Stark 2016).

The second characteristic of algorithmic management pertains to the constant performance evaluation of workers, which is also enabled by tracking based on gathered data. This may take various forms. Information about workers' behavior may be automatically ranked to compare workers' performance, and behavioral anomalies can be constantly reported to control centers for further review by humans. Given the scale of operations, a common form of evaluation on digital platforms is peer and customer reviews (Hansen et al 2015; Orlikowski and Scott 2015; Yoganarasimhan 2013), which places significant weight on the quality of reviews fed into the algorithm. In many cases, user reviews are subjective and idiosyncratic (Orlikowski and Scott 2015) and vulnerable to gaming and revenge-seeking behavior (Luca and Zervas 2015). Although performance evaluation is commonly used to reward or penalize workers in traditional work environments, algorithmic management practices include constant and real-time performance evaluation based on many micro-tasks, leading to a large volume of performance evaluations every day (Chen and Horton 2016; Xuegei and Joshi 2016).

The third characteristic of algorithmic management is the automatic implementation of decisions. Algorithmic management is characterized by little or no human intervention. Algorithms calculate and form decisions that are typically enacted automatically (Rosenblat and Stark 2016). This embodies the notion that "algorithms do things" (Gillespie 2014; Orlikowski and Scott 2015), and their effect is significant on the resulting process. Algorithms are the basic element of every computer program and conduct ranking, rating, coding, calculating, searching, finding, filtering and other tasks based on available data. For any given situation, a specific algorithm reinforces one order at the expense of others to discern a result that can be implemented (Orlikowski and Scott 2015, p. 210). Automatic implementation allows companies to speed up processes and respond immediately to constantly changing variables. In "traditional" work environments, decision implementation is the responsibility of human managers. Even when technology is involved in managerial decision making, it is most commonly used as a decision support tool that provides relevant data and enables managers to make their final decisions. In contrast, algorithmic management leaves no time to discuss or revise decisions arising from special circumstances not wholly captured by the data. For instance, workers may be kicked out of the system for what is perceived by the algorithm to be a violation, even though it was, in fact, a system malfunction.

The fourth characteristic of algorithmic management is workers' interaction with a "system" rather than humans. The role of human to human interaction differs substantially between algorithmic management and "traditional" technology-supported management practices. In algorithmic management contexts, data-driven management decisions are made solely by algorithms, with little or no human intervention. However, this is not the only procedure rendered non-human. Under algorithmic management, almost all communication is mediated by the platform (Lee et al. 2015). In many cases, workers cannot ask for direct support and are instead referred to email correspondence or chatbots (Schreiber 2017). Although workers under algorithmic management surveillance are "quasi-employees," they have little interaction with peers and co-workers on the platform. In the absence of a human boss or co-workers, there is no opportunity for social exchange. In comparison with "traditional" management contexts, workers may feel they are working for an abstract "system" rather than an organization composed of people. Without this social interaction, they may feel isolated. The social aspects of work are absent, and workers tend not to build either positive or negative social ties. This lack of communication also implies there is little opportunity for any open, two-sided communication, such as suggestions or questioning and discussing management decisions.

The fifth characteristic of algorithmic management is (low) transparency. Algorithms are typically designed based on previously developed sets of rules and instructions. In "traditional" work environments, human communication, decision making and managerial procedures are often influenced by personal and emotional attributes and prone to various behavioral biases (e.g., Walther 2012). As a result, an algorithm that adheres to a generally accepted and justified set of rules can actually increase the transparency of decision making and management (Hansen et al 2015). However, because they operate in highly competitive business environments, companies rarely disclose the "rules" of an algorithm to the public. Moreover, algorithms based on big data and statistics are often too complex to understand, and since they are adaptive in nature, they also frequently change (Rosenblat and Stark 2016). In such situations, transparency in algorithmic management is extremely low. Compared with "traditional" management practices, algorithmic management contexts can provide greater transparency because they rely upon an explicit set of rules. However, in practice, companies are rarely motivated to disclose the underpinning criteria of their algorithms and are sometimes unable to fully explain the results themselves, creating very low transparency for those managed by the algorithms.

Research Design and Methodology

To gain a better understanding of the interplay between algorithmic management and workers' sense of autonomy, this study analyzed interview transcriptions and blog posts capturing Uber driver communications. We aimed to understand how the drivers were trying to make sense of their situation and acted in the setting of Uber (Orlikowski and Baroudi 1991). We conducted a grounded content analysis and applied the principle of multiple interpretations to capture the narratives of drivers based in different cities (Klein and Myers 1999).

Case Selection and Research Setting

In this paper, we analyze our research questions in the socio-technological context of the ride-hailing company, Uber, the world's largest digital platform offering freelancing "quasi-employment" opportunities to drivers. We selected this case in line with Gerring's (2007) notion of extreme-cases. This case has proved prototypical and paradigmatic of the phenomena under consideration. Extreme cases are particularly useful when researchers strive to contribute to the generation of new theory, and in both size and manifestation of emergent algorithmic management practices, Uber is an extreme case. Uber operates in more than 500 cities worldwide and has grown steadily. In 2014, 160,000 Uber drivers operated in the United States, and this number surpassed 400,000 a year later (Rosenblat and Stark 2016). Uber drivers are freelancers who work flexibly and exercise potentially high work autonomy (Greenwood and Wattal 2017; Rosenblat and Stark 2016). They have autonomy over certain work variables, such as work hours, the areas they want to serve, and the cars that they lease or own. Even so, Uber's business model is entirely reliant on drivers behaving as expected. To mitigate the inherent risks of this reliance, Uber has implemented algorithmic management practices designed to govern and enforce its policies by controlling drivers (Lee et al. 2015; Rosenblat and Stark 2016). These practices include a matching mechanism between drivers and riders, a reputation system in which users rate the drivers' behavior, and a built-in navigation system that both directs drivers and reports their whereabouts to the company and consumers.

Uber operates several services. The company initially became famous for its UberBLACK service, which included luxurious cars and competed with limousine-type services. However, as the platform's customer base grew, the two most popular services became the more affordable UberX and UberPOOL. UberX is Uber's basic service, in which private car rides are provided by drivers in the system. UberPOOL, on the other hand, is a ride-sharing option in which Uber passengers are pooled together with strangers heading in the same direction but have different pick-up and drop-off points. Uber claims to use algorithms to match pooled passengers and their routes effectively and calculate the most efficient route between them. UberPOOL is the cheapest option for passengers.

Data Collection and Analysis

Data was gathered between November 2015 and January 2017 from two independent sources: (1) informal and formal interviews, and (2) blog data from the UberPeople website. We applied the principle of multiple interpretations (Klein and Myers 1999), and decided to conduct interviews in both the United States (New York) and Europe (London) to avoid geographical and cultural biases and capture the narratives of drivers in different cities. We also collected tracked data from the blogs of Uber drivers based in these two cities. We worked with multiple investigators and engaged in constant discussion of emergent themes as the research results from blogs and interviews were collected (similar to the procedure used by Vaast et al. 2013).

The combination of data sources allowed us to mitigate possible biases. For instance, we assumed that social desirability bias might have a greater effect on live interviewees than on active blog users, since bloggers make pseudo-anonymous comments aimed at a larger audience. (Indeed, information about drivers' "gaming" behavior was only found in blog data.) On the other hand, interviews enabled us to ask direct questions related to our research focus.

(1) Interview data were collected from both informal and formal interviews. All interviewees were Uber drivers, although some also drove for competing companies. Notes were collected from 15 informal interviews conducted in New York, and based on these initial insights, formal interviews were conducted.

In total, 19 transcribed interviews with Uber drivers were collected (11 from New York and eight from London).

(2) Forum and Blog data (Jones and Alony 2008; Vaast et al. 2013) were collected from *uberpeople.net*, a well-known forum where Uber drivers share opinions, thoughts and feelings. We began by reading forum and blog entries in an unstructured way to gain a cursory grasp of topics drivers addressed in the forum. As of February 2017, about 1.5 million entries were available on the forum. Finally, we considered a subsample comprised of data from November 2016 to January 2017 (the same time frame over which we conducted the interviews). Like Vaast et al. (2013), we filtered entries and focused on the cities of New York and London to ensure consistency with interview data. We used the keywords "control" (190 blog posts), "switch" (39 blog posts), "freelance" (598 blog posts) and "pool" (185 blog posts), as these terms were likely to identify the blog entries relevant to our research question. After this filtering process, 1,012 post entries remained. We also included additional posts in the analysis identified by browsing the forum when they appeared relevant to the research question.

We carried out a grounded analysis of our data (Charmaz 2006). First, we conducted informal interviews with Uber drivers and browsed the forum to identify themes in a grounded manner. We then conducted formal interviews with drivers and filtered blog entries particularly relevant to our broader research scope. We conducted a close examination of the final sample of transcribed interviews and post entries. Assessing the transcribed interviews and the filtered post entries independently enabled categories to be refined. We then jointly discussed the identified categories, referring to theory and the academic literature to inform our data analysis. We analyzed drivers' claims relating to Uber's algorithmic management practices and their own autonomy and examined emergent tensions between the autonomous drivers and the algorithmic management of the Uber platform, as well as how drivers reacted to these tensions (see Vaast et al. 2013).

Results

The Autonomous Worker

The drivers on ride-hailing platforms tended to perceive themselves as autonomous and self-managed. In many cases, Uber drivers reported they had chosen this line of work for the relative freedom it provided. This freedom allowed them to combine their work with family, study or other obligations. They took pride in their control over their own work schedules. Drivers mentioned several recurring topics in this context:

Time Flexibility: Drivers of yellow cabs (in New York) or black cabs (in London) are traditionally employed in set shifts. In comparison, Uber drivers can choose when and for how long they wish to work on any given day. They can also decide to take a break or leave home at any point.

> *... you are your own boss. If you want, you work; if you don't want, you stay home. It depends on you* (Interviewee, New York)

Nevertheless, many drivers reported working eight- to 12-hour days similar to the shifts of traditional taxi companies.

No Direct Supervision/No Boss: Drivers stressed the fact that they answered to no one, especially in reporting their whereabouts every second and feeling that they had to answer to someone else's requests. In many cases, drivers had chosen this work because of its organizational structure and because the classic hierarchal work environment did not suit them.

> *... I see those guys, they are having bosses telling them off – "don't use your cell phone" or something like that, you know? "You can't go in the restroom right now", or you know...* (Interviewee, New York).

Working in Isolation: The drivers were not required to report to an office, socialize with colleagues, or meet the management. In some cases, they did not know anyone else affiliated with the organization for which they were working besides drivers who had originally informed them of this job opportunity. In some cases, drivers did meet peers in busy places for ride hailing, such as airports and downtown city areas. Generally, the drivers expressed no wish to socialize more with their peers. They also reported that Uber made limited attempts to connect drivers.

> [Is Uber organizing an informal exchange between the Uber drivers? Where you meet up and talk about work?] *No, no, no, no, no. They don't do that. Only if the office call you in* (Interviewee, London).

Low Identification: Drivers did not report that they felt a part of the company. They resented being referred to as the company's partners and even denied they shared the same values as the company. In general, the drivers tended to see their participation on the ride-hailing platform as a personal business opportunity, and they described the differences and dichotomy between their own financial and business needs and those of the platform, which did not always align. One example of this dichotomy between what was good for the driver and the company was noted in the UberPeople forum where, in response to a driver who said he would never cancel on passengers, a second driver commented:

> *Good on you for never cancelling, serving Uber so well. Mate, it's a business on this side of the lake; we got to do what is best for our business, not do what Uber wants us to do* (UberPeople London Forum).

Assessing Algorithmic Management in Ride Hailing

All the algorithmic management attributes conceptualized earlier in this paper are evident in Uber's operation. Drivers presented examples of each attribute:

Constant Tracking – Uber drivers are tracked via the Uber app. Their whereabouts are transmitted at all times so the software can track their navigation, their compliance with policy, and their work/idle time. As part of the ride-hailing model, every transaction the driver conducts is mediated by the app, and the company has a complete understanding of where their drivers are and who they are driving at any moment.

> *Uber is going to track driving behavior.*
>
> *I have a strong feeling they've already done this and now they're just putting it out there. Drivers' behaviors means a ton* (UberPeople New York Forum).

Constant Evaluation of Performance – Any passenger can rate a driver at the end of a ride, and vice versa. In addition to grade-based evaluation, Uber also uses tracking data collected to assess performance. Drivers can be compensated according to the number of rides they have completed over the span of a week or month. They can also be penalized for not accepting rides, including UberPOOL requests.

> *They don't want low-rated drivers to get uppity now, do they?* (UberPeople London Forum).

Automatic Implementation of Decisions – Uber's app can automatically penalize drivers who do not act according to the company's policies or needs. The most frequent penalty is a system shut-down or ban, which occurs if a driver maintains a low acceptance rate or receive low customer ratings.

> *I've been doing more Juno than Uber. Uber dropped me from VIP status. Probably for all the Uberpool request denials* (Uber People New York Forum).

Working with the System, not with Humans – When drivers have questions or encounter trouble, they are referred to automatic systems. Any request for support or help when trouble occurs is communicated via email. This isolates the drivers from the company, even when they require "human" support. In many cases, drivers give up or try to devise solutions themselves.

> *You email everything ... If something goes wrong with your app, you just have to wing it* (Interviewee, New York).

Low Transparency – Drivers reported a limited understanding of how the Uber app actually works. They do not know how rides are allocated or how near other drivers are to their current position. In many cases, the system receives explicit information not revealed to the driver for strategic reasons. For example, passenger destinations are withheld from the driver until the passenger enters the car to prevent drivers from strategically cancelling rides.

> *We see a job is coming and it shows me that [the interviewer] is there on that address close to me where I am and she is on UberPOOL or UberX. It doesn't tell me where you're going. When I accept and come to you, I have to touch that I have already met [the interviewer]... Then it tells me where you're going. So at the beginning, I don't know where you are going; maybe you are going far, maybe you are going close* (Interviewee, London).

Power Asymmetry and Resulting Tension

Drivers reported difficulties and challenges when their wish for autonomy conflicted with the platform's use of algorithmic management to exercise control. Surprisingly, most drivers did not report they were disturbed by the tracking of their actions and understood the system incorporates constant passenger evaluations. On their own, these attributes of algorithmic management did not contribute to a perceived lack of control or autonomy to act as they wished. Drivers experienced a loss of autonomy mainly in cases where they felt the system was not transparent and when they felt they were not treated "fairly" or privy to full and relevent information. In such cases, these unknowns hampered their ability to plan ahead and maximize value capture.

Tensions arose from their inability to control or track compensation from driving for Uber. The company's compensation system is opaque and highly complex. Uber takes different levels of commission from different drivers, usually ranging from 20 to 25 percent of the value of the ride. Drivers can also receive additional payments for picking up passengers in "surge" pricing areas, as well as bonuses if they achieve certain goals, such as a minimum number of rides each week. These are based on individualized "special deals" subject to weekly change and are offered to some but not all drivers. In this context, many drivers mentioned UberPOOL. The compensation for UberPOOL rides is even more complex, partly because the algorithm behind it forces drivers to accept all passengers by default, even though acceptance is not always economically beneficial. Drivers find it difficult to determine how much money they will make when choosing UberPOOL options because the calculation is not straightforward.

> *When you pick up UberPOOL, you will not know how much they, the customer will be paying; they can get off and that cycle will continue running, and when you pick up UberPOOL, you don't know how many miles you did with the customer. You don't know how to calculate the way bill. You don't know how much he will pa*y (Interviewee, New York).

Indeed, many drivers expressed negative feelings about UberPOOL. When driving for UberPOOL, Uber automatically calculates a required course between passengers. In many cases, the resulting routes make no sense to either drivers or passengers, and the latter may blame drivers and damage their ratings. As established earlier, complying with UberPOOL is a company requirement, and drivers with low acceptance may be blocked from the system or banned for a period of time. This creates constant tension between the "autonomous" driver and the system.

> *Because everything is controlled by Uber ... Yes, they force you to do UberPOOL. Because let's say we took a shortcut, like trying to stop taking Uber rides – UberPOOL rides – and once we do that they will shut you off* (Interviewee, New York).

> *Either Uber is an employer and Pool trips are mandatory, or we are self-employed and Pool trips are at our discretion, it can't be both!* (UberPeople London Forum)

In addition to Uber's low transparency, drivers expressed resentment that they could not contact a human representative of the company. In one forum case, a driver complained about not receiving his pay rate bonus, known as a "surge", which is given to encourage drivers to travel to areas where demand is higher than supply. Since surge is an automatic system decision, glitches and software bugs can occur, and it is difficult for humans to assess the situation. In this case, money was collected from the "pax" (as the passenger is referred to in the UberPeople forum), but not given to the driver, who had to email pictures and proof and still received an initial refusal because of this misunderstanding. The combination of an automatic system and computer-mediated support encouraged the driver's resentment:

> *As I start pickup up passenger I noticed in App it doesn't show Pax as a 2.5 … Just shows standard -- nothing. I Politely chat with Pax during ride if she paid a Surge. Of course she says yes. After I get home I contact the morons on the Uber App support with PICs of Surge and my Time and car in zone… First moron … says too bad… no surge… I reply back to speak to his manager… Finally the next morning they say OK they will allow the surge to hit my account within 2 billing cycles… Uber sucks … Their supports Sucks* (UberPeople New York Forum).

Situations of power asymmetry between autonomous drivers and algorithmic management enforced via the app result in increased tension. In such situations, drivers are constrained not just in their ability to make choices, but also in their access to information informing rational choices and providing means of communication if they need external help.

Guessing the System

Drivers with limited information from and communication with Uber often tried to supplement their information and make sense of the situation by guessing the system's motivation for its behavior. Drivers meet in forums to connect and attempt to solve questions and problems. For example, in one case, an Uber driver was curious about why he had received many Uber requests, even though he was only number 32 in the airport queue:

> *However my question is that Why Was I being bombarded with local jobs in the airport queue. Why didn't the person in the front of the queue receive these but number 32?* (UberPeople London Forum).

In such cases, the forum members shared their understanding of the system to attempt to explain how the system works.

> Uber Driver A: *Because if everyone in the queue doesn't accept the job it gets passed on*
>
> Uber Driver B: *It's because you do pool jobs as well as wait at airports – it's what idiots do.*
>
> Uber Driver C: *Other local jobs will probably go to the nearest driver (as per normal subject to the usual daily earnings cap, other drivers slightly nearer refusing, etc), regardless of that queue. Hence some drivers at AVA park and wait at the extreme edges of the car park, as they could get a hotel job first, before a terminal pick up* (UberPeople London Forum).

In many cases, drivers dealing with uncertainty and information asymmetry developed theories, stories and urban legends regarding the system and its reasoning. Some drivers believed they were being manipulated out of their earnings and that the rating algorithms were unfair and created a "fixed system."

> *…do you think uber controls rating so naive drivers try harder?*
>
> *Yes I believe that they fudge the ratings of drivers. My weekly emails state I am a 5 star driver. My dashboard states that I am a 4.69 driver* (UberPeople London Forum).

One recurring theory was that it is impossible to get a bonus based on the number of weekly rides because the system does not assign rides when drivers are close to their bonus goal:

> *They control earnings now too – easy to get the first £60 of the day, after that is hours of wait to make any money* (UberPeople London Forum).
>
> *And they're like, you know, all together normally five rides can take me like an hour and a half to two, but those are, you know, those last five rides take me like seven, eight, ten hours, you know. That's because they don't want to give me a ride that is fast, I guess* (Interviewee, New York).

In summary, "guessing the system" leads to the development of theories and stories that try to make sense of the system and account for its asymmetries. These stories often describe malicious attempts by a platform uninterested in drivers' wellbeing and success and encourage drivers' action and resistance.

Regaining Control under Algorithmic Management

Drivers utilized the encouragement and social support they received from the forum to regain control by resisting, switching or gaming the system.

Resisting the System

The first observed behavior was resistance, in which drivers actively stopped doing as they were requested. The drivers exhibited a wide array of resistance methods, such as cancelling passengers through the system and deactivating GPS or the service system itself.

In most cases, drivers used resistance to express their disdain of Uber conditions or mistreatment:

> *If possible refuse all pool trips. Great for Uber, bad for us* (UberPeople New York Forum).
>
> *Turn on all apps and ignore pool and lyft line jobs. Trust me, you will be happier* (UberPeople London Forum).

In some cases drivers also resisted when they felt Uber was asking them to take actions that might jeopardize their health and safety. This applied to cases where UberPOOL sent drivers large numbers of requests and navigation updates while driving:

> *Using your phone when driving or stopping is dangerous enough without doing it multiple times on a journey whilst paying attention to the road/passengers* (UberPeople London Forum).

Some resistance was directed at passengers, especially those who violated drivers' property or treated them with disrespect. Drivers usually tried to avoid people who were intoxicated, and large groups boarding the vehicle, such as "teens … doing party." For instance, some drivers resisted by calling the customer in advance and cancelling requests if they seemed drunk:

> *SUV drivers! Don't allow those teen MOFO's doing party in your car. After accepting SUV late night, just call and ask, if they need AUX court, if Yes, just cancel ride* (UberPeople New York Forum).

In other cases, drivers supported each other and their right way to resist or avoid UberPOOL altogether. A recurring question on many threads was the effectiveness and consequences of such resistance:

> Driver A: *if you do not want to take uberpoop rides then just ignore them. After about 2-3 days of ignoring them you will not receive anymore. I have not received an uberpoop request in months. I guess uber thinks they are punishing me by not sending me any more … poor me. LOL.*
>
> Driver B: *lol same here, I've not received any for a few months now. And that is after telling me it is part of the uber agreement as a whole and I have no choice but to do it.*
>
> Driver C: *has anyone had this problem that you get logged out for not accepting just 1 pool request? Used to be 3 strikes and you're out, now just one! … Is it just me on the naughty hit list or you guys having same issues?* (UberPeople London Forum).

Switching the System

With the introduction of new ride-hailing platforms such as Lyft, Juno, Via and Gett, drivers in New York City actively operated more than one app simultaneously to minimize their idle time. All the drivers we encountered had operated more than one app. In most cases, this was done using a couple of cellphones that operated different platforms simultaneously. When drivers became idle or reached the end of the current ride, they tended to accept a request on a first-come-first-served basis.

> *Make the switch to lyft and save our jobs while we have a chance. Uber just wants to give our jobs to machines and keep lowering rates* (UberPeople New York Forum).

> *You ever heard of Juno? Lyft? Gett? You get logged off … Uber … Go on another platform, and work* (UberPeople New York Forum).

This switching behavior provides drivers with leverage against the platform by lowering the risks associated with a ban from existing platforms and allowing them to threaten to or actually abandon the Uber platform. This is a legal practice, since divers are self-employed. However, this can be problematic for Uber because the company requires a large fleet of drivers.

Gaming the System

Drivers tried to find loopholes in the system they could exploit to increase their potential income. We found that Uber drivers developed and shared mechanisms to trick the system. They, for instance, canceled rides in the system to avoid negative ratings from angry customers, since negative ratings lead to automatic sanctions.

> *I tell them this: "I am going to drop you* [the Uber customers] *off and end the trip" … Then I drop them off and cancel so they cannot rate me, or report the issue immediately as a rude and angry pax* (UberPeople Forum).

Drivers also discussed how to game Uber's request to accept all rides, including the unpopular UberPOOL. One method suggested by drivers in the forum was to accept the first passenger in UberPOOL but then log off the system to avoid acceptance of subsequent UberPOOL passengers. Uber encourages drivers to take UberPOOL rides by setting its commission at just 10 percent for the first passenger. This means that drivers who perform this "trick" win in two ways: first for having a solo passenger instead of a full car, and second for getting to keep a higher percentage of income because of a 10 percent commission instead of the 30 percent typical for UberX.

> *U just log off after your first uber pool then u do not get a 2nd matching trip.*

> *Simply press go offline in note section (left top corner) after accepting first trip, uber will not send u any trips after current 10% trip* (Uberpeople London Forum).

However, drivers also noted that Uber actively tries to prevent such system abuse.

> *Now you cannot ignore the 2nd request. As the system will automatically add the 2nd job onto the system. Didn't you receive the email update in relation to this? That's because many Drivers were accepting one pool job paying 10% to Uber. Uber got pissed* (Uberpeople London Forum).

Lastly, drivers attempted to use the online forum to collectively game the system. In the absence of any official union, drivers utilized the UberPeople platform to promote ideas for mutinies or rebellious acts that would improve their conditions. One possibility mentioned in the forum was organizing a mass deactivation of drivers from the system, which would then lower supply and increase surge pricing.

> Driver A: *Guys stay logged off until surge.*

> Driver B: *why?*

> Driver A: *Less supply high demand = surge.*

> Driver B: *Uber will find out if people are manipulating the system.*

> Driver A: *They already know cos it happens every week. Deactivation en masse coming soon. Watch this space* (UberPeople New York Forum).

Figure 1 shows an emergent model that combines the algorithmic management attributes and drivers' resulting behavior identified from our findings.

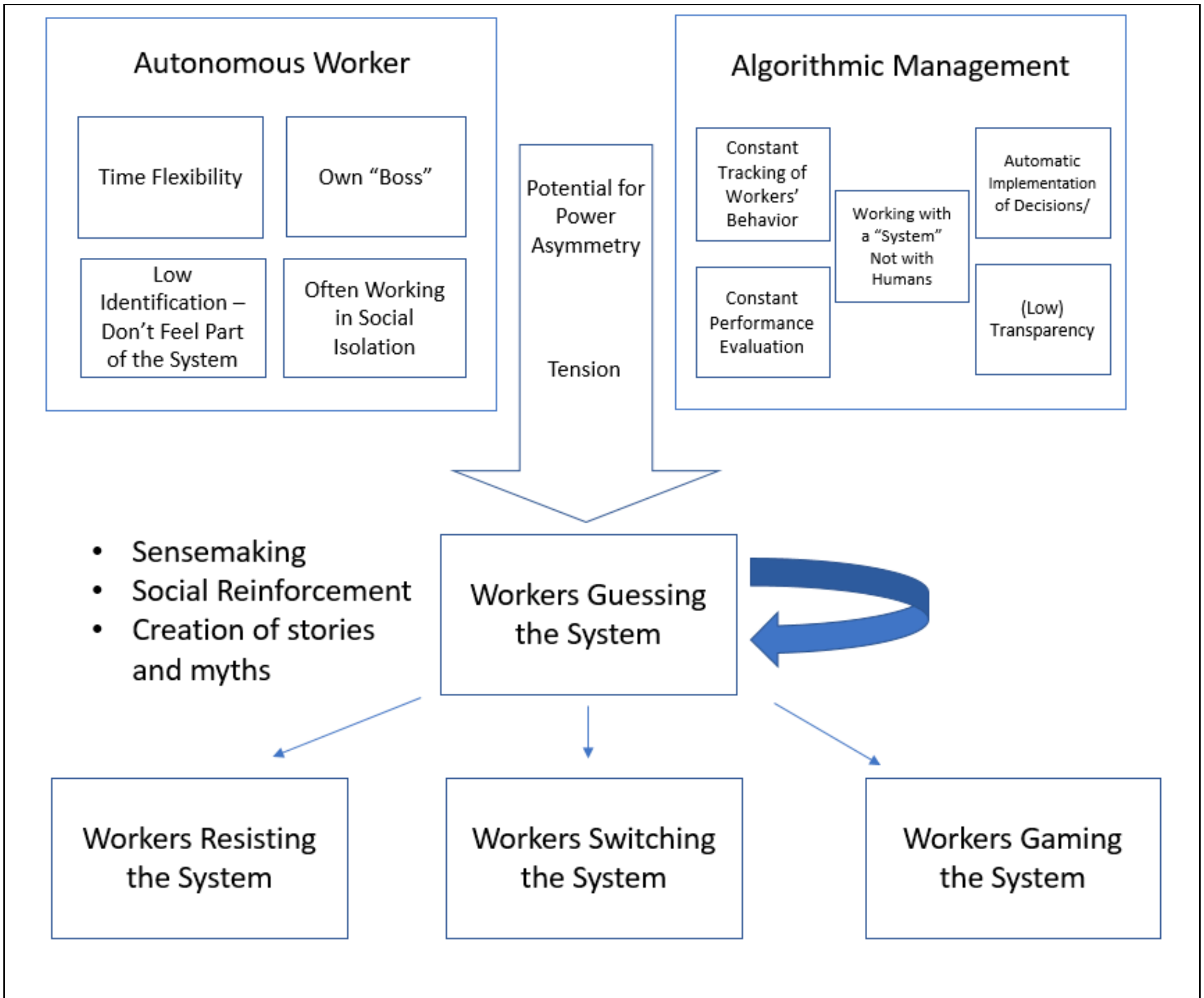

Figure 1. Research Model

Discussion

This study has addressed the timely topic of algorithmic management and is among the first in the IS management discipline to discuss this phenomenon. We introduced three research streams to inform our work: work autonomy (e.g., Langfred 2007; Mazmanian et al. 2013), freelance or "quasi-employment" on digital platforms (e.g., Chen and Horton 2016; Xuegei and Joshi 2016), and previous literature on the social study of algorithms (e.g. Dourish 2016, Orlikowski and Scott 2015, Rosenblat and Stark 2016).

By drawing on existing literature, we conceptualized major characteristics of algorithmic management and discussed how these characteristics differ from "traditional" or technology-mediated management practices. We identified several unique attributes of algorithmic management: tracking of workers' behavior; constant performance evaluation; automatic implementation of decisions; working with a "system" rather than with humans; and low transparency (in most cases).

Then, the emergent tension between algorithmic management and workers' autonomy was empirically analyzed through the case of the Uber platform. We identified tension based on power asymmetry: on one hand, drivers not officially employed by Uber often chose the job for the freedom and autonomy they hoped it would provide; and on the other hand, a platform programmed to constantly oversee, govern and control these drivers.

Finally, we analyzed how workers responded to and resolved these tensions and found they actively tried to regain some of their lost control and sense of autonomy. We reported four observed driver behaviors. Drivers tried to guess and make sense of the system's intentions. They utilized forums such as UberPeople to share these stories and gain social support. In many cases, these stories were echoed by other drivers, and together created an urge to act. This resulted in a range of practices to resist the system, including switching to alternative systems and even gaming the system to their advantage.

Our analysis of the Uber case sheds light on issues in implementing other algorithmic management-related systems. While not all systems will exhibit each attribute in our suggested model, its elements are also evident in other platforms, such as Mechanical Turk (Irani 2015; Orlikowski and Scott 2015; Xuegei and Joshi 2016) and automatic financial services (Callon and Muniesa 2005).

Our first and major contribution is the conceptualization of algorithmic management and its understanding within the IS management discipline. IS scholars have stressed the importance of studying the socio-technical aspects of algorithms (Orlikowski and Scott 2015), and early work in HCI and computer science literature coined the term "algorithmic management" (Lee et al. 2015). However, no generally accepted definition of this term yet exists within IS management sciences. As far as we know, this is the first work to address attributes of algorithmic management in relation to the IS discipline by focusing on the interplay between tech-supported management and workers' autonomy. Thus, we have contributed to a better understanding of how the implementation of algorithms unfolds in social contexts shaped by human behavior.

Second, we have contributed to literature on "quasi-employment" on digital platforms, where workers (or Uber drivers) might not be officially employed by a company, but instead, work as freelancers for platforms that match them with potential customers and tasks. While freelancing and self-employment practices increase worker freedoms, we illustrate that the implementation of algorithmic management practices may do exactly the opposite, increasing power asymmetry in favor of the platform and creating a worker that feels controlled and micro-managed, creating an asymmetric relationship between platform and the worker.

Third, we also contribute to literature studying work autonomy (e.g., Langfred 2007; Mazmanian et al. 2013) on digital platforms. In line with previous literature on this topic (Mazmanian et al. 2013), we identify a paradox between workers' desire for autonomy and the platform's need for control. These digital platforms attract people who wish to work autonomously and choose their schedule, while at the same time, they require workers' to give up power over many aspects of their work. This is because the information asymmetry, inherent to such systems, weakens workers' power (Lee et al. 2015; Rosenblat and Stark 2016). Based on our empirical data, we find that even on online platforms where they are tracked and evaluated constantly, workers develop practices that provide them with a feeling of regaining agency and control. In some cases, drivers resort to "illegal" practices by trying to game the system and violating the terms of use. This echoes previous research into "gaming" found in other tech-related contexts, such as Luca and Zervas's (2015) observation of gaming behavior in the context of review fraud on the Yelp platform. In this regard, our study shows that implementations of algorithmic management which reduce workers' sense of autonomy and control may not only be ethically questionable, but also hurtful to the company itself.

Fourth, in this study, we have sought to illuminate social and human factors in a highly technological context where workers often feel they are working for a system rather than for humans and lack social relationships in their daily work environment. At a time when Uber is testing automated cars that may replace drivers in the future (Coeckelbergh 2016), we show that when workers are treated like machines through algorithmic management, they employ "human" response mechanisms. It is worth noting that in an environment in which interactions between drivers are not supported or even desirable for Uber, drivers informally gather together through blog forums and other tools to make sense of the system and their experiences and socially reinforce their peers. We observe that drivers exhibit such collective action by using informal structures. One could argue that these are not utilized merely to regain agency, but also to satisfy their desire of social exchange in the absence of a social work environment.

This study has several managerial implications. First, it highlights the importance of transparency. In theory, algorithmic management can increase system transparency because it is built around set rules and procedures. However, in the case of Uber, transparency has been reduced to service the company's strategy. Our study shows that Uber's strategy is widely perceived as negative by drivers and may even be counterproductive because it triggers such negative reactions. Therefore, companies should consider how they can balance their needs and with greater transparency to provide their "workers" with a real sense of fairness and partnership. Companies might consider showcasing detailed and illustrative system feedback to their workers, or even empower workers by identifying ways for them to participate democratically in decision algorithms and policies. In any case, this study hints that algorithmic management platform owners cannot expect to be both "partners" with their workers and to keep their algorithms completely opaque.

A second managerial implication is the importance of the human element, even in an algorithmically managed system. The importance of human interaction is most evident in the context of support. When drivers were faced with problems or troubles, they reported interactions with driver support via email to be problematic. Drivers hoped that Uber would help them in times of need, but were disappointed when this took time and resulted in automated email responses. A feasible approach might be to preserve the human element in the company's provision of support. One of Uber's major competitors in New York City is Juno. Unlike Uber, Juno employs a human customer support system that answers immediately and helps drivers with any questions or problems. Several drivers identified this as one of the benefits of and reasons for switching. Both transparency and human support in time of need may help address the feelings of "dehumanization" drivers reported when left at the mercy of algorithms or the computerized system.

Limitations and Future Work

We focused on how drivers perceive Uber and their subjective understanding and experience of the app. We did not interview representatives of the company and did not acquire exact details of the Uber platform's inner workings. In some cases, it might be the case that users have exaggerated or embellished certain features of the system. We believe that our data was sufficient, since this study focused on drivers' beliefs, thoughts and reactions. However, future research addressing the implementation of such systems should consider both sides of this equation.

This study focused on two major cities, New York and London, and combined interviews and forum data. Our focus on two cities allowed us to address potential cultural and geographical biases. Use of the UberPeople Forum allowed us to tackle the "social desirability" bias inherent in interviews. However, we did not perform a complete comparative analysis, nor did we focus on analyzing differences based on each city's competitive environment. We are aware that certain aspects, including exact compensation schemes, might vary by location and change based on the point of time the drivers decided to work for Uber.

We identified many other interesting aspects in our data. However, due to length limitations and the need to narrow this report's scope, we were not able to discuss those in detail. Among others, we identified several sub-groups of Uber drivers – some were very dissatisfied working for Uber and thus more likely to game the system, while another small group of drivers were very satisfied with the working agreements negotiated with the Uber platform. Because algorithms constantly change over time and adapt to new situational contexts, we expect that a time analysis might have been able to identify some data variances. For instance, it is likely that the Uber platform is aware of the fact that some of the drivers are gaming the system – and reacts by changing the algorithms to better identify and fight such behavior (as the drivers also suggest, see Uber drivers comment on page 12). More research is needed to further document these aspects.

Lastly, this empirical research selected to focus on Uber and its ride-hailing platform. Doing so, we elaborated on previous papers written on the Uber platform that had identified a link between Uber and algorithmic management (Lee et al. 2015; Rosenblat & Stark 2016). This field is currently growing, with new companies and platforms joining on a daily basis. Future research is required to explore users' behaviors on other platforms and in other industries in order to broaden its scope. We encourage researchers to utilize the algorithmic management framework presented in the paper and test it in these new contexts.

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