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Algorithms as co-workers: Human algorithm role interactions in algorithmic work

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Abstract

In algorithmic work, algorithms execute operational and management tasks such as work allocation, task tracking and performance evaluation. Humans and algorithms interact with one another to accomplish work so that the algorithm takes on the role of a co-worker. Human–algorithm interactions are characterised by problematic issues such as absence of mutually co-constructed dialogue, lack of transparency regarding how algorithmic outputs are generated, and difficulty of over-riding algorithmic directive – conditions that create lack of clarity for the human worker. This article examines human–algorithm role interactions in algorithmic work. Drawing on the theoretical framing of organisational roles, we theorise on the algorithm as role sender and the human as the role taker. We explain how the algorithm is a multi-role sender with entangled roles, while the human as role taker experiences algorithm-driven role conflict and role ambiguity. Further, while the algorithm records all of the human's task actions, it is ignorant of the human's cognitive reactions – it undergoes what we conceptualise as 'broken loop learning'. The empirical context of our study is algorithm-driven taxi driving (in the United States) exemplified by companies such as Uber. We draw from data that include interviews with 15 Uber drivers, a netnographic study of 1700 discussion threads

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among Uber drivers from two popular online forums, and analysis of Uber's web pages. Implications for IS scholarship, practice and policy are discussed.

KEYWORDS
algorithm-driven role ambiguity, algorithm-driven role conflict, algorithmic work, broken loop learning, dark side of algorithmic work, human–algorithm role interaction

1 | INTRODUCTION

A distinctive feature of contemporary organisational work is algorithms[1] and humans interacting to accomplish work tasks. Known as 'algorithmic work' (Schildt, 2017), such work is exemplified in jobs such as ridesharing (e.g., Uber), delivery service (e.g., Deliveroo) and micro-task execution, primarily on external platforms such as Amazon Mechanical Turk (M-Turk) (Gray & Suri, 2019). Algorithms execute operational tasks such as goal setting, scheduling and task allocation (e.g., Parent-Rocheleau & Parker, 2021) and managerial tasks such as performance management and rewards and penalty apportionment (Gal et al., 2017; Hansen & Flyverbom, 2015). The human executes work tasks through interactions with the algorithm rather than with other humans. The algorithm, in turn, combines the data provided by the human (e.g., by tracking his/her inputs through an app interface) with other data (e.g., data from enterprise systems, data repositories, sensors) for further computation, such as performance evaluation, and action, such as reward assessment (Faraj et al., 2018; Gal et al., 2017; Jain et al., 2018). In this way, the algorithm effectively takes on the *role* of a co-worker,[2] and the human and the algorithm engage in interactions to complete the work, interactions that resemble workplace interactions between humans in traditional work.

However, such interactions hold several problematic characteristics. Often the human does not fully understand the outputs generated by the algorithms (Faraj et al., 2018) because they are generated by complex computations on large volumes of data. Further complicating matters, multiple algorithms feed into one another without human intervention. For instance, in the case of ridesharing taxi drivers working for companies such as Uber, the algorithm assists the driver with route guidance and passenger pick-up. However, it also tracks the route and ride time and can automatically propagate this information to other algorithms to assess driver performance and compensation (Rosenblat & Stark, 2016). While co-constructed dialogue makes two-way explanation and clarification possible in human–human interactions, there is an absence of such co-construction when humans interact with algorithms. Moreover, organisational policies and/or the need to execute tasks 'right away' further eliminate the opportunity for the human to seek clarification or override algorithmic orders (Zarsky, 2016). Given these conditions, humans engaged in algorithmic work face a number of problems. Humans may perceive their interactions with algorithms as difficult and confusing (Page et al., 2017). They may not understand whether or not they should conform to the algorithm's work instructions, what tasks to execute and the potential consequences from non-conformance. They may perceive the algorithm to be unfair, inaccurate (Parent-Rocheleau & Parker, 2021) or stifling (Gal et al., 2017; Zarsky, 2016) and yet may be reluctant to over-rule it (Markus, 2017). Such conditions can lead to confusion for the human and resistance to algorithmic work (Kellogg et al., 2020). Emerging studies call for understanding why and how these problematic issues happen, and their associated effects, with a view to effect better design of algorithms and algorithmic work (Schildt, 2017).

Role theory provides a theoretical basis to examine workplace interactions (Ebbers & Wijnberg, 2017; Graen, 1976; Katz & Kahn, 1978). It offers a set of concepts that explain humans' understanding of their work, conditions which may hinder such understanding, and the social structure of positions through which they interact with co-workers. It emphasises the notion of organisational roles, which captures expectations of the individual's tasks and responsibilities as well as those of co-workers. In algorithmic work, algorithms take on the role of co-workers and interact with the human roles. Thus, to explain the problematic scenarios in algorithmic work presented above, the objective of our study is to investigate the *role interaction between the human and the algorithm* in algorithmic work.

We conduct a qualitative study with the role framing as a theoretically sensitising lens. In particular, we study the work-related actions of the human and the algorithm, what information they send one another and how, and the impacts on the human's actions. The empirical context of our study is algorithm-driven ride sharing exemplified by companies such as Uber. Drivers execute their job through algorithms embedded in smartphone apps. These algorithms are responsible for assigning passengers to drivers, providing pick-up and drop-off locations and recommending driving routes. They also calculate compensation and incentives. We draw on data that include interviews with 15 Uber drivers, a netnographic study of nearly 1700 discussion threads among Uber drivers from two online forums and archival analysis of Uber's web pages. The data refer to ridesharing drivers in the United States.

We extend the information systems (IS) literature on algorithmic work in a novel conceptual direction by investigating the micro-level context of the human's day-to-day interaction with the algorithm. We find that the human, as a role taker, perceives the algorithm as role sender and views it as having multiple roles that are entangled with one another due to interconnected algorithmic computations. Consequently, the human experiences algorithm-driven role conflict and role ambiguity. These novel types of role conflict and role ambiguity emerge specifically in the context of human–algorithm interactions in algorithmic work and are shaped by the algorithms. The human's reactions to algorithm-driven role conflict and role ambiguity are both task-related and cognitive. While the task-related reactions are fed back to the algorithm, such that it 'learns' from them, the cognitive ones are not; we characterise this phenomenon as 'broken loop learning'.

Our investigation suggests that human–algorithm interaction in algorithmic work constitutes negative experiences for the human and incomplete and obstructed learning for the algorithm. Organisations can benefit from our findings to better understand how humans interact with their algorithm counterparts at work and thus design and manage algorithms and algorithmic work processes more effectively. We also highlight the need to focus on policy for work-related well-being of algorithmic workers, the lack of which can affect both individual and organisational performance.

2 | BACKGROUND

In this section, we first describe algorithmic work. Then, we present characteristics of human–algorithm interactions in algorithmic work and explain how the algorithm takes on the role of a co-worker. Next, we present concepts from organisational role theory and the notions of role sender and role receiver as key aspects of human–human interactions in the organisational context. Thereupon, we identify emerging problematic scenarios in human–algorithm interactions and examine them through the framing of organisational roles in order to lay out our research objective.

2.1 | Algorithmic work

Algorithmic work (Lee et al., 2015; Schildt, 2017) is work in which algorithms execute a variety of operational and managerial tasks traditionally undertaken by humans. Operational tasks include allocating and scheduling work tasks to, and tracking task performance of, the human (e.g., Parent-Rocheleau & Parker, 2021). For example, M-Turk allocates different kinds of tasks to humans such as identifying and matching pictures (Gray & Suri, 2019). Managerial tasks include tracking the performance of the human, comparing it with desired standards and delivering rewards, penalties and nudges (Gal et al., 2017; Hansen & Flyverbom, 2015). For instance, Deliveroo calculates delivery rates for drivers based on delivery performance such as time taken (Duggan et al., 2020; Woodcock, 2020). Ridesharing algorithms monitor drivers' actions (e.g., mobile phone use or sudden braking) during a ride, and issue alerts as needed (Möhlmann et al., 2021). They nudge drivers to continue working until a driver-specified earnings threshold is met.

Typically, different interconnected algorithms execute the tasks, often in real time, with the outputs of one algorithm serving as the inputs into others. The algorithms, both scripted and machine-learning-based, are embedded into work processes (Lyytinen et al., 2020; Tarafdar et al., 2019). They automatically capture and store digital traces of the human's actions throughout different work processes to calculate further parameters for other tasks (Schildt, 2017). For example, algorithms may use data about the human's task completion time to (automatically) assess his or her performance and calculate salary increment, with no human involvement or co-constructed dialogue (Gal et al., 2017; Momin & Mishra, 2015). In this way, multiple levers of organisational processes and control can be embedded in the logic of the algorithm. Algorithmic work is distinct from augmentation, in which humans use the outputs of algorithms as aids to make decisions, typically in business analytics applications such as legal decisions (Corbett-Davies et al., 2017), mortgage approval (Markus, 2017) and medical diagnosis (Wynants et al., 2020). It is also distinct from automation where the algorithm, being the engine of a robot or machine, executes a series of programmed steps to accomplish a specific and bounded physical activity, often in factory or warehouse settings.

2.2 | Human–algorithm interactions in algorithmic work

A key component of algorithmic work is that humans and algorithms interact with one another. The interactions happen through a digital interface (e.g., an ‘app’) and are mediated by underlying algorithmic computations. Algorithms ask humans to execute specific tasks based on the computational outputs, through the interface (Baird & Maruping, 2021; Luca et al., 2016). The human responds to the algorithm's request by executing the tasks. The tasks can involve physical activities enabled by a digital interface (such as Uber driver picking up a customer) or can be digital in nature and executed through the digital interface (such as those on crowdsourced platforms). In this way, the algorithm has the ability to track and record the human's activities. This record forms the basis of the algorithm's subsequent computations such as comparison of the human's performance against goals, performance assessment, rewards and compensation and future tasks (Parent-Rocheleau & Parker, 2021). The algorithm then conveys the outputs of these computations to the human through the same interface, to which the human responds by doing further tasks. Such interactions between algorithms and humans resemble workplace interactions that happen between humans in traditional work. In this way, algorithms work with humans, becoming an organisational member.

Algorithmic work can be found in a variety of settings such as ridesharing, delivery services and micro-task execution through crowdsourcing platforms (Gray & Suri, 2019). Policy and legal discourses are increasingly pointing out that humans executing algorithmic work (e.g., drivers who work for ridesharing companies) should be treated as employees even when they are gig workers.[3] A key reason for this is that they execute their work in organisation-like settings wherein the algorithm schedules tasks (e.g., rides in the case of ridesharing platforms), evaluates performance (e.g., frequency of and customer satisfaction with rides) and determines compensation (e.g., ride rates) much like an organisational supervisor. The algorithm is the primary (and often the only) entity with which the human interacts to execute their work so that the algorithm becomes an organisational member and a co-worker.

2.3 | Organisational roles

Since humans and algorithms interact as co-workers in algorithmic work, we turn to the theory of organisational roles (Horrocks & Jackson, 1973; Kahn et al., 1964) as our theoretical framing to examine human–algorithm interaction. This theory provides a conceptual foundation to explain workplace interactions between organisational members. It examines relational exchanges in human–human interactions (Floyd & Lane, 2000) and investigates social cues that shape job expectations (e.g., Katz & Kahn, 1978). We examine the human–algorithm interaction (i.e., between a focal individual and the closely related co-worker, the algorithm) by conceptually framing it via a relational approach (Chen et al., 2013). Specifically, we investigate it in the context of everyday and ongoing work-task execution to explain how humans and algorithms interact in a relational way while embedded in the larger edifice of organisational tasks and relationships.

Roles are socially constructed expectations and norms of human behaviour (Marrone et al., 2007). They can be societal[4] (e.g., cultural roles such as through marriage and family) or organisational (roles designed by formal organisational hierarchies, such as supervisor/subordinate relationships; Pas et al., 2014). Our focus is on the latter where organisational members interact with one another through the structure of organisational roles, which represent appropriate and expected behaviours and actions (e.g., Katz & Kahn, 1978). An individual's role is a position within the organisation that specifies the work tasks and responsibilities they are is expected to perform (Cooper et al., 2001; Ilgen & Hollenbeck, 1991; Perrone et al., 2003; Rogers & Molnar, 1976). Individuals act according to expectations of their own role and expect behaviours of their co-workers according to the latter's roles (Graen, 1976). Therefore, roles guide the individual's workplace behaviour and interactions with co-workers (Gross et al., 1966; Horrocks & Jackson, 1973). Each individual interacts regularly with a set of individuals in other roles including immediate supervisor and subordinates, as well as those from other departments with whom they closely work.

Role interactions are exchanges between 'role sender' and 'role taker'. Role senders, typically managers or supervisors, 'send' role expectations to the focal individual, the role taker. Role expectations indicate what the role taker is expected to do and provide indications about rewards and sanctions associated with role compliance (Marrone et al., 2007). Role senders can exert power to influence the focal person to act in conformity with their role expectations via actions such as awarding or withholding raises and promotions. The role taker 'takes' the role. Namely, they develop an understanding of their role by interpreting the role expectations communicated by the role sender (Horrocks & Jackson, 1973; Kahn et al., 1964; Katz & Kahn, 1978), the situational context and organisational norms (Gross et al., 1966; Horrocks & Jackson, 1973). They execute the role through specific actions such as task execution or refusal to execute. Role takers also provide role-related feedback (e.g., difficulties and issues in executing the role) to the role sender. Role senders, in turn, consider this feedback along with the role taker's actions and performance, modifying their role expectations and subsequent role sending information if necessary. To ensure that they convey role expectations that are reasonable, the role sender needs to have adequate understanding of the role taker's views (Gross et al., 1966; Horrocks & Jackson, 1973; Kahn et al., 1964; King & King, 1990).

2.4 | Problematic issues in human–algorithm interactions

Table 1 gives an account of key aspects of algorithmic work, corresponding implications for human–algorithm interactions and associated problematic aspects. In algorithmic work, algorithms *undertake operational and managerial tasks*. Humans and algorithms *interact directly* with one another and thus humans relate to algorithms as co-workers, similar to how humans do with other humans. During these human–algorithm interactions, the human perceives *the outputs of the algorithms* as work-related information from a co-worker (e.g., Martin et al., 2014) rather than as computational outputs from an application. For instance, in ridesharing contexts, the outputs of the algorithm are perceived as work instructions (e.g., pick up a passenger or perform a task), compensation (e.g., rate per task), rewards and penalties (e.g., increase or decrease in the rate per task) and recommendations (e.g., GPS route guidance in a ride share journey). Further, the algorithm takes on the *role of a co-worker* who conveys such information. For example, using metrics to calculate one's performance is similar to a supervisor evaluating an employee's performance (Brynjolfsson & McAfee, 2014). Recent literature depicts algorithms as bosses (Möhlmann et al., 2021) or as prescriptive agents that can take on supervisory roles (Baird & Maruping, 2021).

TABLE 1 Problematic issues in human-algorithm interactions

Aspects of algorithmic work	Human-algorithm interactions	Problematic issues
Tasks undertaken by the algorithm	• Operational tasks: allocating and scheduling work tasks to humans; tracking task activities of humans (e.g., Parent-Rocheleau & Parker, 2021) • Managerial tasks: tracking the performance of humans, comparing it with desired standards, and delivering rewards, penalties and nudges back to the human (Gal et al., 2017; Hansen & Flyverbom, 2015)	• Algorithms automatically capture digital traces of the human's task actions to calculate further parameters such as performance and rewards (Schildt, 2017) with no human involvement or co-constructed dialogue (Gal et al., 2017; Momin & Mishra, 2015)
Interaction of the algorithm with the human	• Interactions occur through digital interfaces (e.g., an app) and are mediated by underlying algorithmic computations • Humans relate to algorithms as co-workers (Page et al., 2017)	• Computational logic behind the algorithm's outputs is not always transparent (e.g., Bernstein, 2017; Dolata et al., 2021; Feuerriegel et al., 2020)
Outputs of the algorithm	• Perceived by the human as work instructions (e.g., pick up a passengers), work reward/compensation (e.g., payment for a micro-task or a passenger ride), or nudges (e.g., warning for sudden braking) (Martin et al., 2014)	• Human may not understand the work instructions and why the algorithm gives them (Pasquale, 2015) • Human may not be able to seek clarification or override the algorithm when they think the work instructions from the algorithm are inconsistent or incorrect (Marabelli et al., 2021)
Role of the algorithm	• Algorithms take on the role of an organisational member (Parent-Rocheleau & Parker, 2021); They are perceived by the human as a boss (Möhlmann et al., 2021) or supervisor (Baird & Maruping, 2021)	• Human does not trust the algorithm (Glikson & Woolley, 2020) • Human may feel the algorithm is unfair (Parent-Rocheleau & Parker, 2021) and feel stifled and controlled by it (Gal et al., 2017; Zarsky, 2016) • Employees may resist algorithmic work (Kellogg et al., 2020)

However, these aspects of algorithmic work have distinctive and potentially problematic characteristics. First, in the interaction of the algorithm with the human, the logic behind the algorithms' computations is not always transparent (e.g., Bernstein, 2017; Dolata et al., 2021; Feuerriegel et al., 2020). This happens because the algorithms are themselves complex with numerous parameters, large datasets and probabilistic calculations as in the case of machine learning (Faraj et al., 2018). As a consequence, humans may not understand the work instructions that are the output of the algorithms and may not understand why the algorithm gives them (Pasquale, 2015). Indeed, even the algorithm's designers might not know exactly why an algorithm provides a certain output because algorithms evolve (and learn) as they are used, as is the case for most ML systems (Hosanagar & Jair, 2018). This can make communication from the algorithm unclear to the human (Parent-Rocheleau & Parker, 2021; Rahman, 2021). Yet, the algorithm's work instructions may be mandatory and not following them might lead to penalties for the human as observed in the case of algorithmic ridesharing (Page et al., 2017). Additionally, when the human thinks the algorithm is incorrect or inconsistent, they may not be able to seek clarification or override the algorithm because speed of execution is prioritised and organisational policies may discourage or prohibit overriding (Marabelli et al., 2021). For instance, ridesharing drivers do not always know why they are told to do something, yet they cannot ask the app that manages their rides. Moreover, it is not always clear who is responsible for the consequences of not following the algorithm's instructions (Diakopoulos, 2016; Shin & Park, 2019; Zarsky, 2016).

Studies are beginning to uncover how humans react to the problems outlined above. Humans may be reluctant to over-rule the algorithm and may erroneously believe that algorithms are always 'right' (McAfee & Brynjolfsson, 2012; Newell & Marabelli, 2015). At the other extreme, when algorithms evaluate work performance, humans may feel the algorithm is unfair or inaccurate (Parent-Rocheleau & Parker, 2021) and feel stifled and controlled by it (Gal et al., 2017; Zarsky, 2016). They may become upset because of the algorithm's lack of transparency (Schafheitle et al., 2020). In addition, humans may try to game the algorithm in attempts to maximise rewards (Christin, 2017) and performance scores (Rahman, 2021). Employees have engaged in collective resistance to human–algorithm interaction leading to consequences such as leaving the organisation altogether (Kellogg et al., 2020). The literature also looks at the human's lack of trust in the algorithm such as believing that outputs are not reliable, particularly if the former does not perceive a personal benefit from the algorithm's outputs (Glikson & Woolley, 2020) or feels like they are constantly being tracked and evaluated (Möhlmann et al., 2021; Mohlmann & Zalmanson, 2017).

The above examples exemplify the complexity of human–algorithm interactions in algorithmic work. On the one hand, the algorithm takes on the role of an organisational member and co-worker. The information provided by the algorithm is therefore seen by the human not just as the computational output from an application but as a work instruction. On the other hand, these very instructions and the consequences of not following them may be ambiguous to the human, who in turn, may be conflicted as to how to respond and when to follow or not follow the algorithm's work instructions. They may experience lack of clarity and frustration, and their work performance may be adversely affected. This raises the important need to better understand the interactions between the human and the algorithm because such interactions form the very basis of algorithmic work (Glikson & Woolley, 2020). The literature on organisational roles theorises these notions of ambiguity and lack of clarity through the concepts of 'Role conflict' and 'Role ambiguity'. We therefore next turn to these two concepts.

2.5 | Role perceptions of the role taker: Role conflict and role ambiguity

The role taker's understanding of the information sent by the role sender is central to how they perceive the role. Uncertainties arise when such information is contradictory, unclear or inadequate. The literature addresses such uncertainties through the concepts of role conflict and role ambiguity (Cooper et al., 2001; Fisher & Gitelson, 1983; Kahn et al., 1964; Tubre & Collins, 2000).

Role conflict surfaces when the role taker is caught in a crossfire of discordant and irreconcilable role expectations (Ebbers & Wijnberg, 2017; Nicholson & Goh, 1983, p. 149). This can happen when the role taker has *different* roles (each with a different role sender) that have incompatible requirements, such that compliance with one impedes the accomplishment of another, known as inter-role conflict (Anicich & Hirsch, 2017; Floyd & Lane, 2000; Kahn et al., 1964; Pillemer & Rothbard, 2018; Rizzo et al., 1970). A second kind of role conflict, intra-role conflict (Anicich & Hirsch, 2017) happens when the role taker has a *single* role but interacts with people from different stakeholder groups who send contradictory role expectations for the same role, such as in the case of boundary spanners who bridge different departments, or salespeople who bridge with customers.

Role ambiguity represents uncertainty about what is expected in the role, how to achieve role expectations or the consequences of poor role performance (Ebbers & Wijnberg, 2017). It happens when the role sender does not send clear and adequate information regarding work tasks, work procedures and performance evaluation criteria (Kahn et al., 1964; Nicholson & Goh, 1983). The role taker thus does not know what his or her tasks are, what kind of behaviours will be punished or rewarded or what the outcomes of good or bad performance will be. Role ambiguity is exacerbated when the role sender conveys vague role expectations to the role taker (Peterson et al., 1995).

Role ambiguity and role conflict can lead to decreased work performance and job satisfaction, reduced effectiveness and increased negative emotions such as feelings of futility or anger for the role taker (Cooper et al., 2001; Graen, 1976; Kahn et al., 1964; McGrath, 1976). Role takers experiencing role ambiguity and role conflict are expected to be able to discuss their problems with the role sender for rectification (Gross et al., 1966; Horrocks & Jackson, 1973).

Research on role theory has focussed on the role taker's behavioural and cognitive responses, especially with regard to role conflict and role ambiguity. Little attention has been paid to the role senders' actions and how they shape the role takers' understanding of the role. The interaction between the role sender and role taker has thus been only partially studied (Jackson & Schuler, 1985; Van Sell et al., 1981), and recent studies have called for a fuller examination (Ebbers & Wijnberg, 2017).

The above discussion brings us to our research objective. As noted, in algorithmic work, the algorithm takes on the role of an organisational member that the human interacts with in order to perform their work. Drawing from role theory, human–algorithm interactions can be viewed as *role interactions* between humans and algorithms wherein the role of the algorithm interacts with the role of the human. As explained above, these interactions are fraught with a number of problems for which there is a lack of theoretical understanding. Our research objective is therefore to investigate these role interactions.

3 | METHODS

The empirical context of our study focusses on algorithm-based ridesharing, which is one of the most widely prevalent forms of algorithmic work (Gray & Suri, 2019). We next provide methodological details.

3.1 | Research design and approach

Our research design and approach were determined by the research question and our literature-based understanding of algorithmic work. Our research objective was to discover *how* role interactions unfold in algorithmic work, which lent itself well to a qualitative study. Algorithmic work is an emerging phenomenon for which the literature is relatively young, rendering qualitative methods that help generate new theoretical insights appropriate. Our research objective also required participants to be actual ridesharing drivers who interact with the algorithm in real ride sharing situations because it is their experiences that we were interested in, rendering the experimental method unsuitable. Furthermore, a survey method would not allow us to follow up on responses and probe further on the rich contextual circumstance of the work of ridesharing drivers (i.e., time pressure, traffic, safety, passenger interactions, the actual driving and multiple sensory and cognitive factors). The aim of our fieldwork was to surface new insights into human–algorithms interaction in the contextualised circumstance of algorithmic ride sharing. Therefore, our approach considers the subject's view as constituting the account from which theoretical understanding is generated (Markus & Rowe, 2018). Accordingly, our first line of primary data collection relied on interviews with Uber drivers. We note that some of our interviewees may drive for other platforms in parallel, but this was not the focus of our study.

3.2 | Contextual familiarity, pre-fieldwork preparation and selection of data sources

Following editorial comments from this journal (Davison, 2021), we report on our preparations before entering the field and how that shaped our data source selection and data collection strategy. We first undertook a number of rides (e.g., Uber, Lyft) as passengers to familiarise ourselves with the context of a ride, e.g., passenger inputs into the ride sharing app, driver actions, pressures facing drivers and passenger–driver interaction. We also looked at news and press articles about ride sharing. We discovered that it is particularly difficult to interview ridesharing drivers because they just do not have the time given their personal circumstances and focus on earnings' maximisation. Their time-related opportunity costs are high because time translates directly into the number of rides and earnings. Further, drivers often work long hours and thus are difficult to approach for an interview outside their work hours. Moreover, the negative press coverage[5] of companies such as Uber has made drivers wary of being interviewed and revealing their experience/feelings. All of this led us to anticipate that recruiting drivers for interviewing would be challenging. When we started with the interviews, our experience of recruiting confirmed our pre-field work preparation. Indeed, few responded to electronic and physical flyer recruitments and several drivers we contacted either refused to be interviewed or kept rescheduling interviews because they were too busy.

We further noted that a driver's in-person contact with the company is limited. The company communicates with drivers almost exclusively through text messages and emails, and through the proprietary app. Furthermore, drivers' face-to-face interactions with other drivers are infrequent. In our pilot interviews, drivers mentioned this and suggested we look at two of the most popular online forums where they communicate with one another about their experiences working for the company, using the app, and interacting with passengers. Drivers use these forums to share tips (e.g., how to increase earnings and tackle difficult passengers), share knowledge about traffic in specific areas and discuss their company's policies related to rates and incentives (Clark, 2015; Lee et al., 2015; Rosenblat & Stark, 2016). These online forums serve as the drivers' means of socialisation and discussion with one another. Therefore, they contain credible digital traces of work-related communication among them. Hence, we also decided to collect data (drivers' posts) on two online forums of Uber drivers through a netnography (Kozinets, 2002). This enabled us to collect observational data that were spontaneous and not influenced by conversations with the researchers. Digital trace data generated on online platforms is increasingly used for the purpose of analysing human perceptions vis-à-vis socio-technical phenomena in IS research (e.g., Barrett et al., 2016; Bauer et al., 2016; Tarafdar & Ray, 2021; Vaast & Levina, 2015).

We combined findings from the interviews and netnography. This approach helped us to obtain data directly from drivers (interviews) as well as about their discussions in forums (online observations). Interviews sensitised us to the nature of human–algorithm interaction; they helped us probe into the drivers' direct experiences of how they interacted with the Uber app, the nature of the algorithm's outputs, and their responses to it. We leveraged the netnography to expand on and augment our interview findings. Having these two independent sources of primary data helped us to make sense of our (richer) findings with greater confidence. Similar research approaches are being adopted to investigate contemporary IS phenomena (e.g., De-Moya & Pallud, 2020).

Given the difficulties of recruiting, we surmised that taking a serial interview-netnography approach might require an inordinately long time such that there was the risk of the algorithm changing drastically between the two data sets. We planned to have the interview and forum data collection more or less coincide in time (January–December 2017). However, because of our difficulty recruiting, we continued to recruit through March 2018 to get to a point where we felt we were consistently not seeing new issues emerge.

3.3 | Data collection

Interviews: We conducted 15 interviews over the period January 2017 – March 2018 with individuals who provide driver services to Uber through their proprietary app. We recruited interviewees through postings on email lists and social media, by distributing flyers in our community and by leveraging our personal networks of friends and acquaintances. Given the difficulties noted above, we used a convenience sample. The study participants voluntarily consented to participate in interviews. We did not recruit any study participant while being customers/riders. We did so to avoid the risk of physical danger in interviewing one's driver on duty, as well as the risk of collecting biased data, since taking on the role of a passenger can pressure the driver to participate since the passenger writes a review after the ride. The principle of voluntary participation may be violated in such a case.

Prior to the interviews, we conducted a pilot study through open-ended interviews with three Uber drivers, aimed at uncovering how they interacted with the algorithm. We focussed on the research topic of understanding the human–algorithm interaction. We probed on the person's experience as a driver, their interactions with the Uber app (the primary way in which they interact with the algorithm), the way they executed their driving tasks and how their interactions with the app affected their work in general (navigating traffic, interacting with passengers, etc.). Analysis of the pilot study informed the development of a semi-structured interview protocol (see Appendix A).

We conducted the interviews either remotely (phone/videocall) or in person, depending on the driver's location, with interviews lasting 45 min on average. The demographic details of the study participants (cf. Table 2) include: driving experience (average 1 year, maximum of 2 years, minimum several weeks); gender (5 female and 10 male drivers); region (6 states across the United States) and age (ranging from 20's to 60's, 6 being in their 30's). We note that while we generated 26 questions in the protocol for thoroughness, interviewees often answered multiple questions at once. For instance, they provided a recollection of their most recent ride as an example of what they liked the least as well as reported features that they like or do not like. In this way, we did not need to probe again on those topics. All interviews were audio-recorded and professionally transcribed. We observed that the breakthrough issues and key findings already emerged in the first 10 interviews. However, we did not want to prematurely claim to have reached saturation, and thus probed through further interviews.

Netnography: Our second source of data draws from online forum posts of Uber drivers. We performed archival analysis on two online forums. We analysed discussion threads where Uber drivers shared their personal experiences about their work from the period January–December 2017. The forums (Uberpeople.net and Uberforum.com) are online platforms used by drivers to share stories, advice and complaints. Neither of these forums is affiliated with

TABLE 2 Interviewee characteristics

Pseudonym	Gender	Age	Has driven	State (USA)	Interview length
Kevin	M	20–29	1 year	Massachusetts	54 min 4 s
Jack	M	20–29	1.5 years	Massachusetts	36 min 10s
George	M	20–29	1.5 years	Massachusetts	54 min 38 s
Jim	M	20–29	1.5 year	Massachusetts	39 min 55 s
Amaya	F	30–39	1 year	California	22 min 47 s
Tanya	F	30–39	1 year	Washington, DC	35 min 5 s
Nick	M	30–39	<1 year	Massachusetts	30 min 8 s
Sam	M	30–39	<1 year	Vermont	57 min 3 s
Manny	M	30–39	1 year	Vermont	48 min 54 s
Greg	M	30–39	2 years	Utah	1 h 1 min 14 s
Michael	M	40–49	<1 year	Massachusetts	44 min 16 s
Mark	M	40–49	1.5 years	North Carolina	45 min 42 s
Jen	F	40–49	<1 year	North Carolina	1 h 10 min 7 s
Jade	F	60–69	<1 year	California	44 min 37 s
Kahn	M	60–69	2 years	California	57 min 59 s

Uber – they are independent communities of drivers. In order to post content, one needs to create a free account. However, no account is needed to search or browse the content of discussions, which is what we did. Therefore, we did not create an account; we observed the discussions as non-participants, without influencing them.

Our pilot study revealed that drivers' most common activities were: picking up passengers, driving, negotiating traffic and going to designated areas to follow fare incentives. We reasoned that these activities would form the majority of the driver's interaction with the algorithm. Since our objective was to study these interactions, we identified keywords that signified these activities in order to search for the posts. From the pilot study, we noted the terminology that interviewees used to describe such interactions: navigation (i.e., GPS), going where asked to (i.e., surge), getting paid (i.e., fares) and driving conditions (i.e., traffic). We drew on this terminology to identify the following keywords: GPS, Fare, Surge and Traffic. We further note that these keywords were used in the context of multiple tasks and matters important to the driver. The term *GPS* was used in all the key work activities of passenger pickup, drop off, driving and negotiating traffic, implying that mentioning GPS would likely indicate one or more of these tasks; *fare* symbolised their earnings, which was a primary concern for drivers; *surge* was the primary way to earn extra money and *traffic* encompassed the primary aspects of their actual driving tasks. We thus surmised that these keywords would collectively capture the drivers' key work activities and thus, their interactions with the algorithm.

In Uberpeople.net, each of the four keywords yielded ~10 pages of search results, with 10–15 discussion threads for each page, resulting in 100–150 threads for each keyword, on average. The four keywords returned ~500 threads. In Uberforum.com, each keyword yielded 300 threads, with a total of 1200 threads for the four keywords. Across the two forums, we analysed 1700 discussion threads. The number of posts in each thread ranged widely, from 2 to 15.

Webpage documents: We also examined Uber's website and other related websites (such as news articles) to gather information about Uber's app, driver policies, terms and conditions of work and other relevant aspects of the driver's work. This allowed us to partly understand how the app worked and potentially relevant policies. We compared the participants' responses with this information and were able to identify some points of driver misunderstandings or misaligned expectations, which informed our analysis.

3.4 | Data analysis

The analysis includes data from both interviews and netnography. We first analysed all the interview and forum text sentence by sentence to identify themes pertaining to the driver's interaction with the Uber app. We drew on the concepts from the role literature covered in our background section: role sending, role taking and role perceptions. These concepts corresponded with the following aspects of the human–algorithm interaction: (1) the nature of the actions/outputs of the algorithm (role sending); (2) the human's actions in response to the algorithm's actions/outputs (role taking) and (3) the human's perception of the algorithm in context of the interaction (role perceptions). For each data source, this yielded three sets of texts corresponding to each of these three aspects. Thus, we had a total of six sets of texts.

Next, we focussed on the three sets from the interview data. Those portions of text that indicated the three themes above (i.e., nature of the action of the algorithm, driver's response to algorithm's actions, driver's perception of the algorithm) were analysed through a combination of open and axial coding. Selective coding was applied to identify distinct sub-themes under each of the themes. In identifying the sub-themes, we iterated between the data and the concepts in the literature on organisational roles such as lack of clarity about instructions relating to tasks (e.g., sub-theme: 'unexplained' in Appendix B), conflict between different tasks (e.g., sub-theme: 'conveyed logically isolated tasks' in Appendix B) and ambiguous or inadequate information (e.g., sub-theme: 'did not convey essential information' in a timely manner in Appendix B). Our approach was aimed at making sense of the data in the framing of the literature concepts in order to identify the sub-themes. As we moved through the texts, we either performed open coding to categorise the emerging text into new sub-themes or axial coding to categorise it under existing sub-themes. Two researchers, one of them an author, initially coded 10% of the interviews and met to resolve any discrepancies in codes through discussion. Then, one of the researchers finished coding the rest of the interviews based on the agreed set of codes, discussing and resolving any ambiguities with the other researcher.

Next, we turned to the three sets of text from the forum threads, corresponding to the three main themes. A third researcher, also an author, took each set and analysed it for sub-themes, performing both open and axial coding. Open coding was done to identify new sub-themes under each theme. Axial coding was done against the set of codes that had emerged from the interview data. We found many of the same sub-themes, which validated and increased confidence in our findings from the interview data. Further, we found additional examples of these sub-themes, which allowed us to analyse the sub-themes better and augment our understanding of them. The final codes and their sub-codes are listed in Appendix B. We next present our findings. Names of all interviewees and forum members have been changed.

4 | FINDINGS

The algorithm[6] executed a number of functions. It matched drivers with passengers seeking to go from one place to another, gave drivers directions for picking and dropping them off, facilitated payments and provided navigation guidance. The algorithm was the only entity that conveyed work-related information to the driver. In response, the driver executed his or her work tasks. Furthermore, the algorithm also evaluated the driver's performance and determined rewards or consequences. To do this, it tracked the driver's workflow in terms of route travelled, distance covered, time taken and number of rides undertaken. The algorithm computed and communicated to the driver fare rates, money earned, passenger feedback and performance ratings. In this back-and-forth way, the algorithm and the driver interacted with one another in their respective roles. We elaborate on three sets of findings that describe this interaction and dynamics.

First, we describe findings about the nature of the actions of the algorithm, such as what sort of task-related instructions it conveyed to the driver and how it did so. The second set of findings relates to the driver's response to the actions of the algorithm. The third set of findings relates to the driver's perception of the algorithm's role and how the algorithm shaped important aspects of the driver's work and emotions. We share these findings in the following sections.

4.1 | Nature of the algorithm's actions

We found that the algorithm's actions had the following characteristics: (1) did not *explain* the *reason* behind its instructions; (2) asked the human to execute *tasks that were logically isolated from and in conflict* with one another; (3) *lacked a holistic understanding of the human's work* and (4) *did not convey essential information in a timely manner*. We next explain these characteristics of the algorithm's actions.

4.1.1 | Algorithm did not explain the reasoning behind instructions

The algorithm gave many micro-level instructions to the driver such as pick up this person, go to this location or accept two rides in this area within an hour to receive an incentive. However, the driver did not always feel it was clear what computational logic or reason led to the work information conveyed by the algorithm for key aspects of their work. For example, drivers were not given a reason for why they got an incentive (e.g., a higher rate) on a particular day. Jim, an Uber driver in his twenties, reflected on when he thought he would be able to catch another rate promotion:

> Sometimes they'll do promotions if you haven't driven in a while. If you drive a lot they just won't send them so I'm not sure if it's an incentive to get people who don't normally drive, or if they have some sort of formula that calculates, OK, this person drives all the time. Don't give him a promotion ‘cause he doesn't need to make more money. I don't know if that's true. [Interviewee Jim]

Here, Jim expresses confusion about why promotions are generated and is unsure about what might trigger him to receive another one. This also was the case in how rewards and punishments were communicated by the algorithm. One driver described how they were denied privileges to drive for Uber and not allowed to take rides. This was done without reason:

> Forum Member A: Been driving for them over 1000 trips and yesterday I tried to turn on the app and it immediately went back to the offline mode. I contacted customer support and later in the day got a message saying that I violated their terms of employment. 4.8 rating and no issues with customers that I know of. Any guesses?
>
> Forum Member B: Let me guess they refuse to tell you what the actual violation was right.
>
> Forum Member A: Correct. I asked for specifics and just got a reply stating ‘Your account has been suspended for activity that violates our terms and conditions. As [a] result, Uber has discontinued partnership with you’.

In the above, even upon requesting clarification, the driver was left in the dark as to why the algorithm made the particular decision. Such unexplained instructions from the algorithm added uncertainty to the driver's day-to-day tasks.

4.1.2 | Algorithm asked the driver to execute logically un-connected and conflicting tasks

Each instruction of the algorithm appeared to be produced in isolation, without reconciliation with past or future instructions. This meant that instructions often logically contradicted one another. For example, the algorithm would incentivise drivers to perform a certain task but then not follow up with the promised task. Drivers were urged through text and email to go to a specific ‘surge’ area of high passenger demand for a higher rate. This often happened when many people were trying to get to or from large events at specific places such as a sports stadium or during rush hour from office areas. However, upon reaching the surge area, interviewees often reported not receiving any ride requests:

> So when you try to go up there and go online to get the trip, sometimes the entire surge disappears and you will be waiting up there for like more than half an hour and never receive a trip. So many drivers maybe. Like a flow of drivers waiting around to pick people up. [Interviewee Kevin]

Kevin, an Uber driver in his twenties, expresses his frustration at being incentivised by the algorithm to go to a surge area, just to sit around without picking up any passengers. The fact that the original instruction was not connected to the subsequent ride request instruction was frustrating. He tries to understand the logical explanation for the disconnect but is ultimately unsure why this happens. This happened so often that drivers referred to it as 'chasing the surge' and were warned by others to avoid it.

Another kind of inconsistency occurred when the requirements of two different tasks were incompatible with one another. For example, drivers were incentivised to complete a minimum number of rides from a given pick-up area during a short time span. However, the drop-off destination could be too far for them to come back to that area in time. Jade, an Uber driver in her sixties, describes how:

> They would encourage drivers to come out at peak hours and then say if you want to drive, pick up passengers from this area between 5 o'clock and 7 o'clock, Monday to Friday, then we will guarantee that you make $20 an hour. But you need to make sure that you pick up two passengers at least within the certain zone etc. So I did find that to be a bit strange because there would be times I'd be driving a customer and they'd dispatch me to somewhere where I'd be far so I couldn't really make that two rides in an hour to get that guaranteed hourly rate. [Interviewee Jade]

She expresses dismay that the algorithm would show such inconsistency in its instructions.

4.1.3 | Algorithm lacked holistic understanding of the driver's work

The drivers perceived the algorithm to be unaware of the broader context in which the outputs were conveyed. One driver reported how this lack of understanding cost him:

> I dropped off a Uber rider to their destination. His friend decided they were not done partying for the night and wanted me to take him to another destination. He put in his request and instead of me getting the job another Uber driver 7 min away got it. My passenger was [already] in the car and was wanting me to take him. I really lost out. [Forum member M]

Here, the driver points out how the algorithm had no idea that this newly generated ride request was connected with the current ride. It would have been preferable for everyone involved if the driver could just continue driving this passenger to his destination. Instead, the algorithm treated the new ride as an isolated ride request rather than connecting that ride to the bigger picture. In general, drivers frequently expressed frustration that the algorithm did not understand the broader context of the user's goals. Drivers felt that such understanding could improve work conditions for the driver or improve her or his efficiency in relation to picking up passengers.

4.1.4 | Algorithm did not send essential task information to the driver in a timely manner

Drivers needed certain information to coordinate and plan their tasks well. However, even when the algorithm had the information, it often presented that information too late to inform the driver's decisions. For instance, drivers complained about not knowing a passenger's destination until after they had gotten into the car:

> And that's the one thing I don't like about it, about the app … it doesn't tell you where the person is going until you pick the person up and you start the trip. And then it tells you. Of course you can cancel it, but then who really wants to cancel a trip when you have the person already. You're there, you're ready to pick them up, and then you see, oh my God, they're going to [a far away place]. [Interviewee Tanya]

Here Tanya, a driver in her thirties, is left in a quandary when she finds out the destination. Having the information earlier would have helped her decide whether to take the trip at all. By presenting it so late, drivers were expected to make task decisions without essential details. Thus, the driver would have to take the time and effort to drive to the pickup location without knowing whether they would ultimately end up with a passenger.

4.2 | Driver's response to algorithm's actions

Our second set of findings describes the driver's actions in response to the algorithm's actions. We identified three types of driver responses: (1) *Executed* instructions; (2) *ignored* instructions and engaged in gaming or (3) used *workarounds*.

4.2.1 | Driver executed instructions

One response of drivers to the algorithm's actions was to execute the instructions given to them. It was also the case that many drivers just accepted instructions almost automatically because of the rapid pace at which they received them. They had to carry out work tasks at the pace at which the algorithm delivered them, with no time to reflect. For instance, Jen told us that:

> I wound up getting a ride that was a 2.1 surge and I didn't even know it till afterwards. I didn't even know it was a surge until after the ride was over because I was dropping one person off and before I'd even dropped the person off, I had already had a request for another ride and I had already accepted it. So I was already on my way on the other ride. I didn't even look, I just accepted the ride. [Interviewee Jen]

This rapid-fire of instructions made it difficult to evaluate the feasibility or desirability of taking a ride request. Jen conveys her feeling of being rushed and her lack of perceived control over making a more intentional decision about which rides she will accept. She just goes with what the algorithm proposes without even realising the consequences until a later time. This instance was a positive surprise, but other cases were not.

Drivers also executed instructions due to ambiguity about the consequences of not doing so; they speculated on the consequences of actions such as ignoring a ride instruction. As a result, a strong sentiment was that drivers had to accept most instructions despite their preferences: '*So I prefer not to do rideshares at all, but at the time you don't have much choice because you are not allowed to decline too many requests either*' [*Interviewee Jade*]. New drivers executed whatever instruction was given to them in an attempt to keep their acceptance rate high.

4.2.2 | Driver ignored instructions and engaged in gaming

Drivers also ignored instructions they thought were not correct. Here Amaya explained how she was assigned a ride that would take her too far out of the way towards the end of her shift:

> Sometimes [at the end of the day] it's counterproductive to drive another ride [far away] if you need to be somewhere by a certain time, like to hang out with friends or you have a date, or whatever. It's really annoying to be like at the will [of the system]. You'd like to make as much money as you can, but it's like sometimes the system isn't allowing for your specified preferences when matching with riders. [Interviewee Amaya]

Amaya mentioned she ignores many of these instructions that are impractical for her. We found that drivers had to balance their own needs and work schedule against instructions that would make it challenging to respect those time boundaries. Ignoring instructions that pushed too far on those boundaries was one way of accomplishing that.

Drivers also ignored navigation instructions that were suboptimal if they thought there were no penalties. For instance, Sam explained how he felt that having knowledge of a better route justified ignoring an instruction: '*No, it tells you like how much time (the suggested route) should take, but there's nothing, there's no penalties or anything, if you do not stick with it (the route) … There's no penalty on that because, again, you're the local person (who knows the route)*'. *[Interviewee Sam]* However, other drivers said they followed the navigation instructions scrupulously because they thought they would be penalised if they did not.

Drivers also engaged in gaming. That is, they tried to get away with ignoring instructions when they did not agree with them. Greg explains how he would decline rides and try to get away with as many refusals as he could. However, he was not always successful and explains the snag when he did not strategies well:

> Because they were sending me requests to go and pick someone 15, 20 minutes from the airport and if I didn't want to, I could decline it [on the app]. But then if I had too many declines in one day, they didn't like that. Closed my account completely. [Interviewee Greg]

Greg goes on to explain how he could still recover from that mistake by reducing the number of subsequent declines:

> They call it acceptance rate. 'They say your acceptance rate is too low … I usually brought it back up within a week and then they were happy. They'd send me another one saying you're fine now'. [Interviewee Greg]

This example illustrates how Greg games the algorithm to stay in the game of being an Uber driver.

4.2.3 | Driver used workarounds

Often, the driver was left to make up for a deficit in the algorithm's instructions. For example, when the GPS gave road directions that were suboptimal or incorrect, drivers had to come up with workarounds:

> Forum member O: Bad navigation is the second highest [problem]. You will learn where GPS screws up in the city. I combated this by saving good addresses for common destinations in Boston that also have GPS issues. Back bay area, Newbury Street will often try to send you on a public alley instead of on the correct st. Watch for this. South station is another one that GPS fails on due to it being so close to 93. I used points for the train side and the bus side. The prudential tower, otherwise known as 800 Bolyston street, is another bad one. I use '821 Bolyston street' for this one.
>
> Forum member P: GPS has problems with anything on Atlantic Ave. One should ignore the GPS when doing pickups or dropoffs on Atlantic Ave.
>
> Forum member Q: Said one pax from Cambridge 'I'm so glad you know your way around Boston. I had an Uber driver from Springfield who was not familiar with Boston and did not know where Newbury St is and tried to drop me off in an alley'. Yep, Uber GPS will have you drop off in the alley behind Newbury Street!

To counter the misleading navigation instructions, drivers had to learn better routes. However, drivers complained that making up for the deficits of the algorithm was '*Ridiculous!*' and that '*there's a vast amount of knowledge needed to avoid looking like a fool…*' *[Forum Member T]*. The drivers performed much unseen workaround human labor to ensure smooth task execution.

4.3 | Driver's perception of the algorithm

The driver perceived the algorithm in four ways: (1) it represented *multiple types of co-workers*; (2) it was *impersonal*; (3) its actions *could reduce the driver's work performance and earnings* and (4) its actions could *lead to negative emotions for the driver*. The following sections describes these perceptions.

4.3.1 | Algorithm as multiple types of coworkers

Drivers perceived the algorithm to be multiple types of co-workers. Navigation instructions, for example, were treated as a task from a knowledgeable peer, which would at times be followed and at other times could be ignored. Ride requests were a different matter. Following these instructions (or not) was related to drivers' performance evaluation. In this case, the algorithm was perceived as the boss that determined the rates they would get and whether they would get any rides at all.

Drivers in some instances subscribed to a view of themselves as being in control and the algorithm as a peer to support them:

> if I don't want to pick someone up again then I don't have to, you know. That's why I gave them a low rating … so I feel like I have some sort of control over my own business. [Interviewee Greg]

However, in other instances, the same drivers realised that they were not actually in control and the algorithm seemed like a boss. They were at the whim of the algorithm's instructions:

> I think that's what is frustrating is they act like you get your own business and you set your own hours and get the benefits of that but then you get an email to say we're going to drop your account because you didn't accept a high enough percentage of rides. [Interviewee Greg]

Frustration arose from such contradicting perceptions.

4.3.2 | Impersonal algorithm

The algorithm was impersonal. When it gave out an instruction that the driver found difficult to execute, he or she had to make the decision about whether to carry out the task, without any discussion with the algorithm:

> I would have been done for the night, but no, they were going to the airport and I was 5 minutes away from my apartment. I needed to go to bed. So what are you gonna do, kick them out say, 'Oh sorry you're going really far. I'm not going to bring you' [Interviewee Jim]

Here the algorithm has given the human a task that goes against his entered preference of going towards home at the end of the day. Despite this mistake, it is the driver who had to either give the passenger the bad news of not going to the airport, without the option of consulting with the algorithm, or choose to satisfy the passenger by proceeding with the ride in order to avoid getting a bad rating. While the human was torn with their feelings of empathy when considering the social dynamics associated with this customer interaction, the algorithm remains silent and does not factor any such emotions into its insistence on this task.

4.3.3 | Algorithm's actions could reduce the driver's performance rating and earnings

The algorithm could negatively impact drivers' earnings and performance ratings. For example, Kahn described how the algorithm's incomplete information about riders prevented him from being able to finalise a pick-up. This jeopardised his earnings and possibly his performance rating:

> Sometimes when I go to pick up the Uber Pool customer, there are two riders. They [each] pay one rider fee, but they each have 2 big luggage that fill up the car … I already had two passengers in the car, there come another two with a lot of luggage. I have to reject them. Ask them to take another car. [Interviewee Kahn]

Kahn explains how frequently the lack of information about additional bulky items such as luggage, wheelchair, pet, or child seat made it difficult to know whether he would be able to fit the next rider. He spent time and fuel to reach the passenger, only to find that he was unable to give him or her a ride. He explains how he was not only penalised for refusing to accept the ride, he also incurred the costs of fuel and opportunity cost of lost earnings from not picking up another rider.

The algorithms' outputs were often instrumental in the driver receiving bad ratings, which could affect his or her eligibility to work. A forum member described how the passenger's rating of a driver can take a hit when the driver is faced with a conflict between what the algorithm (GPS) suggested and what the passenger wanted:

> Some pax [passenger]will rate the route you take because they don't like how you went but you are just following Uber's route … This is my new pet peeve when Pax rate a driver they get several buttons to choose if it is less than 5 stars.
> professionalism, cleanliness, driving etc. one is Navigation … Pax think they are rating the navigation not necessarily the driver … So if they had a good driver who they liked, but didn't like the route Uber chose, why should the driver take the hit? That is really not on the driver. [Forum Member T]

Here, the driver received a bad rating for following the GPS; some passengers 'complain' about over reliance on GPS. However, others are suspicious if a driver deviates from it. What made drivers even more anxious is that it is not clear how much customer ratings factor into their performance evaluation, nor to what extent they can deviate from the app-prescribed GPS route before the algorithm would penalise them for taking an inappropriate route.

Other impacts on earnings were more direct. When drivers rushed to pick up a passenger during a surge only to have the surge end before arriving, they had to forgo the surge earnings and yet spend time and fuel. Other times the extent of the damage was beyond a single ride – drivers described how if someone brought in extremely strong-smelling foods, it took time to have the car cleaned or to wait for it to air out. The algorithm did not account for these types of situations in determining compensation.

4.3.4 | Algorithm's actions could lead to negative emotions for the driver

Commonly, drivers expressed emotional irritation when they felt they were forced to take on a task even when the algorithm instructions were logically inconsistent:

> When it says drive towards your destination and pick up rides on the way to your destination, there are times like, let's say I'm in Boston and I want to come back to Waltham. I'll … drive west [towards Waltham] and I'll get a ride [on the way] and I think, 'Oh I'm dropping off west like Watertown or Waltham or some area around here [Waltham] on the way.' But, no, it's like taking me back to Boston. [Interviewee Jim]

This was a frequent irritation, especially when drivers wanted to finish their shift. Several drivers expressed frustration at similar experiences. They felt they could not win either way. If they refused to drive the passenger, they felt bad about letting the rider down and feared for their own performance ratings. If they carried out the ride, they remained frustrated and tired, staying on shift for longer than they wanted. It was an emotional lose-lose situation.

We also observed more extreme and longer-lasting psychological effects on the driver. Below, a driver describes how the algorithm's inability to convey contextual information about a passenger led to her having to stop driving for the rest of the day:

> I got a guy in the car (was it last week or the week before?) that smelled like he'd smoked two joints inside of a closet. Oh yeah. And that's not the first time either. I drove fifty feet and I said, 'I am cancelling now, you've got to get out'. And I hit Do Not Charge Rider because I just didn't want him in my car… I was so upset and I immediately drove away … somebody reeking of pot at 10:30 in the morning, that bothers me. I actually had to … So I had to shut off the app. I had to, you know, just … I completely shut down because it just, for some reason it just shook me up that much [Interviewee Jen]

Here Jen not only loses income from cancelling a ride, but for the rest of the day, she has to cope with the emotional trauma that she experiences. Other drivers described situations when intoxicated passengers who had entered a wrong address in the app verbally abused them when they refused to execute the passengers' instructions to go to a different address. The algorithm takes the passenger input at face value and does not know about the context of such situations. These experiences were so negative that several drivers talked about how they avoided late night driving or going to bars to try to avoid such situations.

5 | DISCUSSION

We conceptualise the algorithm as the *role sender* (Kahn et al., 1964) who sent task-related information to the human. From the human's response, we see that they acted on the work tasks given to them by the algorithm. The human was thus the *role taker* (Horrocks & Jackson, 1973). In Figure 1 below, we depict our theorization of the interactions between the algorithm role sender and human role taker. In summary, the algorithm role sender had multiple roles that were entangled with one another as shown by the chaotic lines in the role-sender's box on the left. It executed actions of role sending that were unexplained, logically isolated and conflicting, context unaware, and untimely, and it communicated the associated information to the human role taker. The human role taker experienced algorithm-driven role conflict and role ambiguity as a result of the algorithm's role-sending actions as shown in the role-taker's box on the right. The human's consequent response was, executing task actions and experiencing cognitive reactions, as shown by the two blue arrows in the role taker's box respectively. The task actions were of three types - task execution as instructed, task execution not as instructed but through workarounds, and task non-execution in the form of ignoring instructions and gaming the algorithm. In addition to engaging in task actions, the human experienced cognitive reactions. These were of two types: a lack of psychological well-being and negative emotions towards his or her work role. While the task actions were recorded through the app interface and fed back to the algorithm role sender, the cognitive reactions remained within the human role taker and were not communicated back to the algorithm role sender.

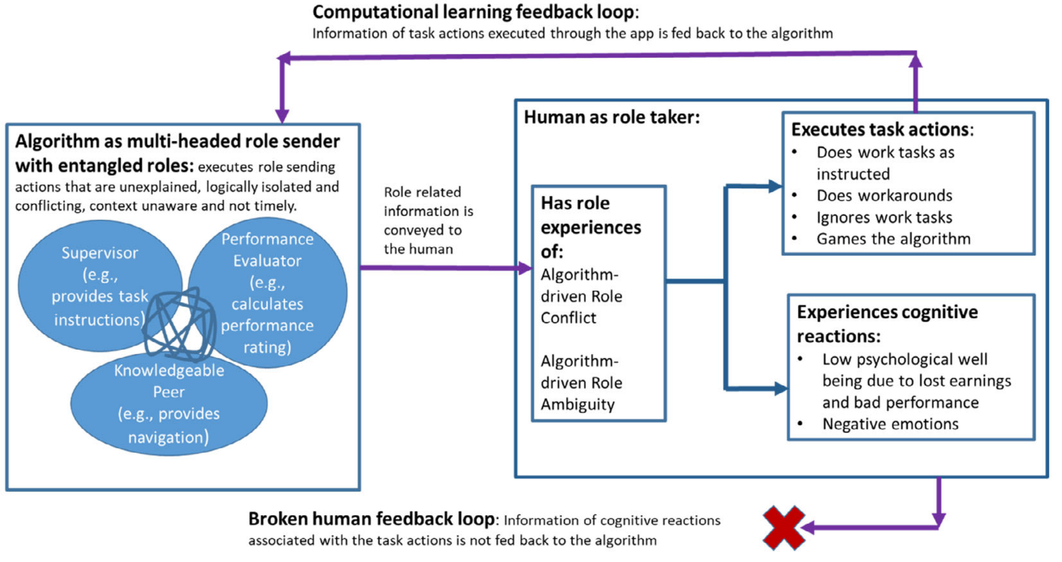

FIGURE 1 Theorising role interactions in algorithmic work

5.1 | Algorithm as multi-headed role sender with entangled roles

The algorithm communicated information of three types and each was associated with a different role. The first type was task instructions - it instructed the driver about which passengers to pick up, provided pick-up and drop-off locations, and decided what price the customer would pay. This was the supervisor role (Horrocks & Jackson, 1973; Kahn et al., 1964). The second type was information related to the human's performance. The algorithm tracked the driver's workflow in terms of routes travelled, distance covered, time taken and number of rides undertaken. It also solicited customer input. Based on all of this information, it calculated and communicated fare rates (e.g., promotional rates for surges), money earned, passenger feedback and performance ratings to the driver. This combined the roles of supervisor and performance evaluator. The third kind of information was about task-related suggestions such as driving directions. The human often perceived this as a knowledgeable peer role - these were work-related suggestions which did not always have to be followed, depending on road conditions and the human's knowledge of the situation. We thus theorise the algorithm as a *multi-headed role sender* because the human perceived it as having not one, but multiple roles. In contrast, in human-human role interactions, a particular role sender typically has one role. The role taker has an understanding of 'who' the role sender is, vis-à-vis organisational hierarchy and work relationship (e.g., supervisor, line manager, peer; Kahn et al., 1964). The role taker can gauge the extent of the role sender's organisational influence and authority and respond accordingly (Horrocks & Jackson, 1973). For instance, work communicated by supervisors is perceived as more pressing (e.g., Kahn et al., 1964).

Further, the demarcation between the roles was not clear due to multiple layers of connected algorithmic calculations. For example, when the algorithm was conveying navigation instructions as a peer, even if the human disagreed and did not follow the instructions, they were aware that their actions were being recorded and could potentially negatively affect their performance rating by the algorithm in the role of supervisor and performance evaluator. Thus, not only was the algorithm a multi-headed role sender, the roles were *entangled* in the same interaction. Therefore, there was *rapid switching* of the algorithm's roles even within the same working session. During the course of a ride, the algorithm took on the role of supervisor (passenger pick instructions), peer (navigation instructions), and supervisor/performance evaluator (registering passenger feedback and calculating driver rating). As Table 1 shows, recent research in the context of ride sharing has commented on the (single) role of the algorithm as a 'boss' because of the drivers' feeling of being tracked (Möhlmann et al., 2021). We go beyond this and theorise a broader scenario suggesting that the algorithm is not perceived as having a single role, but many roles which are transitory and entangled.

5.2 | Human as role taker experiences algorithm-driven role conflict and role ambiguity

The human found the algorithm's multi-headed-ness unsettling. It created *conflict*. Due to logical isolation, the instructions communicated by the Uber app and coming from the different roles were often mutually incompatible. The algorithmic computations did not take into account the inconsistencies between different instructions. For example, drivers got incentives to pick up customers from a certain area (performance evaluator role). However, they also had to execute a minimum number of rides to receive the incentive, no matter how far away they had to take the rider (supervisor role). Receiving such inconsistent directions from the algorithm in multiple roles left the human in a quandary attempting to satisfy multiple conflicting instructions. Another kind of conflict manifested when the algorithm came up with tasks that provided 'no-win' tradeoffs, coming from different roles. For example, drivers choosing between following a surge instruction (supervisor role) and potentially facing the prospect of no customers because of the sudden influx of drivers, and not following the surge but risking to miss out on the higher rate and a lower performance rating because of non-compliance (performance evaluator role). This is a novel type of intra-role conflict that happened because the driver received contradictory information, not from *different entities* as in the case of traditional role conflict (Anicich & Hirsch, 2017), but due to the entangled roles of the same entity, the algorithm. Moreover, due to the continual and rapid switching in the algorithm's role, the human was forced to quickly transition between different types of role behaviours, for example from that of supervisee (when receiving ride instructions) to that of peer (for route directions). Indeed, even a single action of the algorithm (e.g., giving route instructions) could embody multiple roles (in this case, the friendly peer and the evaluator). Due to its multi-headed nature, the algorithm was essentially *multiple and different role senders*, each sending distinct and incompatible role information to the human.

Further, because of the algorithm's lack of holistic understanding of the driver's work, it was not context aware. There was conflict between the algorithm's instructions and the human's judgement about what was expected. For example, when the algorithm communicated information that contradicted what the driver expected (e.g., a different GPS route than one the driver expected to be faster), the driver was often torn between which action to take. Or, deciding whether to follow instructions to drop a passenger off far away for their last pickup of the day, despite having specified in the app that they were headed home and being almost there. This was an instantiation of classical role conflict where information by the role sender conflicts with what the role taker expects (e.g., Kahn et al., 1964).

As a result of these conditions, the human experienced incompatible and contradictory expectations in their work. We characterise this as *algorithm-driven role conflict*.

The human further experienced *ambiguity* because the algorithm did not provide clarity regarding key aspects of their work role. Due to unexplained reasoning, the driver received work instructions from the different role senders such as ride assignment (supervisor), route navigation (peer) and surge chase instructions (supervisor), without understanding why. Furthermore, the driver did not understand how his or her actions would be evaluated. For example, it was not clear to the driver what sorts of work actions would be compensated well (e.g., to chase/not chase a surge or follow/not follow the suggested navigation route). The algorithm did not explain how earnings were calculated, leaving drivers to guess what they needed to do to increase earnings. They often speculated reasons for low earnings and the type of actions they should be taking to avoid it.

The algorithm did not provide essential task information such as the passenger's space requirements in a timely manner; the human was left to figure out what do. There was haziness in how different pieces of information recorded by the algorithm (e.g., passenger rating, number of rides, number of refusals) contributed to the driver's performance evaluation. Incentives and rewards (e.g., surge opportunities), compensation (e.g., payment rates), ratings and penalties were retrospectively calculated based on recorded driver actions. Yet, it was not clear to the driver how this was done. Thus, the driver was unsure how to improve his or her performance. Such lack of clarity is referred to in the literature as role ambiguity (Kahn et al., 1964). It arises from lack of information required for adequate performance of one's role (Peterson et al., 1995). In the case of algorithmic work, it was due to inadequate and partial information provided by the algorithm in the different and entangled roles; we conceptualise this lack of clarity as *algorithm-driven role ambiguity*.

The literature has articulated a number of issues associated with human-algorithm interactions as we described in Table 1. We suggest that these two concepts can partly explain these issues.

5.3 | Broken loop learning in algorithmic work

We theorise the human's reaction to algorithm-driven role conflict and role ambiguity in a two-fold characterisation. The first focusses on task actions. In many instances, the human addressed the given work tasks by executing them as instructed. For instance, picking up rides, going to the destination, following a reasonable route, or following a surge announcement. In other instances, the human did not execute the task as instructed but executed workarounds such as doing the task in a different way (e.g., following a different navigation route than what the GPS suggested). In yet other instances, the human ignored the task altogether (e.g., by refusing a ride, refusing to follow a surge) or gamed the algorithm (e.g., switching to the rider app and waiting for an opportune time to turn on the driver app, to control incoming ride requests). The algorithm automatically recorded these task actions, as our data shows. For example, when the human was unable to give a ride to an airport-bound passenger because they did not know beforehand the passenger had excess luggage that would not fit in the car, the algorithm recorded this as a refusal to take the ride. In other words, the human's task actions were recorded as emotion-free actions. However, they were not so.

This brings us to the second reaction of the human, which was cognitive in nature. The human did not have certainty regarding key aspects of their work. On many occasions it was not clear how drivers could increase their performance rating or improve their earnings. They thus experienced anxiety and dissatisfaction over the lost earnings. They did not know to what extent the algorithm had the ability to hurt them or what would happen if they did not follow the algorithm. When they tried to game the algorithm, such as by turning off the app near a bar to avoid drunk customers, or near an airport to avoid long-distance rides, as our data shows, they did so because they were worried they would get an undesirable passenger match. While the algorithm registered these actions (i.e., logging off the app), it did not register the reasoning behind them because it could only record those actions which were entered through the app. Neither did it record the humans' frustrations when they followed difficult instructions (e.g., pick up passengers travelling a long distance when they were ready to stop for the day).

Role theory suggests that role senders need to obtain feedback from role takers in order to modify role expectations, if necessary (Gross et al., 1966; Horrocks & Jackson, 1973; Kahn et al., 1964; King & King, 1990). Such feedback forms the basis of effective role sending; it should encompass information on task execution (e.g., what the role taker does), task performance (e.g., how the role taker performs), and cognitive role perceptions (e.g., what difficulties the role taker might have experienced).

In algorithmic work, we theorise that feedback should happen through two pathways from the human to the algorithm. The first pathway is based on the human's task actions which are automatically recorded through the app interface. They form the inputs to AI-based learning algorithms and are used to calculate subsequent outputs regarding future tasks, performance and incentives. This is shown by the computational learning feedback loop through which the actions recorded by the app are fed back. The second pathway relates to the human's cognitive reactions such as the frustrations, dissatisfactions, anxieties and reasoning associated with them.

However, these are not recorded by the app and thus are not communicated back to the algorithm for future computations. For example, as our data shows, the driver does not (cannot) 'tell' the algorithm that they did not understand why their passenger rate decreased suddenly. They might assume that this happened because of a bad customer rating and might in response do extra things for the passenger. The algorithm cannot be aware of and learn from these cognitive reactions because they are not recorded by the system. The algorithm's learning regarding the human's emotional reactions simply does not take place; it is non-existent. While the human has to continually deal with algorithm-driven role conflict and role ambiguity, the algorithm never learns about what the human experiences. This ‘human’ feedback loop is therefore ‘broken’ as depicted in Figure 1. We characterise this as *broken loop learning* by the algorithm. There is partial learning - based only on the computational learning feedback loop, but impoverished and thwarted with respect to the human feedback loop.

In summary, it is evident how the algorithm as role sender cannot develop a complete understanding of the human as role taker, cannot adjust its subsequent role sending actions, and cannot respond deliberately (except by happenstance) to address the human's algorithm-driven role conflict and role ambiguity. This is in contrast to the situation between human role senders and human role takers, where different forms of feedback can be communicated from the latter to the former (Kahn et al., 1964).

6 | CONTRIBUTIONS AND IMPLICATIONS

In algorithmic work, the efforts of humans and algorithms intertwine in the execution of work. In this study we find that they interact, whether as peers or as supervisor and subordinate. For convenience, we have, in this paper, referred to such work relationships as co-worker relationships regardless of the specific type of relationship. We contribute to the IS literature on algorithmic work by investigating the role interaction between algorithm and human; we theorise how the algorithm works as role sender, how the human reacts as role taker, what the algorithm does and does not ‘learn’ and the implications of incomplete learning. Below, we lay out our study's theoretical contributions, potential for further research and practical implications.

6.1 | Theoretical contributions

Researchers are calling for a human-centered approach to the study of algorithmic work that considers the perceptions and behaviours of the human, rather than just focussing on the features of the algorithm (Glikson & Woolley, 2020). Such an approach is more holistic because it takes into account the human-algorithm interaction. We develop novel theorization of the interaction between humans and algorithms, unpack its key aspects, and thus unveil challenges for organisations aiming to implement algorithmic work. We do this by adopting the lens of organisational roles and conceptualising the algorithm as role sender and the human as role taker. This framing allows us to understand the human-algorithm interaction in light of its problematic properties and to consider how it can be improved. We extend the IS literature in a novel conceptual direction by investigating the micro-level context of the human's day-to-day tasks and interaction with the algorithm. Our investigation leads us to suggest that human-algorithm interaction characterising algorithmic work constitutes the lived experience of problematic perceptions for the human and incomplete and obstructed learning for the algorithm.

6.1.1 | The algorithm learns, but how well?

The basis of algorithmic work is the ability of multiple layers of algorithms to learn about organisational tasks through computational learning techniques applied to process data and to execute operational and managerial actions based on such learning. The efficacy of algorithms depends on how well they continually learn, improve and refine their results based on new data. We find conditions that hinder such learning. Specifically, the algorithm's learning does not take into account the human's emotional reactions and is blind to the human's reasoning behind his or her task-related actions. It records the task actions as ‘systems inputs’ that are emotion free, and focusses on improving the technical accuracy of its outputs. As a consequence, broken loop learning emerges. Due to broken loop learning, the algorithm cannot improve or adjust its approach in a way that can mitigate algorithm-driven role conflict and role ambiguity for the human. One may well ask, ‘The algorithm improves, but what does it improve and for whom?’ To our knowledge, ours is the first study to suggest the notion of broken loop learning and identify its implications for algorithmic work.

In traditional human-human role relationships, the role sender, such as a supervisor, would be familiar with the role taker's tasks and how they relate to one another (Horrocks & Jackson, 1973). In contrast, the algorithm role sender's outputs are connected to one another in the *computational* sense as a sequence of tasks (e.g., pick up passenger, drive to destination, drop off passenger), but not in the *contextual* sense (e.g., motivations for driving, driving preferences, driving habits). Its understanding of the human's context of work is partial and its role sending is done under conditions of such partial knowledge. The human is left to tackle the consequent contradictions and lack of direction and guidance. Studies have commented on the lack of consciousness (Harari, 2017), sentience (Sprague, 2015) and thinking (Gray & Suri, 2019) of algorithms. The role framing allows us to go further and explain how and why this happens. We take a socio-technical approach to analysing algorithmic work. In other words, we highlight both the technical characteristics of the algorithm and the reactions of the human that are hidden from the algorithm.

By unpacking the algorithm's role sending actions, we also contribute to the role literature in that the role sender's actions have been relatively under-researched (Ebbers & Wijnberg, 2017). By focussing on the algorithm as well as the human, our study brings to the surface problematic aspects of algorithmic role sending. Namely, we uncover that role sending information in algorithmic work is unexplained, incomplete and conflicting. It comes simultaneously and rapidly from multiple entangled roles by the same role sender. It is (under) informed by broken loop learning. The literature examines role conflict when the role taker experiences role conflict due to contradictory actions of multiple role senders (Anicich & Hirsch, 2017). We reveal a distinctive aspect of algorithmic role conflict in that it emanates from a single role sender, the algorithm, which takes on multiple and entangled roles in a rapidly continual fashion. We believe role theory researchers will find this of interest in comparing with human role sending.

6.1.2 | Going from an instrumental to a humanistic approach for framing algorithmic work

Research has largely adopted an instrumental view of the problematic situations of algorithmic work. For example, it has focussed on the transparency of technical computations such as explain-ability, observability and system fairness including privacy of individual data and bias minimization of protected attributes (Hosanagar & Jair, 2018; Parent-Rocheleau & Parker, 2021). We develop a sociotechnical view that focusses on the human's interaction with the algorithm. Algorithm-driven role conflict and role ambiguity reveal novel IS-centric ways in which role conflict and role ambiguity can emerge in algorithmic work. More importantly, they also unveil complex organisational challenges in mitigating them. For example, it is easy to suggest that increasing the transparency of algorithms can reduce algorithm-driven role ambiguity. However, greater transparency makes algorithms vulnerable to gaming (Hosanagar & Jair, 2018) and increases the possibility of imitation of the algorithm's logic (which is often a strategic asset) by competitors. Further, even if the human role taker does not agree with the logic presented by a more transparent algorithm, they may still feel bound to execute its instruction because they may perceive the algorithm in a particular role, e.g., as a supervisor. Thus, the matter of ignoring the algorithm's instructions is not straightforward, even if transparency is present.

The concept of broken loop learning suggests a lack of equilibrium between the technical and social aspects of algorithmic learning. If left unchecked over time, the algorithm would become progressively less knowledgeable about the context around the human's task actions. Its role sending would become increasingly divergent from the human's actual situation, leading to greater role conflict and role ambiguity. One way for the human to react to this is to simply accommodate the algorithm. We observed instances of such behaviour where humans tried to execute the algorithm's instructions even if they were inconvenient or detrimental to the human's well-being. For instance, accepting ride sharing requests that were far away despite wanting to sign off for the night. Another fall-out of prolonged role conflict and role ambiguity is the role taker's lack of trust on the role sender. Lack of trust of algorithms is an important theme in the literature (Glikson & Woolley, 2020); our study uncovers a possible cause.

AI-based algorithms currently work on correlational rather than causal models, a problem for which preliminary technical solutions such as causal inference models are being investigated (Prosperi et al., 2020). However, broken loop learning serves as a caution, that even if such models (when they mature) were to be applied in algorithmic work, they would address the computational learning loop only. The algorithm would still not be fully cognizant of 'why' things happen, unless the broken loop that carries the human's cognitive reactions is repaired. Our focus on the lived experience of the human takes into account the 'voice' of the human in improving the algorithm, rather just the automated task inputs, allowing for a more humanistic approach and taking an important step towards mitigating the precariousness (e.g. Popan, 2021) that is associated with this type of work.

6.1.3 | Sociotechnical levers in the design of algorithmic work

Research shows that role senders should continually and iteratively adjust their role sending in response to feedback from role takers for effective role interactions (Chen et al., 2013). Our study suggests that it is necessary to attend to both the machine learning feedback loop and the (broken) human feedback loop in the design of algorithmic work and algorithms in order to facilitate such effective role interactions. While the algorithm as role sender can modify its outputs based on information about the human role taker's *task actions* because they are automatically captured by the interface, it cannot respond to the human's *cognitive reactions* despite them being equally important. Algorithmic work design should enable the human to ask questions, seek clarifications and provide feedback regarding the confusions, discrepancies and frustrations emanating from the broken feedback loop. It is possible to facilitate this through design features in the app interface, such as through form and free text entries. Such measures should be complemented with human feedback captured outside the automated process to address the intricacy of the exchange in an effective and sensitive manner. *The joint content of both the app and human enabled exchange should provide inputs for the algorithm's further learning*.

Traditionally, a particular role sender has a single role (e.g., Gross et al., 1966), in contrast to algorithmic work where the human perceives that they are interacting with a multi-headed role sender. Algorithmic work should be designed to be responsive to the human's experience of algorithm-driven role conflict and role ambiguity. This can be done through complementary technical and social means. For example, a high level of transparency vis-à-vis the algorithm's outputs may not be possible or desirable. In such cases it may help to sensitise and guide the human with regard to the different roles that the algorithm could take, so they can make sense of their experiences. To alleviate algorithm-driven role conflict and ambiguity that arises from conflicting and logically unexplained information conveyed by the algorithm, it may help to at least convey to the human that algorithms deal with large numbers of parameters and datasets and are complex so that their outputs may occasionally be incomprehensible. Providing instructions on what the human should do if they do not understand would give some assurance. Such communication can be designed through the app or channelled outside it.

By suggesting such new design aspects, our study addresses calls for understanding how algorithms should change in response to ongoing human-algorithm interactions (Rahwan et al., 2019).

6.2 | Future research, boundary conditions and limitations

In focussing on the human-algorithm role interaction, our study draws attention to the relational exchange that takes place between humans and algorithms in algorithmic work. We suggest that future research should investigate ways to further understand and elevate the quality of this relational exchange. Research on algorithm and interface design should consider how to address aspects such as lack of context awareness and unexplained outputs through appropriate nudges and cues provided to the human. Research on work design may consider examining how individuals make sense of the different roles of the algorithm as well as strategies for transitioning and segmentation. Work design scholars could also examine how to alleviate the possible lack of fairness (Kordzadeh & Ghasemaghaei, 2021) that can arise from algorithm-driven role conflict and role ambiguity. Emerging studies suggest that the roles of supervisor and subordinate can be fluid and shift back-and-forth (Baird & Maruping, 2021). Future research could thus examine if there is a supervisory role of the human and a subordinate role of the algorithm, or if the algorithm can become a role taker and the human a role sender. Control theory can be used as a possible theoretical framing since algorithms are increasingly tasked with enacting the controls previously administered by human managers in order to guide the behaviour of human subordinates.

Broken loop learning highlights an impoverished aspect of human-algorithm interaction. It highlights the risk of developing agentic algorithms (Baird & Maruping, 2021) that interact with humans but do not fully know, and cannot react to, what the human experiences. Future research should therefore look at ways to repair the broken loop by examining how feedback on the human's cognitive reactions can be incorporated into the design of algorithms (e.g., learning strategies), work processes and interfaces (e.g., by capturing human cues). Consequences of sustained algorithm-driven role conflict and role ambiguity such as depletion of cognitive resources (e.g., Ashforth et al., 2000) should also be considered. Our findings can be extended to human-robot interaction. Anecdotal evidence suggests[7] that the interaction between humans and robots is expected to be one of the defining tensions of the modern workplace (e.g., in manufacturing, retail, hospitality, logistics and distribution, construction) because humans working with robots perceive robots to be relationally inscrutable.

Our theoretical insights are subject to certain contextual boundary conditions (Busse et al., 2017) that suggest specific contexts to which they could be generalised (Whetten, 1989). The notion of algorithm as role sender and human as role taker, together with the concepts of algorithm-driven role conflict and role ambiguity and the associated effects are applicable to different types of algorithmic work (e.g., algorithm-based ride sharing, delivery and micro-work on crowdsourced platforms). We expect that the fallouts associated with broken loop learning will be more prominent in algorithmic work where the human undertakes repetitive tasks within a physical workflow, e.g., in algorithm-based ride sharing or delivery, rather than in algorithmic work that deals with discrete and not necessarily similar micro-tasks such as those on M-Turk.

A limitation of our study is that it assumes the technical 'correctness' of algorithms, in that we assume the algorithm's outputs are consistent with its design and there is no technical malfunction. While this is a reasonable assumption (the Uber algorithm has large scale commercial deployment), it does not account for situations in which the human might need to respond to actual technical mistakes. Algorithms in algorithmic work are complex and genuine technical mistakes in design are not improbable. Future research should examine rectification attempts concerning both technical solutions (i.e., the machine learning feedback loop) and human feedback and assurance (i.e., human feedback loop). Another limitation is that we confine our focus to the algorithm's role sending. Future research should consider interactions with role sending of other entities such as human co-workers, e.g., as in the case of ridesharing taxis, customers.

6.3 | Managerial and policy implications

Algorithmic work is prompting a two-pronged response. From the world of managerial practice, senior executives and CEOs are increasingly held to account for potential negative effects on those who actually do the work

(Rosenblat, 2018). Concurrently, policy makers and governments are looking at whether employment regulation is keeping pace with the changing world of work (e.g., Taylor et al., 2017). Indeed, various policy-informing studies have put forward definitions of what 'good work' should look like; attributes relevant to our study include worker satisfaction, well-being, and autonomy (Cheese, 2017; UK Government Industrial Strategy White paper, 2017).

Organisations with business models or key processes relying on algorithmic work can use our findings to better understand the efficacy of their algorithms' learning and associated effects on their human workforce. They may benefit from recognising that even as human workers face algorithm-driven conflicts and ambiguities, they do not have the opportunity to convey that back to the algorithm, their primary co-worker. There is a stifling of the full expression of their lived work experience, to the detriment of their wellbeing. This mirrors ethical concerns in the literature (e.g., Gal et al., 2020) suggesting that datafication and opacity embedded in algorithms hinder organisational members' ability to fully develop their virtue. While virtue is not the focus of our study, what is clear from our results is that the broken human loop does not aid in good work. Organisational leaders are increasingly managing complex human –algorithm systems (Glikson & Woolley, 2020). Our study makes the case for having resources (humans and/or IS) to repair the broken loop to enable communication between the individual and the organisation. For example, companies can gather feedback from humans regarding their cognitive and emotional experiences with the algorithm (e.g., through call/support centers, surveys, or formally scheduled sessions such as focus groups), which they can analyse and incorporate into algorithm and work design.

For policy-informing bodies, we highlight the need for policies that focus on preserving the work-related wellbeing of individuals engaged in algorithmic work and maintaining the 'decency' of such work. Ongoing algorithm-driven role conflict and role ambiguity may be detrimental to both. Organisations, especially those having temporary workers, may not have an incentive to mitigate them. Indeed, algorithmic workers are being referred to as digital precariat (Popan, 2021). Regulatory policies are thus needed and may be key to a sustainable foundation for this type of work.

6.4 | Concluding comments

Our study examines human-algorithm interactions in the framing of organisational roles. In doing so, it develops a socio-technical explanation of possible problematic scenarios in algorithmic work with regard to both the algorithm (i.e., broken loop learning) and the human (i.e., their ongoing experience of algorithm-driven role conflict and role ambiguity). We hope that scholars will build on our study to further examine human-algorithm interaction with a view to improving it.

DATA AVAILABILITY STATEMENT

Research data are not shared.

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ENDNOTES

[1] An 'algorithm' is defined as a 'finite set of rules which gives a sequence of operations for solving a specific type of problem' (Knuth, 1997, p. 4). Applied to business processes, it is a software program that takes in business-specific data, applies computational logic, and provides outputs (Aho et al., 1983). The computations are both scripted (i.e., containing logic embodied by a fixed set of instructions until a solution is reached) or AI-based (i.e., containing logic that provides learning-driven and probabilistic outcomes based on the data fed into it; Faraj et al., 2018).

[2] We use the term co-worker to refer to those who work in the same organisational setting, irrespective of their position in the organisational hierarchy.

[3] See for example, https://documents.latimes.com/california-labor-commissions-ruling-uber-employee-status/.

[4] Studies on societal roles focus on gendered considerations of skills, careers, labor market participation and occupations, and on ideal expectations such as career-home balance by women. They draw from sociological theories on gender roles (Pas et al., 2014; Tomlinson, 2006). They are outside the scope of our study.

[5] Newcomer, E., and Stone, B. 2018. "The Fall of Travis Kalanick was a Lot Weirder and Darker than You Thought," Bloomberg Businessweek (Retrieved January 13, 2019 from https://www.bloomberg.com/news/features/2018-01-18/the-fall-of-travis-kalanick-was-a-lot-weirder-and-darker-than-you-thought).
Taylor, K. 2017. "40 of the Biggest Scandals in Uber's History," Business Insider (Retrieved January 13, 2019 from https://www.businessinsider.com/uber-company-scandals-and-controversies-2017-11).

[6] Henceforth we refer to the multitude of algorithms as simply 'algorithm'.

[7] https://www.washingtonpost.com/technology/2019/06/06/walmart-turns-robots-its-human-workers-who-feel-like-machines/?noredirect=on&utm_term=.b64484b561a5.

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APPENDIX A

A.1 | Interview questions

Questions relating to the driver

What is your motivation for driving?
Tell me about your experience as an Uber driver
How regularly do you drive? (Are there incentives for driving more?)
What do you like the most about driving for Uber?
What do you like the least?
Does anything cause you anxiety?
Tell me about your most recent ride
How do you get compensated (e.g., amount of time driving or distance or others)?
What has been your experience regarding the compensation from Uber?
How important is the passenger rating to you? What are the consequences of a low rating?
Does the surge request influence your driving strategy?

Questions relating to the app

Describe the key features: GPS, ability to select a passenger, etc.
Which of these features do you use the most and why?
Which of these features do you not use and why?
What do you like about the features of the user interface?
What are the troublesome aspects of the user interface?
Describe some instances when you have been pleasantly surprised or irritated with the functionality of Uber

Questions relating to tasks

Describe instances where you had a difference of opinion with what the application was telling you to do.
Describe instances where you sensed a conflict between what the application was asking you to do versus what the passenger wanted.
Describe instances where you were confused and could not understand what you were required to do with the application.

To what extent are you required to follow what the app tells you to do?	
Questions relating to the interaction (driver, passengers)	
Describe instances where you have not been pleased with the passenger's behaviour	
Describe instances where the passenger has not been pleased with the experience of the ride	
Describe instances when you have been satisfied with a particular passenger or ride	
Describe instances when you have not been satisfied with a particular passenger or ride	
Describe your experiences regarding Uber Share.	

APPENDIX B

B.1 | Themes and sub-themes

The distribution of codes within each theme is indicated by the percentages stated in sub-themes.

Theme	Sub-themes	Examples
Nature of the actions of the algorithm	*Unexplained* Interviews: 25% Forum: 53%	*Interview*: *Got a message saying that I violated their terms of employment. 4.8 rating and no issues with customers that I know of… 'Your account has been suspended for activity that violates our terms and conditions'.* *Forum*: *Every time a rider cancels a ride 2 times in a row with a driver the driver is taken off line for a period of time. The messages that appears is 'It appears you are no longer accepting rides at this time. Please try logging back in at a later time'. When the riders cancel my acceptance rate also went down. Uber support said they do this to protect your acceptance rating for going down even more. Why would my acceptance rating be affected by riders who cancel on me?*
	Conveyed logically isolated tasks Interviews: 12% Forum: 10%	*Interview*: *They would encourage drivers to come out at peak hours and then say if you want to drive, pick up passengers from this area between 5 o'clock and 7 o'clock Monday to Friday then we will guarantee that you make $20 an hour but you need to make sure that you pick up two passengers at least within the certain zone* etc. *So I did find that to be a bit strange because there would be times I'd be driving a customer and they'd dispatch me to somewhere where I'd be far so I couldn't really make that two rides in an hour to get that guaranteed hourly rate.* *Forum*: *Even if you make no mistake and simply follow the navigation, a passenger can ding you because their route is their favorite, perhaps quicker, or more direct.*

(Continues)

Theme	Sub-themes	Examples
	Lacked holistic understanding of the driver's work Interviews: 44% Forum: 16%	Interview: *If you need to be somewhere by a certain time…sometimes the system isn't allowing for your specified preferences when matching with riders. You're driving to places that you don't necessarily want to go that far [at that time]. I feel like it is fair to set like a minimum 20 or 30 mile radius.* Interview: *So with Uber we have a queue and so once you're within a certain radius of the airport you are entered into a queue and actually it pops up on your phone and it tells you which number you are in the queue…And so what was happening was like for example I wanted to just serve the airport and so my expectation was that when I was in a queue I would only be getting requests from the airport queue but they would also send me requests from like a 20-mile radius queue*
	Did not convey essential information in a timely manner Interviews: 19% Forum: 21%	Interview: *And that's the one thing I don't like about it, about the app, because it doesn't tell you where the person is going until you pick the person up and you start the trip. And then it tells you of course you can cancel it but then who really wants to cancel a trip when you have the person already, you're there, you're ready to pick them up and then you see oh, my God, they're going to [a far away place]. [Interviewee Tanya].* Forum: *And then I had a request it didn't show long distance but when I picked her up she had to go to Northborough it was 42 miles and it took me 55 minutes because of mass pike was closed I had to go through Storrow and got on mass pike at Newton corner.* *So I think we cannot rely on long distance notification anymore you never know what you will miss*
Driver's response to algorithm's actions	*Using workarounds* Interviews: 18% Forum: 20%	Forum member O: *Bad navigation is the second highest [problem]. You will learn where gps screws up in the city. I combated this by saving good addresses for common destinations in Boston that also have gps issues.* Interview: *One example would be like construction and the map doesn't read it, I knew earlier that night I ran across that area, so I'll take a different route*
	Ignoring instructions and gaming Interviews: 36% Forum: 70%	Interview: *Because they were sending me requests to go and pick someone 15, 20 minutes from the airport and if I didn't want to I could decline it [on the app]. But then if I had too many declines in one day*

Theme	Sub-themes	Examples
		they didn't like that. Closed my account completely. [Interviewee Greg]
	Executing instructions Interviews: 46% Forum: 10%	*Interview*: *I've not turned down a ride. So when I, I never really got, so I know where to go pick up a person and then when I accepted them they would tell me where they needed to go and it never was like a crazy distance, like it never was out of state or anything [Interviewee Jack]*
Driver's perception of the algorithm	*Multiple types of coworkers* Interviews: 14% Forum: 15%	*Interview*: Driver perceives algorithm as different roles in different contexts: *Yeah, it's more of a tool, it's a tool to connect me to the person who needs a ride. And I'm paying the 25% to the tool to connect, to be able to find one person and the other. Because I can't, this is my car, my car, this is my, you know, this is my, essentially my house, you know. [Interviewee Jen]* versus: *'I was like okay, so you're telling me I get to run my own business but I also at the same time don't get to run it how I want, you know'.*
	Impersonal Interviews: 23% Forum: 11%	*Interview*: *It doesn't tell you that until you accept a ride, until after you accept the ride, after you pick up the person, once the person's in your car and you start driving the ride, then it will throw you the destination… I would have been done for the night, but no they were going to the airport and I was 5 minutes away from my apartment. I needed to go to bed. They didn't tell me that they were going to the airport until once they were in my car. So what are you gonna do, kick them out say oh sorry you're going really far I'm not going to bring you [Interviewee Jim]*
	Algorithm's actions could hurt driver's work performance and earnings Interviews: 43% Forum: 40%	*Forum*: *Pax think they are rating the navigation not necessarily the driver… So if they had a good driver who they liked. But didn't like the route Uber chose why should the driver take the hit?* *Forum*: *I got so tired last night getting short trips from the airport so I decided to wait for the request that shows 40+ minutes but in about 30 requests that came in none of them showed long distance and i hit no thanks,so my acceptance rating from 75%Dropped down to 36% just in two hours.*
	Algorithm's actions could lead to negative emotions for the driver Interviews: 20% Forum: 34%	*Interview*: *I got a guy in the car was it last week or the week before, that smelled like he'd smoked two joints inside of a closet. Oh yeah, and that's not the first time either. I drove fifty feet and I said, 'I am cancelling now,*

(Continues)

Theme	Sub-themes	Examples
		you've got to get out'. And I hit Do Not Charge Rider because I just didn't want him in my car … I was so upset and I immediately drove away … somebody reeking of pot at 10.30 in the morning, that bothers me. I actually had to … So I had to shut off the app. I had to call my sponsor. I had to, you know, just … I completely shut down because it just, for some reason it just shook me up that much [Interviewee Jen]