MIS Quarterly

RESEARCH ARTICLE

WHEN ALGORITHMS DELEGATE TO HUMANS: EXPLORING HUMAN-ALGORITHM INTERACTION AT UBER[1]

Marta Stelmaszak
Isenberg School of Management, University of Massachusetts Amherst
Amherst, MA, U.S.A. {mstelmaszak@isenberg.umass.edu}

Mareike Möhlmann
Computer Information Systems, Bentley University
Waltham, MA, U.S.A. {mmoehlmann@bentley.edu}

Carsten Sørensen
Department of Digitalization, Copenhagen Business School
Copenhagen, DENMARK {cso.digi@cbs.dk}

Algorithms are increasingly seen as capable of autonomously initiating and managing interactions with humans—for example, through delegating the rights and responsibilities for successful outcomes of shared tasks without human intervention. While research into such interactions primarily focuses on dyadic configurations, complex settings where multiple agents work together have become a nexus of more nuanced interactions that go beyond the dyad. This paper explores such interactions through the lens of delegation by investigating how many algorithms delegate to many humans in a multi-agent setting. Analyzing patent data and interviews with drivers and passengers, we unpack delegation in the context of the ride-hailing application Uber. We theorize distributed delegation as a construct capturing collective hybrid appraisal, collective hybrid distribution, and collective hybrid coordination, in which a collective of algorithms delegates by drawing on inputs from multiple human agents. Our findings highlight that distributed delegation is collective, hybrid, and relational by nature, and demonstrate the extent to which human inputs are necessary for collectives of algorithms to exercise the capacity to delegate. Distributed delegation as a continuum of algorithmic and human involvement poses a challenge for recent theories suggesting the unprecedented autonomy of algorithms from humans.

Keywords: IS delegation, human-AI interaction, artificial intelligence, algorithms, patents

Introduction

Recent advancements in artificial intelligence (AI) have led to claims of information systems (IS) artifacts, in general, and model-based algorithms, in particular, becoming increasingly agentic (Baird & Maruping, 2021; Murray et al., 2021; Zhang et al., 2021). Such algorithms are thought to be imbued with agency, which is “the ability to accept rights and responsibilities for ambiguous tasks and outcomes under uncertainty and to decide and act autonomously” (Baird & Maruping, 2021, p. 316). Claims of algorithms’ increased agency (Zhang et al., 2021) are based on their perceived autonomy, which is the capacity to act independently without human intervention, enabling them to make decisions and act with material outcomes (Berente et al., 2021). Growing algorithmic autonomy has led to widespread fears about loss of control and the concern that AI based on such algorithms is becoming too powerful, resulting in concerns about human displacement and obsolescence.[2]

[1] Erik Monteiro was the accepting senior editor for this paper. Stefan Seidel served as the associate editor.
[2] https://futureoflife.org/open-letter/pause-giant-ai-experiments/

Algorithmic autonomy challenges the established understanding of interaction between humans and algorithms, with the apparent shift away from assuming primacy of human agency (Baird & Maruping, 2021). Autonomous algorithms are seen as increasingly assuming rights and responsibilities, managing interactions, or even initiating actions requiring responses from humans (Baird & Maruping, 2021). Recent research, consequently, explores how humans and algorithms can work together (Glaser et al., 2021; Jain et al., 2018; Raisch & Krakowski, 2021), in mixed configurations (Rai et al., 2019; Yoo et al., 2010), through mutual augmentation (Fügener et al., 2021; Grønsund & Aanestad, 2020), or the joint configuration of human and IS decision-making (Shrestha et al., 2019; see also Murray et al., 2021). Understanding emerging possibilities in the interactions between humans and algorithms has become "perhaps the key managerial issue of our time" (Berente et al., 2021, p. 1440; see also Anthony et al., 2023). Interestingly, this literature predominantly provides insight into human-algorithm interaction between one human and one algorithm, or many humans, such as teams, with one algorithm.

However, many contexts where humans and algorithms work together are multi-agent settings: They involve complex interactions between humans and multiple simple-reflex and model-based algorithms. The ride-hailing application Uber, for example, coordinates matchmaking across its platform sides to match multiple riders and drivers to successfully complete rides. Numerous algorithms implemented on the platform interact with many human users, i.e., Uber drivers and riders, taking into consideration real-time supply and demand information from all drivers and riders logged into the Uber app in close geographical proximity (Faraj & Pachidi, 2021; Möhlmann et al., 2021; Wiener et al., 2023; Tarafdar et al., 2023). Yet the seemingly simple and almost instantaneous match of a rider to a driver involves interactions between multiple different algorithms, such as the service request algorithm, the location determination algorithm, and the matching module, and large groups of riders and drivers whose decisions to request a ride and accept or reject a request impact the overall task outcome in minute detail. In other words, multi-agent settings seem to foster the perception of the autonomy of multiple algorithms as a result of the way in which they interact with multiple human agents.

While a closer unpacking of human-algorithm interactions in multi-agent settings is pivotal, as such settings are now commonplace, theorizing accounting for the large number of agents is lacking. Baird and Maruping (2021) frame the interaction between humans and algorithms as delegation, which is "transferring rights and responsibilities for task execution and outcomes to another" (p. 317). They claim that their delegation framework can yield nuanced insights into such interaction, and especially into algorithms that are seemingly gaining autonomy in delegating. As Baird and Maruping stress (2021, p. 335), there is an urgent need to expand the delegation framework to settings with a higher number of agents, but so far, we know little about human-algorithm interactions beyond the dyad (see Shaikh & Vaast, 2023). If the capacity to delegate is the cornerstone of algorithmic autonomy, we ask: *How do many algorithms delegate to many humans in a multi-agent setting?* While delegation in multi-agent settings can also cover delegating by humans to algorithms, we focus on delegations by multiple algorithms to multiple humans (platform participants—one primary exchange partner and indirect support crowds—rather than developers or engineers) in a context that is heavily reliant on human data.

To address this research question, we conducted a qualitative case study of the ride-hailing application Uber. We collected U.S. Uber patents (n = 63), which allowed for an in-depth exploration of the conceptual design of Uber's algorithms, and conducted semi-structured interviews with Uber drivers and riders (n = 22). We found that to delegate, algorithms must work together and draw on inputs from multiple humans through ongoing and continuous relationships. We theorize *distributed delegation* as a construct capturing *collective hybrid appraisal*, *collective hybrid distribution*, and *collective hybrid coordination*. Delegations in multi-agent settings are distributed in the sense that to delegate, a collective of algorithms must work together by drawing on human inputs through ongoing relationships. Human inputs are provided in the form of trace data (by-product data generated passively from interactions) and choice data (generated actively from choices and decisions made) that feed into delegations, as well as delegation interventions when the ongoing delegation cycle necessary to complete a task breaks down.

Our findings demonstrate the extent to which human agents' involvement is necessary for algorithms to exercise the capacity to delegate, how such capacity resides in the collective work of many algorithms, and how it relies on relationships between agents distributed across multiple delegations. Importantly, we found that in the Uber case, neither the collective of algorithms, nor participating humans, delegate all rights and responsibilities completely; rather, distributed delegation lies on a continuum between algorithmic and human agents. The existence of distributed delegation poses a challenge for recent research suggesting the unprecedented autonomy of algorithms from human intervention and involvement. Indeed, our findings indicate that in multi-agent settings that heavily rely on human user data, algorithms may not be as autonomous as anticipated in prior research. Instead, our findings suggest that algorithmic agency is the collective, hybrid, and relational capacity to act, involving collectives of algorithms working together with required human inputs, and that it emerges over time from ongoing interactions. We argue that our findings extend to other contexts where multiple algorithms delegate to numerous humans and where these algorithms appraise, distribute, and coordinate other humans and their activities—for example, in AI decision-making systems in healthcare or the judiciary. In practice, our findings help in designing human-algorithm interaction with attention to multi-agent settings and highlight when human inputs are required for an efficient flow of such interactions.

Conceptual Background

From IS Agency to the Rise of Algorithmic Agency

The question of IS agency has been studied for decades (Zhang et al., 2021).[3] While IS agency may not share the same characteristics as human agency, the former nevertheless complements the latter with its capacity for taking action in relation to its environment (Zhang et al., 2021). Thus, IS agency has traditionally been conceived of and studied in relation to human agency—e.g., through a sociomaterial lens in systems that rely on both IS and human agents interacting in the completion of tasks (Zhang et al., 2021). These existing theories suggest that IS agency is always, in one way or another, dependent on human agency (Lyytinen et al., 2021).

However, recent IS literature presents a turning point. Moving away from "the human agency primacy assumption" (Baird & Maruping, 2021, p. 315), it highlights the increase of agency on the part of tools and technologies underpinned by algorithms, such as machine learning and AI (e.g., Baird & Maruping, 2021; Berente et al., 2021; Zhang et al., 2021). According to this literature, algorithms exhibit agency, which can be broadly conceived of as a capacity to act in, respond to, and shape an environment (Emirbayer & Mische, 1998). While the literature uses various terms, e.g., machine learning, AI, or algorithms, it can be synthesized as referring to *algorithmic agency*, which is the ability of algorithms to accept rights and responsibilities for ambiguous tasks and outcomes under certainty and to decide and act autonomously (after Baird & Maruping, 2021, p. 316). Unlike traditional views on IS agency, this new generation of algorithmic agency is thought to capture the increasing capacity of algorithms to learn, make decisions, and act without human oversight, monitoring, or control (Berente et al., 2021; Möhlmann et al., 2021; Murray et al., 2021; Russell, 2019). Recent research is replete with examples of algorithmic agency that claim to go beyond what prior IS agents were able to do "to such an extent that perceptions of their independent agency arise" (Zhang et al., 2021, p. 1197). This literature addresses how algorithms are increasingly replacing human "mental functions" (Leontief, 1983), that is, the sociocognitive processes of coordinating, planning, managing, making decisions, and acting (Baird & Maruping, 2021; Grønsund & Aanestad, 2020; Möhlmann et al., 2021; Ransbotham et al., 2016). They are thought to act directly in response to various stimuli (e.g., voice-based virtual assistants), evaluate deviations from the norm (e.g., smart lights), proactively apply reasoning to anticipate needs (e.g., digital content compilation), manage a workforce, and even decide by themselves, in the case of autonomous vehicles or automated financial portfolio management, for instance (Baird & Maruping, 2021).

One of the cornerstones of algorithmic agency claims is autonomy. Algorithms are seen as autonomous if they can act without the direct intervention of humans (or other agents) (Jennings, 2000; see also Baird & Maruping, 2021). They possess "a temporally embedded capacity to intentionally constrain, complement, and substitute for humans" (Murray et al., 2021, p. 553). Autonomous algorithms can learn and execute actions independently and without direct and continuous input from humans (Zhang et al., 2021, p. 1197). Algorithmic autonomy, then, can be defined as the capacity of algorithms to act on their own, without human intervention, and to make decisions to act in the world with material outcomes, often without human intervention or even human knowledge (Baird & Maruping, 2021; Berente et al., 2021; Murray et al., 2021). In sum, algorithmic autonomy is often cited in the literature as a proof of increased algorithmic agency.

The inner complexity of algorithms often remains hidden in the literature (Shaikh & Vaast, 2023), denoted, for example, only as "the algorithm" (e.g., Grønsund & Aanestad, 2020). While all algorithms take input information about their environments and perform actions on this basis (Russell & Norvig, 2016), different algorithms draw on dissimilar types of data, use various methods, and have diverse goals. To this end, Russell and Norvig (2016) distinguish between two fundamental types of agents. We apply their fundamental distinction between simple-reflex agents that neither track history nor contain models, and model-based agents that operate on an internal state keeping track of past interactions. Simple-reflex agents in the case of Uber include, for instance, algorithms recording the number of vehicles available, the direction and destination of vehicles, and drivers currently ready to pick

[3] For example, from the perspective of distributed cognition (e.g., Hutchins, 1995), critical realism (e.g., Leonardi, 2011), actor-network theory (e.g., Latour, 1987), or sociomateriality (e.g., Barad, 2003; Orlikowski, 2007). For a detailed review, see Zhang et al. (2021).

up passengers. Model-based agents, in contrast, contain aggregated data, which can be queried and updated—e.g., the driver profiling algorithm that maintains data about a driver's past behavior to better detect potential trip anomalies. These two types of agents seemingly have different capabilities and capacities for autonomy. Yet so far, questions of algorithmic agency have not engaged with the diversity of algorithms and have not made specific claims as to where and how their autonomy arises.

Human-Algorithm Interaction

The perceived emergence of algorithmic agency has spurred a rethinking of existing knowledge on human-algorithm interaction. As algorithms gain autonomy, the interactions among them, as well as with human agents, form new configurations. This has made such interactions a prominent issue for researchers and practitioners interested in investigating the configurations of human-algorithm interaction under the seemingly changed conditions of algorithmic agency and autonomy (Berente et al., 2021). This research puts forward claims regarding algorithmic autonomy and the increase in algorithmic agency and also investigates novel interactions that emerge between humans and algorithms, as summarized in Table 1.

Recent research has emphasized algorithmic autonomy in several ways, showing, for example, that algorithms can perform cognitive tasks on par with humans (Anthony et al., 2022; Grønsund & Aanestad, 2020; Möhlmann et al., 2021; Jussupow et al., 2021), may exhibit intentionality (Murray et al., 2021), and may act in their interest (p. 464). Others see the capacity for independent decision-making as a hallmark of algorithmic autonomy (e.g., Shrestha et al., 2019; Lebovitz et al., 2022). Finally, a collection of papers perceives the autonomy of algorithms as the capacity to delegate through a transfer of rights and responsibilities for task execution and outcomes to another agent (Baird & Maruping, 2021). The capacity to delegate to other agents is perceived as a unique characteristic and distinguishing factor of algorithms that exhibit agency: The fact that they can delegate to other agents is seen in literature as evidence for their agency (Baird & Maruping, 2021; see also Fügener et al., 2022; Lyytinen et al., 2021).

Increasingly autonomous algorithms are thought to enter into new configurations of interactions with humans—e.g., through mutual augmentation (Fügener et al., 2021; Grønsund & Aanestad, 2020; Raisch & Krakowski, 2021), conjoined agency (Murray et al., 2021), or various ways of joint human and IS decision-making (Shrestha et al., 2019). Two main cardinalities of such configurations have been covered in the literature: one-to-one, in the study of dyadic configurations of one human interacting with one algorithm, and many-to-one, in the study of configurations of many humans interacting with one algorithm.

Dyadic configurations include, for instance, studies of medical decision-making, where a single radiologist consults with what they assume is a single entity (Jussupow et al., 2021; Lebovitz et al., 2022). Such studies emphasize the human side of the interaction and often do not engage with the complexity of algorithms, instead referring to "the algorithm" (e.g., Grønsund & Aanestad, 2020). Studies drawing on many-to-one configurations acknowledge that there are numerous humans interacting with one algorithm, reflecting typical organizational conditions with several humans involved in any given task (e.g., Anthony et al., 2022; Lyytinen et al., 2021). This allows us to understand in more detail that different humans may contribute different strengths to the interaction and can also interact with other humans resulting in positive or negative outcomes (Fügener et al., 2021). Finally, one paper focuses on interactions between many algorithms (Shaikh & Vaast, 2023), uncovering the complex interactions that play out between the many algorithms involved in performing a task.

While insightful, the literature does not extend to the cardinality where many algorithms interact with many humans. Arguably, an investigation of such many-to-many interactions is called for since the work of algorithms can be assumed to involve interactions with both users and other algorithms (Shaikh & Vaast, 2023). In studies of algorithmic agency, no algorithm can be assumed to act alone; rather, algorithms initialize the action of, source, and rely on other algorithms (Shaikh & Vaast, 2023). Simultaneously, "interactions are important because seldom does an algorithm operate in isolation without initialization by a human" (Shaikh & Vaast, 2023, p. 2). In fact, it has been suggested that humans are almost always involved in how algorithms work (Shaikh & Vaast, 2023; see also Ekbia & Nardi, 2017), yet the extent and detail of this involvement have not yet been studied.

Investigating many-to-many interactions is needed, as most tasks that algorithms are designed to tackle are far more complex than what is encompassed by the dyadic one-to-one configuration. Such tasks often call for multi-agent settings where humans and algorithms "rarely function in isolation and often coordinate with and rely upon other human agents and IS artifacts" (Baird & Maruping, 2021, p. 335). Platforms serve as a prime example of a multi-agent setting where numerous algorithms interact with numerous humans participating on the platform (Baird & Maruping, 2021; Rai et al., 2019).

Table 1. Recent Research on Human-Algorithm Interaction

Paper	Increased algorithmic agency	Algorithmic autonomy as a key characteristic of algorithmic agency	Configuration of human-algorithm interactions	Cardinality
Baird & Maruping (2021)	Agency resides in the capacity of algorithms to delegate, that is, to engage in "transferring rights and responsibilities for task execution and outcomes to another." (p. 317)	Agentic IS artifacts "are no longer passive tools waiting to be used, are no longer always subordinate to the human agent, and can now assume responsibility for tasks with ambiguous requirements and for seeking optimal outcomes under uncertainty" (p. 315), they have the capacity to learn, adapt, act autonomously.	One human interacts with one agentic IS artifact around a task that needs to be completed or a desired outcome, where rights and responsibilities for tasks and outcomes are delegated between the two.	ONE human with ONE algorithm (one-to-one)
Fügener et al. (2022)	Agency is the capacity to delegate.	Algorithms are an actor that can perform tasks and delegate tasks to another actor.	At least one human interacts with one image classification algorithm through a conscious decision to delegate, where the algorithm can also delegate to a human through inversion, to complete a task.	
Ge et al. (2021)	Algorithms may best be left to themselves, as there are negative use cases "where leaving too much control to humans over when to use a [robo-advisor] may be counterproductive." (p. 775)	Robo-advisors provide automated, algorithm-based advice without human involvement.	A human interacts with a robo-advisor in a conscious, designed way to complete a task.	
Grønsund & Aanestad (2020)	Algorithms have the capacity to automate or augment human agency.	Algorithms can perform "cognitive, discretionary, and decision-making tasks that humans used to perform." (p. 1)	Human-machine configurations are sets of "relations between human(s) and machine(s) with a certain division of tasks and responsibilities between them." (p. 3)	
Jussupow et al. (2021)	Algorithms can augment human decision-making.	Computer-aided intelligent diagnosis systems based on algorithms "accomplish tasks that were previously regarded as uniquely human." (p. 713)	A human medical practitioner interacts with one AI computer-aided intelligent diagnosis system.	
Lebovitz et al. (2022)	Algorithms' strengths contribute to decision-making systems.	AI tools, for example machine learning algorithms, that are opaque to users, make decisions by themselves.	A human radiologist interacts with an AI tool in an intentional way to form a diagnosis as part of their job.	
Murray et al. (2021)	Conjoined agency between humans and algorithms, "a shared capacity between humans and nonhumans to exercise intentionality." (p. 553)	Algorithms are technologies that "have the ability to parse through large amounts of data, acquire skills and knowledge, and operate autonomously" (p. 552) and that "possess a temporally embedded capacity to intentionally constrain, complement, and substitute for humans." (p. 553)	The four forms of conjoined agency are: (1) conjoined agency with assisting technologies, (2) conjoined agency with arresting technologies, (3) conjoined agency with augmenting technologies, and (4) conjoined agency with automating technologies, impact organizational routines.	
Möhlmann et al. (2021)	Algorithms can carry out coordination and control functions traditionally performed by managers, to the extent that some workers suggest they are "working for an algorithm" (algorithmic management).	Platforms such as Uber make extensive use of algorithmic management to manage a distributed workforce efficiently and accurately in a highly automated and data-driven fashion.	Platforms collect large amounts of data (among others, about the platform workers) to develop and improve learning algorithms to monitor and control platform workers. Platform workers show responses to algorithmic management, which dynamically feed back into the balancing act between algorithmic matching and algorithmic control.	

Schuetz & Venkatesh (2020)	Cognitive computing systems challenge fundamental assumptions of: “(1) the direction of the user-artifact relationship, (2) the artifact’s awareness of its environment, (3) functional transparency, (4) reliability, and (5) the user’s awareness of artifact use.” (p. 460)	Cognitive computing systems [based on algorithms] in complex systems with users in which they are no longer just tools but active agents that “may act in their own interests.” (p. 464)	Humans interact with cognitive computing systems, and “to date, research has assumed that users are aware that they are using an artifact.” (p. 467)	
Tarafdar et al. (2023)	Humans interact with algorithms to accomplish work results in algorithmic work where “the human executes work tasks through interactions with the algorithm rather than with other humans.” (p. 233)	Algorithms as “a software program that takes in business-specific data, applies computational logic, and provides outputs.” (p. 258)	The algorithm takes on the role of a co-worker and “the human and the algorithm engage in interactions to complete the work, interactions that resemble workplace interactions between humans in traditional work.” (p. 233)	
Anthony et al. (2023)	Agency emerges from the interactions between humans and technology.	Algorithms perform the cognitive tasks associated with humans as constantly changing, invisible, and inscrutable actors within a system of work.	Many humans interact with AI as “an active counterpart in a system of interactions.” (p. 9)	**MANY humans with ONE algorithm (many-to-one)**
Fügener et al. (2021)	Algorithms are partners that provide recommendations for solving complex tasks.	Algorithms can make humans “start acting more like machines or cyborgs” (p. 1528) where humans strive to match the performance of the algorithm they are working with.	A group of humans interacts with a single AI.	
Jain et al. (2021)	Algorithmic agency may have ultimate control over designs that combine humans and algorithms.	Algorithms have the capacity to enhance human intelligence and human beings can enhance them in turn.	Many humans interact with AI; therefore, “consideration of some more granular architectures of how human beings and AI can collaborate” (p. 680) is required.	
Lyytinen et al. (2021)	Algorithmic agency as complementing and amplifying capacities of metahuman systems.	Algorithms are technologies that have the capacity to have authority and resources to accomplish tasks.	Humans and AI delegate and monitor the performance of tasks, and can appear in different configurations: human, machine, or mixed, where “delegating grants authority and resources to agents to accomplish tasks.” (p. 436)	
Shrestha et al. (2019)	The capacity of algorithms to make decisions.	Algorithms can make decisions independently of humans.	Humans interact intentionally with AI when making decisions in three structures: full human-to-AI delegation; hybrid—human-to-AI and AI-to-human—sequential decision-making; and aggregated human-AI decision-making.	
Shaikh & Vaast (2023)	Algorithmic interactions facilitate open source work through managing, organizing, and supervising development work, but “developers are equally likely to augment the work of algorithms as vice versa.” (p. 2)	Algorithms can interact with each other as and when needed in open source development.	Algorithms interacting with each other; “the work of algorithms involves interactions not only with users but also with other algorithms” (p. 1) but “requires a user to start a process where one algorithm begins to source another one.” (p. 2)	**MANY (algorithms with each other)**

Extending Delegation Theory to Multi-Agent Settings

To study interaction between many algorithms and many humans, we drew on Baird and Maruping's (2021) delegation theory. Delegation captures how a human can transfer rights and responsibilities for task execution and outcome achievement to an algorithm and, equally, how the algorithm can delegate back to the human. Such transfer assumes that all rights and responsibilities for a task lie either with an algorithm or with a human and can be delegated to the other as and when needed (i.e., delegation is seen as binary). By synthesizing a large body of previous IS research, Baird and Maruping (2021) differentiate between three delegation mechanisms: appraisal, distribution, and coordination.

Appraisal refers to an agent evaluating the risk and what is at stake when delegating to the other agent (Fadel & Brown, 2010). Appraisal is the assessment of the ability, compatibility, fit of skills, or expected accuracy and quality of the other agent's performance taking over the task in question. *Distribution* is enabled by digital technologies. By decomposing large assignments into identifiable and distinct tasks (Rai et al., 2019; Susskind & Susskind, 2015), responsibilities and rights to perform these tasks can be distributed across agents (Baird & Maruping, 2021). *Coordination* is the alignment of goals between humans and algorithms (Eisenhardt, 1989) and the management of dependencies of tasks and actions (Malone & Crowston, 1994). Indeed, the human and algorithm relationship may be characterized by power asymmetries (Eisenhardt, 1989), and the delegator may have the decision power to decide whether to delegate a task or not.

While we find that Baird and Maruping's framework (2021) presents a valuable starting point, we propose extending and refining their theorization to multi-agent settings. In sum, the framework focuses on simpler cases of delegation in the human-algorithm dyad. Similarly, much of IS research generally tends to zoom into the theorization of the interaction between "the human" (or "many humans") and "the algorithm" (Grønsund & Aanestad, 2020; Murray et al., 2021; Rai et al., 2019). Yet complex problems are often characterized by interactions between many humans and many algorithms (e.g., Shaikh & Vaast, 2023). Thus, we adopt delegation theory to study a multi-agent setting, which in our case is the Uber application, and we focus explicitly on how delegation unfolds from many algorithms to many participating humans.

Research Design

Drawing on grounded theory techniques (Glaser & Strauss, 1967; Urquhart, 2023), we conducted a case study to approach our research question. Our aim was to generate theory (Glaser & Strauss, 1967; Urquhart, 2023), eventually theorizing concepts and their relationships (see Figure 4). Given that "no one enters the research process as a blank state" (Urquhart, 2023, p. 6), our data analysis was shaped by prior literature on human-algorithm interaction and the delegation framework by Baird and Maruping (2021) in particular.[4] Indeed, our research followed both, inductive and deductive impulses and can best be described as abductive (following Urquhart, 2023, who claims that abduction is essential for grounded theory building). While we sought to set aside theoretical ideas in the very early stages of the (overlapping) data collection and analysis, once we discovered the fit of Baird and Maruping's (2021) framework to our emerging insights, we narrowed down our focus by concentrating on data relevant to the three delegation mechanisms (appraisal, distribution, and coordination) outlined in their framework. In subsequent stages we engaged in several iterative rounds of coding, setting aside the emerging theory against this existing literature.

The text below and Figure 1 illustrate the following six widely used grounded theory principles that we were committed to in our data collection and analysis: (1) the aim to generate theory; (2) the iterative processes; (3) the overlapping data collection and analysis; (4) theoretical sampling; (5) open, selective, and theoretical coding; (6) and employing constant comparisons.

Case Study

We conducted a case study of Uber. Founded in 2010, Uber is an app-based ride-hailing platform (Constantiou et al., 2017; Möhlmann et al., 2023). As of 2024, Uber's website states that it offers services in over 10,000 cities globally. The Uber app matches drivers offering rides with passengers seeking rides and includes additional features such as calculating passenger fares and providing built-in navigation (Möhlmann et al., 2021; Wiener et al., 2023). In this study, we focus on the consumer-facing ride-hailing service, and our references to Uber in this paper are restricted to the transportation service provision only (excluding their other services, such as helicopter services and food delivery).

[4] "The characteristic (of having no preconceived theoretical ideas) is often held (erroneously) to imply that the [grounded theory] researcher should not look at the existing literature" (Urquhart, 2023, p. 19).

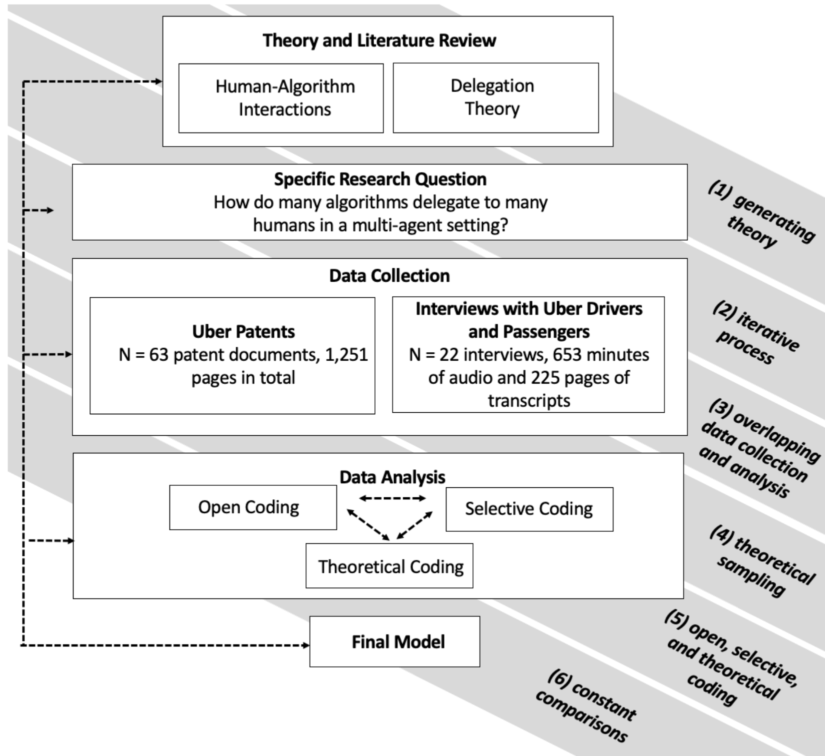

Figure 1. Overview of Data Collection and Analysis

Uber has been studied extensively as a platform that draws on human drivers, human passengers, and algorithms that regulate their interactions (Faraj & Pachidi, 2021; Möhlmann et al., 2023; Tarafdar et al., 2023). We rely on Uber as a revelatory case (Yin, 2018) because the patent data we collected and analyzed offer the opportunity to observe delegations and the inner logic of a platform's algorithms at a level of technical detail previously not researched.

Data Collection

Our initial research interest was broadly human-algorithm interaction, and the current research question was only specified later in the research process when we turned to patent data detailing algorithmic delegations to humans. Patent documents cover extensive descriptions of intellectual property containing technical details (Abbas et al., 2014; Tseng et al., 2007). Because of their exhaustive nature, patents have long been a target of analyses aimed at knowledge discovery as part of patent informatics, whereby various computational techniques, including text segmentation, term association, and topic identification, are used to mine patent text (Abbas et al., 2014; Moehrle et al., 2010; Trippe, 2003; Tseng et al., 2007).

Initially, we identified 503 patents held by Uber Technologies Inc. and registered in the United States Patent and Trademark Office (USPTO) as of January 2021. From reading titles and abstracts, we identified 129 patents pertaining to the transportation service, excluding patents not directly relevant to the empirical object of study, such as those related to self-driving vehicles or freight management. Reading the background sections, we also excluded patents that did not describe interactions between humans and algorithms (Butler et al., 2018), for example, patents concerning machine learning algorithms in identifying street signs or related to details of the user interface. The resulting 63 patents contained a total of 1,251 pages of text and images. Patent data granted us unprecedented access to the technical details of algorithms that reveal intended interactions in the detailed patent descriptions. Patents contain, without unnecessarily technical specifications, nuanced textual and visual descriptions of the specific interactions designed to take place between different elements of the system (Noh et al., 2016) as well as inputs needed from humans. Such detailed descriptions cannot be obtained solely through other means of data collection, such as interviews with users, managers, or data scientists, which give access to and privilege human accounts of using or interacting with technology leaving technology "mute" (Cecez-Kecmanovic et al., 2014).[5] An example of the level of insight that such qualitative patent analysis can offer is included in Appendix A. In the findings, we make references to 11 patents out of the 63 analyzed for readability and clarity, as providing background and explanations for all patents would not be possible within the scope of a paper. Therefore, we selected the most representative patents to illustrate our claims. We provide details of patents used in the findings section in Table 2.

In addition to the patents, we conducted 22 semi-structured interviews in the United States between February and May 2022—12 interviews with Uber riders and 10 with Uber drivers, lasting 30 minutes on average (additional details about study participants are presented in Table 2 below). All interviews were recorded and transcribed. In the interviews, we initially asked informants about their interactions with the Uber app and when or how they delegated a task to another agent or reclaimed it. A summary of the collected data is presented in Table 2.

Data Analysis

We identified categories grounded in the data and named and connected them, thereby laying the foundation for the development of constructs and the relationships between them, eventually allowing us to theorize our model illustrated in Figure 4.

Our data analysis was an iterative process (Glaser & Strauss, 1967; Urquhart, 2023), which resulted in inextricable links between data collection and analysis where the emerging theory influenced our future collection of data to follow the emerging storyline suggested in the data we collected (Urquhart, 2023). To this end, our choice of data sources and data collected was guided by theoretical sampling (Urquhart, 2023). The topics addressed in the interviews changed slightly over time because the emerging findings from the initial data analysis guided us to explicitly query their interactions with algorithms. For example, once human and algorithm interaction emerged as the core theme in our initial analysis of the patent data, we realized that our study would benefit from additional data. Thus, while we initially only analyzed patent data, we then conducted additional semi-structured interviews in order to adequately capture the human perspective of Uber drivers and passengers. Likewise, and as mentioned above, once we discovered the fit of Baird and Maruping's (2021) framework to our emerging insights, we started to focus on collecting data relevant to the delegation mechanisms outlined in their framework.

Given that our research was iterative, our specific research question changed over time. For example, in an earlier version of this manuscript, our intention was to theorize how many humans and many algorithms delegate to each other. Only in later stages of the research process did we narrow down and theorize algorithm-to-human delegation in more depth.

While the process was iterative, we can abstract three distinct stages of coding in our data analysis (see Figure 3 for examples of our coding scheme). First, we openly coded our data (Glaser, 1978; Urquhart, 2023). Given the complexity of the algorithm to human delegations we were investigating, we not only coded text but also worked to increase our understanding by illustrating the complex interactions described in the patents and interviews. A total of 12 maps (similar to Shaikh & Vaast, 2023) detailing delegations across several core patents were constructed and refined; they served as core elements in our understanding of how different algorithms and humans interact—e.g., when selecting a service, establishing a pick-up location, and reporting an incident (see example in Figure 2). The following coding included both text and parts of the figures to ensure that we remained open minded when assigning attributes to data snippets that we identified in both the patent and interview data. Second, we implemented selective coding (Glaser, 1978; Urquhart, 2023) by grouping different codes into higher-level themes and aggregate dimensions. For instance, we realized that some of the algorithmic delegations associated with what we later labeled *collective hybrid appraisal* were conducted by simple-reflex algorithms and others by model-based algorithms. After several iterations, two distinct subthemes emerged; we thus grouped all codes capturing actions by simple-reflex algorithms into the category of *multi-data assembly* and those capturing model-based algorithms into the category of *learning-based assessment*. Finally, in the last stage, we conducted theoretical coding (Glaser, 1978; Urquhart, 2023), with the intention of considering relationships between the different aggregate dimensions. The research team spent many hours discussing the data and theorizing relationships between the emerging concepts. For example, after *collective hybrid appraisal, collective hybrid distribution, and collective hybrid coordination* emerged as distinct categories from our data analysis, we realized that these three delegation mechanisms continuously feed into each other. Many iterations of appraisal, distribution, and coordination are needed and only collectively allow for one single delegation to unfold, resulting in their representation as an ongoing loop of interactions in the final model.

[5] This does not necessarily mean that the solutions described in the patents are actually implemented and currently in use (e.g., some may have been in use in the past, others may be implemented in the future). However, since our research focuses on theory building, we are concerned with identifying empirical descriptions that lead us to theoretical constructs. Whether a specific algorithm is actively deployed during the transportation service is both less relevant and difficult to trace, as algorithms often change and become deployed or rolled back on short notice. Second, given that we complement patent data with semi-structured interviews conducted with Uber drivers and passengers, we mitigate against this lack of certainty in the data.

Table 2. Overview of Types and Sources of Data Collected

Data type	Source	Quantity	Period	Number of patents
US Uber Patents	Collected from USPTO website	*N* = 63 patent documents, 1,251 pages in total	January-February 2021	63
Interviews with Uber riders and drivers	Conducted in the US	*N* = 22 interviews overall (*N* = 12 with Uber riders and *N* = 10 with Uber drivers), around 653 minutes of audio and 225 pages of transcripts in total	February-May 2022	Interview R.1 to Interview R.12 and Interview D.1 to Interview D.10

Details of patents referenced in the Findings section

Reference and Corresponding USPTO Patent Number	Patent title	Patent summary
Patent P.1 US 9230292	Providing on-demand services through the use of portable computing devices	A method to request an on-demand service within a given location, where a number of algorithms determine the location of the rider and possible drivers to allow the most optimal matching of a rider with a driver by the matching algorithm
Patent P.2 US 10402841	Enabling a user to verify a price change for an on-demand service	A method to enable a user to verify a price change displayed in the application interface based on several algorithms establishing a real-time price change for a service in response to change in conditions (so-called “surge pricing”)
Patent P.16 US 9813510	Network system to compute and transmit data based on predictive information	A method to predict the likely acceptance of on-demand service request by a driver and display such predicted service provider in the application interface, where the instant selector algorithm predicts acceptance based on historical data, driver profiles, and rider profiles, and inputs from several other algorithms
Patent P.20 US 10325442	Facilitating direct rider-driver pairing for mass egress areas	A method to allow an easier pairing of drivers and riders in overcrowded areas using a match code, where algorithms create a match code and transmit it to a rider’s device and monitor for the entering of the same code in the driver’s device, indicating a successful pick-up
Patent P.22 US 10733547	Preselection of drivers in a passenger transport system	A method to preselect and predispatch drivers based on a predicted future demand in areas such as airports, where algorithms predict the number of drivers that need to be predispatched based on passenger demand data, location data, and external demand data
Patent P.23 US 10067988	User-based content filtering and ranking to facilitate on-demand services	A method to display service-related content tailored to an individual driver, where algorithms dynamically manage a content database, store driver attributes and preferences, receive dynamic location data, monitor driver location, filter content, and dynamically generate and rank content
Patent P.26 US 10204428	Augmenting transport services using driver profiling	A method to determine a driver’s driving style on the basis of trip data, where algorithms use data about an ongoing trip provided by the driver to compare current data with an established driver profile, determine a confidence score based on previous trips, adjust the score accordingly, and use the score to determine whether a driver should verify themselves
Patent P.34 US 10732000	Promoting user compliance with adaptive checkpoints	A method to determine the optimal route, create checkpoints, and encourage the driver to follow the route, where a number of algorithms are trained to output rules for checkpoints along the route and other algorithms direct drivers to optimal routes by offering rewards upon reaching checkpoints based on location data received from drivers

Patent P.47 US 10559211	Real-time service provider progress monitoring	A method to determine whether the river is making progress toward service completion, where algorithms periodically determine whether the driver is on track based on data received from the driver’s device and a set of preset progress conditions
Patent P.54 US 9723469	Trip anomaly detection system	A method to detect anomalies during a ride based on a comparison of a current ride to a historical ride profile, where the anomaly detection algorithm relies on data and other algorithms to compare current ride data with historical route profiles for a rider and identify anomalies in the current route, subsequently triggering a safety protocol
Patent P.55 US 10423991	Implementing and optimizing safety interventions	A method to train a model to predict the effectiveness of various safety interventions based on different drivers, where different interventions are imposed on drivers and their responses to these interventions are used to improve the model maintained by algorithms, including telematics algorithms, feedback algorithm, machine learning algorithms, matching algorithms, and intervention algorithms

Details of interview participants

Interviewees	Gender	Age	Ethnicity	Interview Modality	Location
Uber riders (*N* = 12) (average duration approx. 35 min)	Four female and eight male participants	Between early twenties and mid-forties	Different ethnic backgrounds	Remote interviews via zoom	Based across the United States
Uber drivers (*N* = 10) (average duration approx. 25 min)	Male participants only	Between early twenties and mid-fifties	Different ethnic backgrounds	In-person interviews	Based in greater Boston

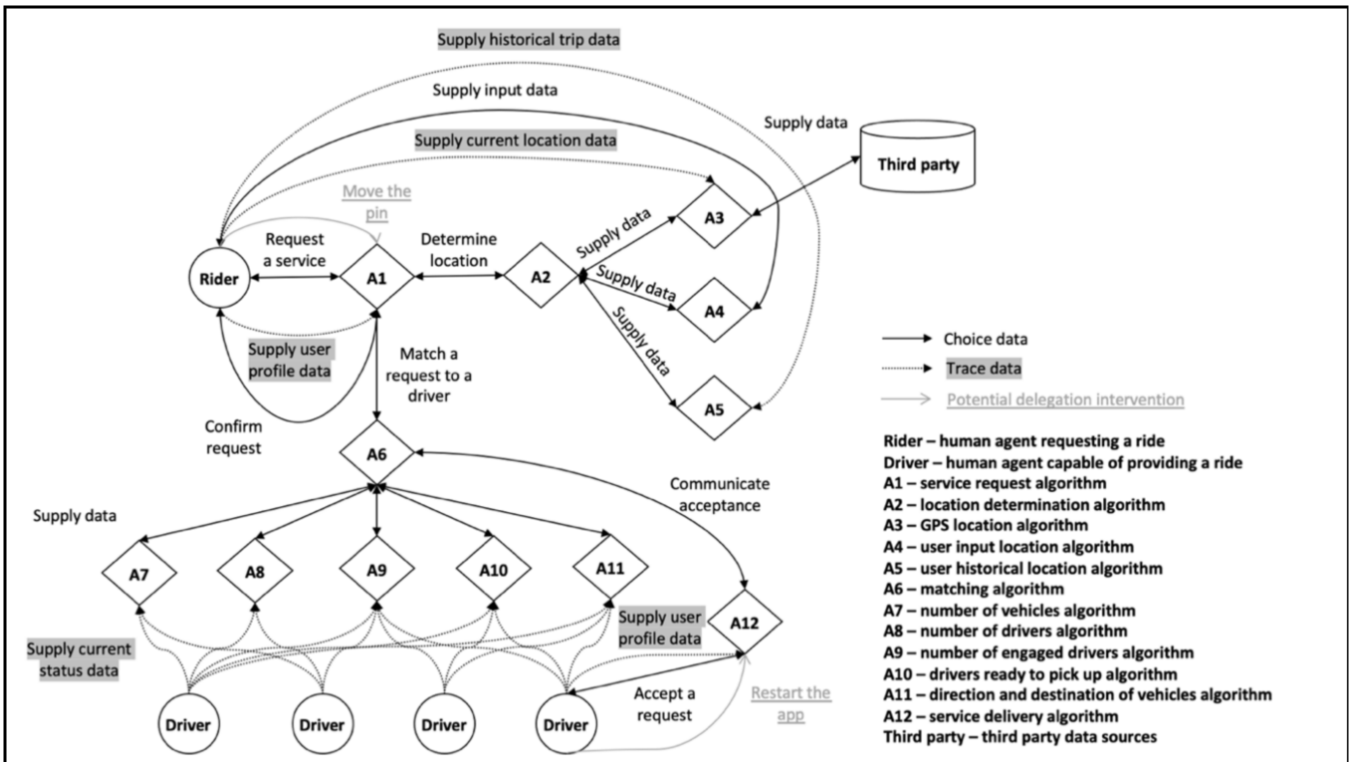

Figure 2. Example of Mapping Out Human-Algorithm Interaction Based on Patent Data (Patent P.1)

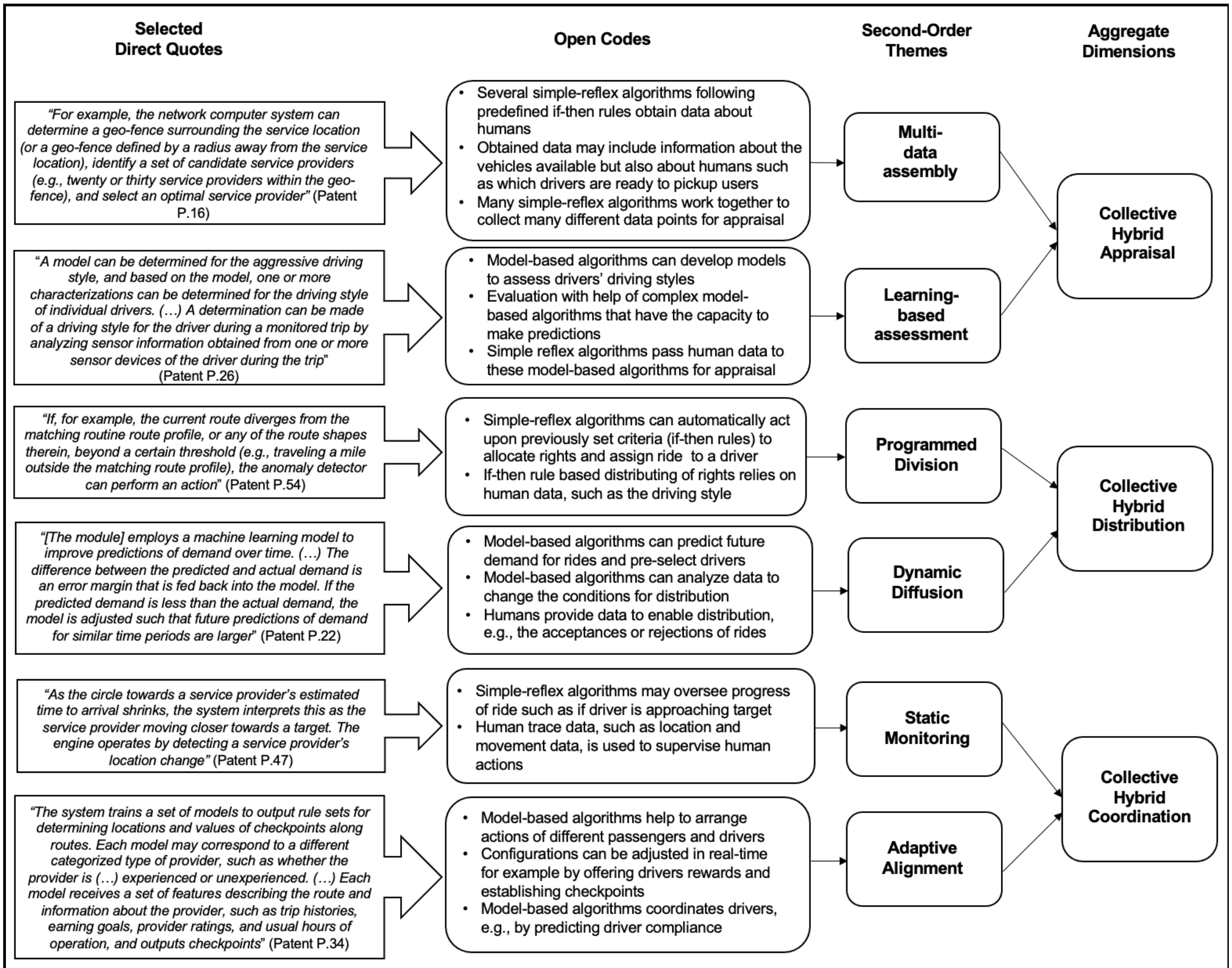

Figure 3. Data Structure

We practiced constant comparisons between the data we labeled as belonging to a specific category with other data in the same category (Urquhart, 2023). Doing so allowed us to clearly define the boundaries of the different categories. For example, open codes from patents and from interviews may use a "different language" (with drivers being more emotional or informal and patents being more abstract and formal) but, in essence, refer to the same mechanism. Constantly comparing emerging insights from the two data sources allowed us to attain more depth when making sense of our findings.

Findings

Our analysis here focuses on delegations involved in completing the shared outcome of a completed ride (Möhlmann et al., 2021). This may include tasks such as the Uber app delegating a choice to a passenger regarding, for instance, which ride they wanted to book (e.g., an UberX ride for up to four passengers or an Uber XL ride for up to six passengers). We explicitly focus on how a collective of algorithms delegates to humans, here drivers and riders, achieving the goal through numerous complex interactions between multiple algorithms and many humans. We distinguish between simple-reflex algorithms that follow static and pre-programmed what-if rules, and model-based algorithms (Russell & Norvig, 2016) that calculate predictions, for example, of the likelihood of a driver accepting a ride. We distinguish between the direct interaction partner who is part of the delegation (i.e., a specific rider requesting a ride of a driver being matched to a ride), and support crowds that indirectly contribute to the delegation taking place (i.e., the accumulation of data on current and historic riders and drivers). We theorize the model of *distributed delegation* illustrated in Figure 4.

Collective Hybrid Appraisal

In order to match a rider to a driver, the Uber algorithms first engage in appraisal to assess the various riders and drivers available and what is at stake when delegating (Baird & Maruping, 2021). Appraisal is carried out not by a single algorithm but by a collective of algorithms working together on collecting, processing, and analyzing data pertaining to numerous different humans. However, activities carried out by the collective of algorithms are not sufficient for appraisal by themselves. Rather, humans participate in appraisal in numerous required ways, making it a hybrid mechanism that involves both algorithms and humans (and their data or interventions). To this end, we define collective hybrid appraisal as a collective of algorithms, with the support of human input, assessing various human users. We distinguish between two types of such appraisal: multi-data assembly and learning-based assessment.

Multi-data assembly is a type of collective hybrid appraisal where different simple-reflex algorithms obtain different data from various humans to appraise all humans and select which one to delegate to. This is best captured by the Uber matching mechanism, which involves obtaining various data to ascertain the right driver for a ride. Uber algorithms here assess various drivers to establish whom to delegate to. This interaction constitutes appraisal, as obtaining such data is needed to select and match a driver to a rider requesting a ride. One key patent described simple-reflex algorithms supplying "information about the number of available vehicles, the number of available drivers, which drivers are currently performing a transport service, which drivers are ready to pick up users, ... etc., in order to properly arrange the transport service between users and drivers" (Patent P.1). The match is made by algorithms that appraise numerous drivers in order to select the best fitting driver following simple selection rules: "The selection engine can identify a plurality of candidate drivers within a certain proximity of the requesting user's current location, and select an optimal driver from the candidate set to service the pick-up request" (Patent P.20) by eliminating drivers currently unavailable, currently performing a service, not ready to pick up riders, located too far, moving in a different direction, etc., thus narrowing down the pool of drivers until the optimal driver is selected.

Multi-data assembly is carried out by simple-reflex algorithms that follow relatively straightforward, prescribed if-then rules to obtain data—such as collect data, compile data, or "monitor vehicle trips of respective users in real time by receiving location data"—and use such data according to if-then rules (Patent P.54, see also Figure 2). These simple-reflex algorithms work together in a collective, i.e., the maintenance of information about drivers in the example above is carried out by at least six different algorithms that need to exchange the data obtained to identify the driver to delegate to. Relying on just one algorithm that collects data about the number of available vehicles in the system would not be sufficient to narrow down the pool of drivers. Other simple-reflex algorithms, therefore, provide additional data, such as the current location of driver vehicles. Only several algorithms working collectively toward one outcome can appraise humans. At the same time, the collective of simple-reflex algorithms collects data about numerous unrelated and unconnected humans who do not work together and are often not even aware of each other in the system. Yet even a collective of Uber algorithms cannot appraise drivers and riders by itself. Rather, human inputs are necessary for assessment to, for example, select the most appropriate driver to delegate to. At the very foundation of appraisal lie historic and real-time trace data provided by humans. Trace data may be provided by direct interaction partners, which are drivers and riders currently on the Uber app. While trace data are passively provided by humans, most drivers and riders are generally aware that Uber is collecting and storing some data about them. To this end, one Uber rider explained that he has limited knowledge about the details but believes that Uber is tracking the following information: "I'm guessing my name and my address, my payment information, my age, like the most frequently used addresses on Uber. Probably like my preferred driver. That's probably the main thing" (Interview R.9).

Trace data, such as different drivers' directions and the destination of vehicles in motion, can also be provided by indirect (current and historic) support crowds that do not participate in the delegation mentioned above. Such data are not provided explicitly for the purpose of appraisal but are a by-product of other activities in the system; they are used in this secondary way to allow algorithms to appraise humans. Trace data are necessary for appraisal, as without them algorithms would be unable to assess the riders and drivers: "The requester data can be used (in part) to determine the current number and/or the current location of requesters for the service (e.g., this can represent the demand for the service) at a given time" (Patent P.2). Thus, multi-data assembly carried out by simple-reflex algorithms is a collective and hybrid appraisal endeavor and is necessary to identify the right human to delegate to.

Learning-based assessment is the second type of collective hybrid appraisal we identified. In this type, model-based algorithms develop, maintain, and update models of each human based on data collected on them for the purpose of appraising all humans and identifying the ones to delegate to. For instance, model-based algorithms model drivers' driving styles to further refine matching with riders:

> *A model can be determined for the aggressive driving style, and based on the model, one or more characterizations can be determined for the driving style of individual drivers. … A determination can be made of a driving style for the driver during a monitored trip by analyzing sensor information obtained from one or more sensor devices.* (Patent P.26)

This constitutes appraisal because Uber algorithms assess the drivers' driving styles and use this assessment to identify which human to delegate to.

Learning-based assessment is carried out by more complex model-based algorithms that have the capacity to develop models, construct profiles, make recommendations, predict, and make refinements:

> *The model(s) can correspond to a multidimensional and learned data structure which is determined from observation (e.g., an observed population of drivers). In such implementations, the model can be developed using a set of ground truth data, which can be obtained from datasets that are relative to the objective for the driver profiling system.* (Patent P.26)

In other words, model-based algorithms build models of drivers and compare them with each other, further refining the accuracy of the models if other model-based algorithms confirm or disprove the identification of a driving style.

However, a single model-based algorithm can hardly work on its own. In most cases, model-based algorithms work in a collective with other model-based algorithms or, at the very least, with a number of simple-reflex algorithms. For instance, the "ground truth" for determining driving styles using model-based algorithms is provided by simple-reflex algorithms supplying data "obtained from drivers on trips where the driver was involved in an accident" (Patent P.26), where the accident is often identified by simple-reflex algorithms engaging in multi-data assembly, as described above, that can indicate that an accident occurred (e.g., a sudden change of speed). Ascertaining a driving style using a model-based algorithm is therefore not possible without working closely with other simple-reflex algorithms. Alternatively, other model-based algorithms are needed to perform appraisal. For example, to assess the effectiveness of safety interventions, one "machine learning model is trained using features derived from trips requested and/or taken by users" (Patent P.55), and then another model can be subsequently be "trained to predict the effectiveness of various interventions on a provider (or a subgroup of providers) based on the safety risk classification of the provider" (Patent P.55), among other data sources. Thus, "the model learns from the results of randomized experiments performed by the travel coordination system using interventions provided by the travel coordination system to providers" (Patent P.55), which is indicative of at least two model-based algorithms working together.

While model-based algorithms engage in learning, this would not be possible without the involvement of humans providing data. The example of ascertaining driving styles clearly demonstrates that multiple unrelated and unconnected humans are involved in appraisal. The algorithms are only able to build models of different driving styles and then compare a given driver to the model by learning from multiple trips of multiple humans and multiple drivers (this includes both current and historic incidents provided both by direct interaction partners and indirect support crowds). For instance, an algorithm can "store route data for the trip as a data point in the user's profile potentially for future matches" (Patent P.54) or, alternatively, "map the current route traveled by the user and driver to the matching route profile in real-time" (Patent P.54). These data are, knowingly but also often unknowingly, steadily supplied by humans directly involved in the interaction. Unlike in the other type of collective hybrid appraisal, algorithms here also rely on a secondary use of interaction data, which humans provide when making decisions, as well as application interface selections. For example, based on the history of a particular rider, the app may propose destinations, such as a rider's home address or their favorite restaurant. As one rider reported: "So I'll type that in. But if I don't know the address, like if I wanted to go to say, a certain restaurant, or something like that, I would just type in the name of the restaurant. And, from there, it would show me my options" (Interview R.9). Without the previous decisions made by the specific interaction partner, the collective of model-based algorithms would not be able to build models and consequently appraise the human. Thus, learning-based assessment is carried out by model-based algorithms in collectives in a hybrid manner, where both the algorithms and the humans participate in appraising the human.

Multi-data assembly can operate on its own or support learning-based assessment by supplying the required amassed data to model-based algorithms that can carry out the second type of appraisal. Learning-based assessment, in turn, often relies on multi-data assembly, and its outputs can also feed into other simple-reflex algorithms engaging in multi-data assembly. We observed appraisal as a complex network that relies on many instances of both types of this mechanism in many relationships and configurations. This further shows that, in this context, appraisal is collective, i.e., it often requires many algorithms of different types working together.

Finally, we would like to note that, at times, appraisal by a collective of algorithms seems to be prone to errors and may occasionally encounter glitches. In these situations, with both types of collective hybrid appraisal, humans may need to engage in interventions that restore the flow of delegation. For example, collective hybrid appraisal relies on the collective of algorithms assessing the rider's exact location. However, the Uber app may not be able to identify the correct location of a rider. Instead, riders occasionally have to manually adjust the pickup location. Otherwise, drivers would not be able to find the rider and the delegation would not be successful. One rider reported: "And so I've had to adjust the pin [icon marking a location on the map]. If I didn't adjust the pin, the car went to the wrong place" (Interview R.12). Therefore, we conclude that appraisal is also hybrid, as human inputs were required in appraisal in all the instances we observed in the form of choice data, trace data, or interventions.

Collective Hybrid Distribution

Matching a rider and a driver also requires the distribution of rights and responsibilities for different parts of the task between agents (Baird & Maruping, 2021). After riders and drivers have been appraised, algorithms assign some rights and responsibilities to them. Such distribution is realized by a collective of algorithms that distribute a specific task (such as accepting a ride) to at least one human, while the involvement of more humans remains necessary for orchestrating efficient distribution on a larger scale, considering that the Uber app matches many drivers and passengers at the same time. To this end, we define collective hybrid distribution as a collective of algorithms, with the support of human input, disseminating rights and responsibilities to many human users. We distinguish between two types of such collective hybrid distribution: programmed division and dynamic diffusion.

Programmed division occurs when simple-reflex algorithms divide rights and responsibilities in response to human data received as per previously programmatically set criteria. For instance, after appraisal, a collective of algorithms may perform a series of activities to divide the responsibility for the trip and assign part of it to a driver who has decision rights to respond to the trip request:

> *Once the optimal service provider is selected the selection engine can generate a service invitation to fulfill the service request, and transmit the service invitation to the optimal service provider's device via the service provider application. Upon receiving the service invitation, the optimal service provider can either accept or reject the invitation.* (Patent P.16)

Upon acceptance, the driver begins to bear the rights and responsibilities of completing the ride, but the driver also has the right to reject the invitation. This is an example of distribution in that the decision rights and responsibilities for achieving a shared outcome—a completed ride—become divided between multiple actors, that is, between algorithms and humans.

In programmed division, distribution is carried out by simple-reflex algorithms that act upon previously set criteria providing conditions for their if-then rules, normally automatically performing division or automatically selecting responses when certain thresholds or conditions are met: "If, for example, the current route diverges from the matching routine route profile, or any of the route shapes therein, beyond a certain threshold (e.g., traveling a mile outside the matching route profile), the anomaly detector can perform an action" (Patent P.54). Therefore, simple-reflex algorithms act on hard-coded rules that dictate what decision or intervention responsibilities should be delegated and under which, very clear, conditions. A collective of simple-reflex algorithms is needed to perform this action; since data about the current trip needs to be collected and supplied, several calculations need to be made to ascertain whether the anomaly threshold has been met, and other data about "route divergence, driver profile data, flagged locations or areas, static activity, traffic data, third party data, and the like" (Patent P.54) need to be cross-referenced. Finally, a separate simple-reflex agent needs to generate and transmit a notification.

Programmed division also relies on numerous humans and their data—e.g., data obtained from direct interaction partners:

> *If a response is received from the mobile device of the user that indicates a negative condition, or if no response is received for a predetermined duration of time, a notification system can automatically perform a number of emergency actions (e.g., transmit more urgent alert, call the user's mobile device, contact emergency response authorities, contact emergency contacts, etc.).* (Patent P.54)

This indicates that the algorithm may involve other humans, such as emergency response services or emergency contacts, if the human who originally obtained intervention rights and responsibilities is nonresponsive.

While algorithms remain responsible for dividing and sharing tasks among other algorithms or other humans, human actors still play a pivotal role in the distribution to Uber drivers or passengers. Humans provide continuous trace data, e.g., current and past trip data, supporting the detection of anomalies through programmed division. They also supply actively provided choice data by reacting to notifications generated by the algorithms. For instance, the "push notification can be transmitted to the rider application, which can cause the rider application to display content (e.g., asking about the user's safety status) and/or output an audio alert or cause the user device to vibrate to get the user's attention" (Patent P.54). If a positive response is received, that is when the user signals that there are no issues: "the anomaly detector can record the positive response in the user's user profile and/or add an additional route shape to the matching route profile" (Patent P.54). To this end, programmed division relies on human inputs to appropriately divide decision and intervention rights and responsibilities between actors. Therefore, this type of distribution is both collective (simple-reflex algorithms working together collectively) and hybrid (it is only possible when some actions are completed by algorithms and some by humans).

Dynamic diffusion signifies model-based algorithms updating when to distribute and what rights and responsibilities to distribute based on the human data they receive. For example, to manage the issue of drivers having to wait for extended periods when picking up riders from airports, algorithms may predict future demand for rides and preselect drivers to "ask the driver to leave the waiting lot and travel towards a specific location (e.g., the airport terminal) before the matching server assigns that driver to provide a ride for a passenger" (Patent P.22). To this end, the algorithms may

> *increase the estimate of demand if one or more large planes have recently landed off schedule. Conversely, the demand estimate can be reduced if a typically busy flight that was scheduled to have landed recently is delayed and yet to arrive … The demand prediction module then outputs the updated estimate of demand as the predicted demand (e.g., for use in determining the number of drivers who should be pre-selected).* (Patent P.22)

This example illustrates the distribution of rights to dispatch a driver based on a dynamic prediction of a potential trip request. The algorithms engage in distribution extended over time where the decision rights to accept or reject a trip are only predicted.

Model-based algorithms in dynamic diffusion analyze data to change the conditions for distribution and identify new, more suitable criteria. Dynamic diffusion requires a collective of algorithms working together on dividing rights and responsibilities. While model-based algorithms are charged with making predictions about distribution, humans provide the needed trace and interaction data. While human users "don't know what type of models they're generating" (Interview R.12), drivers and riders are generally aware that Uber algorithms are "probably building user models to predict" (Interview R.12) different variables, such as demand and supply. Trace data regarding the location and motion of drivers are needed to, for example, correctly predict estimated times of arrival. Interaction data, e.g., invitation acceptance or rejection, are required to form and refine predictions that inform dynamic diffusion. The joint activities of many algorithms and many humans allow for the distribution of decision and intervention rights and responsibilities. The activities of drivers and riders when engaging with Uber form the data foundation fed into the models, which orchestrate distribution.

Programmed division and dynamic diffusion may occur independently depending on a task, e.g., where the distribution criteria do not change, programmed division is sufficient. However, in the highly complex task of providing a transportation service, many situations require dynamic diffusion to adjust the previously static, programmatically set criteria. Some of the patents we analyzed were specifically concerned with a shift from programmed division towards dynamic diffusion to make distribution more elastic and reactive to changing conditions. In sum, these two types are indicative of collective hybrid distribution where the division and sharing of rights and responsibilities involves both algorithmic and human actions, and where algorithms act together in a collective.

Our findings show that collective hybrid distribution is not always a smooth process. We identified instances where distribution encountered glitches and effectively broke down, preventing delegation from continuing as usual. In such situations, we observed humans intervening to return the collective of algorithms to functioning. For instance, in some cases, riders were required to share a PIN [personal identification number] with their driver before the Uber app would continue to display the ride details on the driver's phone, however, some riders never received this information. As one driver explained:

> *Some people don't have any PIN [personal identification number]. But when those people are getting in my car, I have to confirm the trip. So the app told me to put in the PIN number. But when I asked two people, what is your PIN number? They said, "I don't have any PIN." So I just like turned my phone off. When I turned it on again, it's not asking me for a PIN anymore.* (Interview D.2)

In this case, the delegation temporarily broke down, which motivated the driver to intervene by restarting the phone, resulting in a new workflow of the collective of algorithms. Subsequently, delegation could proceed as normal towards a successful trip. Such interventions are therefore sometimes necessary to enable delegation to continue and for the driver to receive more detailed instructions about a specific ride.

Collective Hybrid Coordination

Achieving the outcome of a successful ride that is distributed between algorithms and humans requires managing and aligning actions and tasks toward a shared goal (Baird & Maruping, 2021). After appraising and distributing, actors need to manage and align the dependencies created through delegation. For Uber, coordination is carried out by a collective of algorithms that monitor, manage, and align such dependencies between numerous humans. Human participation is also required to ensure such coordination. We define collective hybrid coordination as a collective of algorithms, with the support of human input, managing and aligning actions and tasks with human users to achieve a shared goal. We identify its two types: static monitoring and adaptive alignment.

Static monitoring occurs when simple-reflex algorithms monitor progress towards a set criterion for the completion of a task based on the human data they have received. For example, when a driver's ride progress is monitored by the Uber app:

> *A real-time progress monitoring system detects the progress of a service provider towards a target destination or multiple target destinations. In some examples, the monitoring is performed using a "shrinking circle attraction engine" which applies a "shrinking circle algorithm" to determine whether the service provider is progressing towards one of the targets or ignoring it.* (Patent P.47)

Uber algorithms can also determine when the task has been completed. In this way, the algorithms can coordinate the achievement of a successful trip by monitoring its progress. Successful delegation to humans requires the development of several algorithms whose sole purpose is to coordinate through monitoring—as, for example, in the case of Patent P.47 on real-time service provider progress monitoring.

This type of static monitoring is carried out by a simple-reflex algorithm that operates as follows: "If the remaining ETA [estimated time of arrival]+duration elapsed - initial ETA <= a threshold of the greater of 2 minutes or the initial ETA*a predetermined buffer value, the service provider is considered to be progressing towards the target" (Patent P.47). This algorithm relies on other simple-reflex algorithms to supply the estimated time of arrival, current time, and similar information. In this way, several simple-reflex algorithms obtain data and compare these with the set criteria to ascertain whether the driver's actions are aligned with the completion of the goal. If they are not aligned, the algorithms can "generate movement recommendations [based on which] the task service can register tasks to track the progress of any movement recommendations sent to service providers" (Patent P.47), following if-then rules. A collective of simple-reflex algorithms can then work together to supervise whether a driver is complying with their actions, and if not, they can recommend course correction to the driver to ensure that the actions become realigned with the goal. This complex task cannot be executed by a single simple-reflex algorithm but rather requires a collective working together (in this case, the real-time progress monitoring algorithm, the shrinking circle algorithm, the supply provisioning algorithm, and the task algorithm).

Successful coordination also depends on the involvement of several humans, both drivers and riders. To this end, the analysis above shows that coordination is carried out by algorithms relying on human input. Trace data, such as location and movement, are required to monitor humans' progress toward the shared goal, as static monitoring cannot take place without such data. Direct human intervention may occasionally be required when the algorithms are "incorrect." Such interventions show that the monitoring of the delegated completion of the trip also relies on humans. Thus, it is a hybrid endeavor.

Adaptive alignment unfolds when model-based algorithms manage and align actions based on real-time human data to ensure a successful outcome. For instance, coordination relies on modifying the actions of drivers and riders who have been delegated to as a way of ensuring their behaviors continue being aligned with the goal, which, in the Uber case, refers to successfully completing a ride. One of the patents describes how Uber algorithms cope with drivers who stray from the suggested route:

> *A system promotes provider movement toward areas of higher demand by establishing checkpoints along a route to an area of high demand. … The provider may be rewarded for staying on the suggested route by earning rewards when a checkpoint is passed. … If a provider strays from the suggested route, the system can adapt to the change and regenerate a route with different checkpoints to encourage the provider to return to the route or to otherwise continue toward the destination.* (Patent P.34)

Here, adaptive alignment differs from static monitoring because, in the light of changing behaviors and conditions, new alignments can be suggested and updated in real time, for example by establishing new checkpoints and rewards to ensure compliance with the suggested route.

Adaptive alignment is carried out by model-based algorithms: "The system trains a set of models to output rule sets for determining locations and values of checkpoints along routes"

(Patent P.34). Such checkpoints are determined by another machine learning model to position them "along a route with which a provider is most likely to comply" (Patent P.34). This example shows that model-based algorithms may train models, predict compliance, or dynamically alter conditions. At the same time, adaptive alignment can only be achieved when a group of algorithms work together in a collective, where several model-based algorithms communicate with each other and with simple-reflex algorithms to adapt where the checkpoints are located. As demonstrated above, each model receives features of the route and the provider from numerous other algorithms that are responsible for storing trip histories, earning goals, and provider ratings. These actions are not all performed by the same algorithm but rather require a collective.

Such alignment also requires the involvement of several humans, as "training data used by the model generator to train the models includes records of past providers, regions with high rates of trip requests" (Patent P.34), indicating that other providers and other riders contribute to managing alignment adaptively. Human inputs are needed for coordination, resulting in Uber's algorithms and users (both drivers and riders) working together in hybrid configurations. For instance, in order to display notifications on a driver's device and to guide their actions toward the desired outcome, the algorithms require trace data, given that "the updates can be triggered by the location of the driver (e.g., the driver passing outside of a geo-fence associated with a content item), changes in the drive status, by an expiration time, and/or by updates in rider demand" (Patent P.23). While these data are obtained as a by-product of activities carried out by humans, interaction data are also required, as they can provide information about prosocial behavior, which serves as a proxy for the degree of goal alignment between drivers and riders: "Data about providers may be collected by the system, for example, via provider interactions with applications on a user device, and via rider feedback about the provider" (Patent P.34). Riders actively provide such data when rating drivers; in particular, they provide data that cannot easily be captured by an algorithm—e.g., data about drivers' personalities or their willingness to provide excellent service to the passenger by going above and beyond by making phone chargers available or giving out water bottles and candy. To this end, one rider reported that his ratings would reflect information that could hardly be collected by the Uber app: "Drivers have water bottles, candy, etc. I've had drivers that gave me phone chargers that I could use—they have already had the cables positioned, and I just had to pick the right one. Those are always great. I can definitely say that" (Interview R.4). Adaptive alignment is thus a form of collective coordination that requires several algorithms working together and is also hybrid, requiring input both from algorithms and humans.

Static monitoring and adaptive alignment usually co-occur, as they are two facets of coordination. Static monitoring is required to monitor compliance, and adaptive alignment is necessary to enforce changes that guarantee the alignment of actions toward a goal. Most often, we observed static monitoring happening before adaptive alignment, as adaptive alignment cannot take place without prior monitoring. Static monitoring would, however, be insufficient to coordinate a trip toward a successful outcome.

Finally, we note that in some instances, collective hybrid coordination was not a seamless process and delegation temporarily broke down. Our findings show that in these cases human agents temporarily bypassed the collective of algorithms to repair the breakdown. This typically involved riders and drivers communicating directly to solve an issue. As one rider reported:

> *I actually message a driver, especially when I'm looking at my app and I'm trying to track the driver and I find out that they are just going in circles. Because you know, when you're looking at the Uber map, you can actually tell when a driver is lost … So I click on the message and say "hello, what's happening?"* (Interview R.3)

In this case, the rider claimed agency to avoid a situation where the driver was unable to complete the ride because of incorrect information provided in the Uber map. At times, such delegation interventions were necessary to ensure that rider and driver interactions were successfully monitored, managed, and aligned.

Overall, we share rich evidence that allowed us to theorize *collective hybrid appraisal, collective hybrid distribution, and collective hybrid coordination*. We introduce our final model next.

Theoretical Integration and Discussion ■

The model in Figure 4 synthesizes our findings, which explain *distributed delegation* as *the transferring of rights and responsibilities in a many-to-many multi-agent setting as a collective of simple-reflex and model-based algorithms working together by drawing on human inputs through continuous relationships with one direct exchange partner and (current and historic) support crowds*. Such delegation is thus distributed over both algorithms and humans, resulting in us recognizing delegation as a continuum, whereby on one end of the spectrum rights and responsibilities reside more with the collective of algorithms, and on the other end, they rest with multiple humans. While the case studied here is asymmetrical in nature given that distributed delegation at Uber is largely dominated by algorithms, neither algorithms nor humans hold all rights and responsibilities. There is always a part of the task that either algorithms or humans are responsible for or have rights to. To this end, our model highlights that distributed delegation is collective, hybrid, and relational by nature, thereby picturing it as a joint effort of many humans and many algorithms working together so that algorithms can delegate to multiple human users. Based on the analysis of the Uber case, we theorize three mechanisms of distributed delegation listed in Table 3.

The model illustrates a collective of algorithms, which includes simple-reflex and model-based algorithms performing distributed delegation to multiple humans. Distributed delegation is based on an ongoing loop of interactions between *collective hybrid appraisal, collective hybrid distribution, and collective hybrid coordination* continuously feeding into each other. Many iterations of appraisal, distribution, and coordination are necessary—only together do these allow delegation to unfold. Many delegations are necessary to attain more complex shared goals such as successfully matching drivers and riders. Distributed delegation requires ongoing relationships between algorithms and humans, given that a continuous stream of human input in the form of passively provided *trace data*, actively provided *choice data*, and *delegation interventions* is provided by a direct exchange partner and the (current and historic) support crowd. Trace data refer to passively provided by-product data generated from interactions (e.g., current location data, profile data, status data). Choice data refer to data generated from active choices and decisions made (e.g., confirm a request, request a service). Delegation interventions refer to human interventions pivotal to mitigate delegation breakdowns in which humans temporarily take over agency (and therefore curtailing algorithmic agency) and claim the rights and responsibilities to intervene. While these exceptional situations may occur infrequently, they are necessary to allow the delegation to successfully proceed.

Table 3. Summary of Theorized Concepts and Definitions

Concept	Definition	
Collective hybrid appraisal	***A collective of algorithms, with the support of human input, assessing various human users.***	
	Multi-data assembly	Multi-data assembly is a type of collective hybrid appraisal where different simple-reflex algorithms obtain different data from various humans to appraise all humans and select which one to delegate to.
	Learning-based assessment	Learning-based assessment is the second type of collective hybrid appraisal that we identified. In this type, model-based algorithms develop, maintain, and update models of each human based on human data to appraise all humans and identify the ones to delegate to.
Collective hybrid distribution	***A collective of algorithms, with the support of human input, disseminating rights and responsibilities to many human users.***	
	Programmed division	Programmed division occurs when simple-reflex algorithms divide rights and responsibilities in response to human data received as per previously programmatically set criteria.
	Dynamic diffusion	Dynamic diffusion occurs when model-based algorithms update when to distribute and what rights and responsibilities to distribute based on the human data they receive.
Collective hybrid coordination	***A collective of algorithms, with the support of human input, managing and aligning actions and tasks with human users to achieve a shared goal.***	
	Static monitoring	Static monitoring occurs when simple-reflex algorithms monitor progress towards a set criterion for the completion of a task based on the human data they have received.
	Adaptive alignment	Adaptive alignment unfolds when model-based algorithms manage and align actions based on real-time human data to ensure a successful outcome.

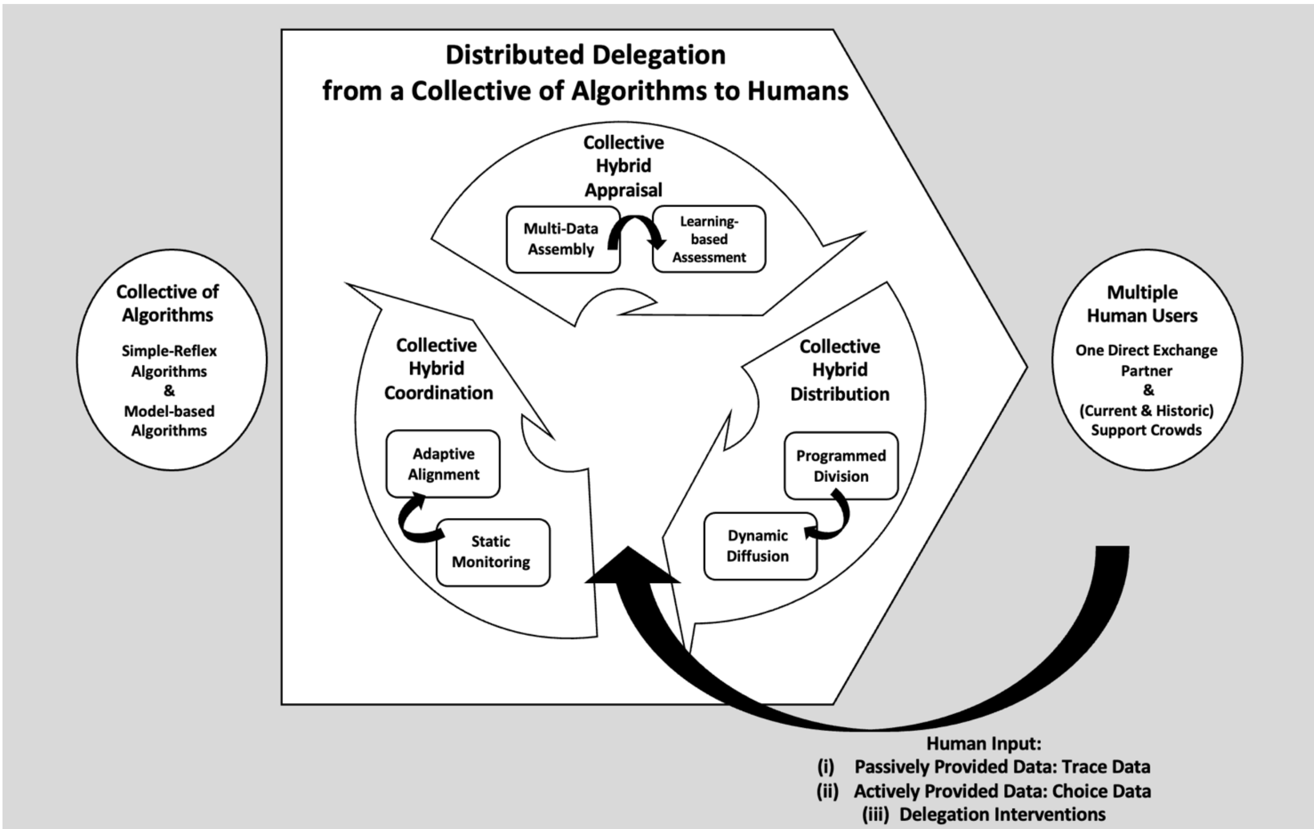

Figure 4. Model of Distributed Delegation from a Collective of Algorithms to Humans

First, distributed delegation unfolds when many algorithms work together (**collective**). Several simple-reflex algorithms collect human data (see *multi-data assembly, programmed division, and static monitoring*), which they feed into multiple learning model-based algorithms that rely on this human input (see *learning-based assessment, dynamic diffusion, and adaptive alignment*). To delegate, multiple algorithms, in the form of simple-reflex and model-based algorithms, work together to complete delegation as a collective, with each algorithm being specialized to perform a different activity that contributes to the overall outcome and the output of some algorithms providing necessary input for others.

Second, distributed delegation requires algorithms to draw on human input, resulting in algorithms and humans that form a symbiosis necessary for delegation (**hybrid**). In the context studied here, one direct human exchange partner and (current and historic) support crowds provide the necessary data, without which algorithms cannot delegate, and direct human exchange partners engage in delegation interventions where glitches and complications occur. For example, model-based algorithms rely on passively provided trace data and actively provided choice data to make recommendations and predictions, as well as human delegation interventions to allow the delegation to proceed in exceptional circumstances.

Third, and following from this, distributed delegation in multi-agent settings that rely heavily on human data is supported by an exchange of data from many past and current users who provide important input for the delegating algorithms, feeding into the ongoing, continuous loop between collective hybrid appraisal, collective hybrid distribution, and collective hybrid coordination (**relational**). With each use, human users continuously provide data, which is stored in the system. Accumulated over time, data build up to large-scale datasets that provide necessary input to train algorithms and thus provide the needed input for their own but also other users' future delegations. The relational nature of distributed delegation shows that algorithms' capacity to delegate emerges on the basis of prior interactions and streams of historical data provided by humans. It also shows that model-based learning algorithms can improve their capability to appraise, distribute, and coordinate, over time. In the following, we discuss the implications for theory and research.

Implications

In this paper, we investigate how many algorithms delegate to many participating humans in a multi-agent setting. Our model and findings have implications for research on delegation, IS autonomy, and algorithmic agency.

First, we extend Baird and Maruping's (2021) theory of delegation to multi-agent settings. While emerging research has started to address contexts in which groups of humans, such as teams or colleagues, interact with an algorithm (e.g., Fügener et al., 2021), much of the prior IS research assumes that delegation between IS and humans can be sufficiently theorized as a dyad (Baird & Maruping, 2021; Berente et al., 2021; Grønsund & Aanestad, 2020), for example, in the context of the worker-algorithm relationship (Möhlmann et al., 2021; Tarafdar et al., 2023). We show that in such multi-agent settings, delegation ceases to be a clear dyad of one human agent delegating to one algorithm (IS agent), and vice versa. Instead, various groups of humans take on different roles, and algorithms with different capabilities participate in delegation. We show that specialized algorithms need to work together in complex configurations of collectives that share a joint goal in order to delegate.

Our model illustrates that in multi-agent settings that rely heavily on human data, such as Uber, the lines of delegation become far less straightforward because delegation presents itself on a continuum—on one end of the spectrum, rights and responsibilities reside with the collective of algorithms; on the other end, they rest with multiple humans. While the case studied here is asymmetrical, given that distributed delegation is largely driven by algorithms, neither algorithms nor humans hold all rights and responsibilities. In such settings, distributed delegation is not a complete and clear-cut transfer from an algorithm to a human but rather a change in the degree of rights and responsibilities held by a collective of algorithms or multiple humans. In other words, delegation in multi-agent settings that rely heavily on human data is not a complete transfer of rights and responsibilities (i.e., it is not binary) but rather a carefully maintained balance of algorithms and humans maintaining, delegating, and receiving some rights and responsibilities as they work together toward successful task completion.

Thus, our findings show that multi-agent settings, like the one studied here, are characterized by hybridity in delegation. These findings add to existing literature by showing that what appears to be autonomous delegation in dyadic settings (Baird & Maruping, 2021; Murray et al., 2021; Zhang et al., 2021; Berente et al., 2021) becomes more when expanded to multi-agent settings, where both humans and algorithms require each other's inputs to delegate. We show that while algorithms in multi-agent settings based heavily on human data may not depend on "direct and continuous input from human agents" (Zhang et al., 2021, p. 1197) to function, they rely on such inputs to delegate and complete tasks. We also show that humans in multi-agent settings who are often portrayed in literature as having little agency (Möhlmann et al., 2021; Tarafdar et al., 2023) are actually required for the work of the collective of algorithms in such settings. Our findings demonstrate the extent to which human agents' involvement—in the form of actively and passively providing data and engaging in delegation interventions—is still necessary for algorithms to exercise the capacity to delegate in the context studied here. In other words, if algorithms need human inputs and involvement to perform delegation, and if delegation is indeed a continuum (see previous paragraph), the question arises whether complete algorithmic autonomy in multi-agent settings (Baird & Maruping, 2021; Murray et al., 2021; Zhang et al., 2021) that heavily rely on human data is possible at all.

Furthermore, our findings add to recent research claiming that a new generation of IS exhibits increased autonomy and agency (e.g., Baird & Maruping, 2021; Zhang et al., 2021; Berente et al., 2021). Drawing on patent data, which allow us to unpack the inner logic of the platform's algorithms with technical detail, we show that the properties of the underlying technology are still those simple-reflex and model-based algorithms developed decades ago that sit at the center of many human-algorithm interactions. Changing perceptions about algorithmic agency may stem from the fact that many delegations employed in practice, like the one studied here, are now collective, hybrid, and relational. The perceived increased agency and performance of typically human tasks (e.g., Baird & Maruping, 2021; Grønsund & Aanestad, 2020; Ransbotham et al., 2016) may be a consequence of different types of algorithms working together in carefully orchestrated collectives that allow them to successfully complete more complex tasks. Even in contexts in which distributed delegation is asymmetrical, as in the Uber case studied here, these algorithms are powered by input data from far-removed current and historic support crowds. This may create the perception of increased agency of complex collectives of algorithms, while the actual agency of a single algorithm involved in these delegations (of which many are needed to form a collective) may not be very different from more traditional IS settings.

Our findings point to an important aspect of algorithmic agency, namely its evolutionary and relational character. Some prior research that has established important foundations for our understanding of human-algorithm interaction has taken a snapshot-in-time perspective, claiming to observe unprecedented algorithmic agency (Baird & Maruping, 2021; Zhang et al., 2021; Berente et al., 2021) and conceiving of the relationship between humans and algorithms as relatively fixed configurations, such as those based predominantly on single, isolated, transactional encounters between one algorithm and one human (Baird & Maruping, 2021; Fügener et al., 2021; Marabelli et al., 2021). However, we show that algorithms' capacity to delegate and act emerges from ongoing relationships between many algorithms and many humans. Every delegation brings in new data, thereby updating and extending training datasets that continuously improve the performance of the collective of algorithms. Thus, any perceived increase in the agency of algorithms would seem to be a result of evolution across many cycles of delegation playing out across an ongoing relationship. Importantly, we show that delegation in multi-agent settings is not a one-off, clean handover of rights and responsibilities but rather a complex cycle of delegations, with collective hybrid appraisal, distribution, and coordination continuously feeding into each other.

Finally, we posit that numerous elements of our model may have applicability to other asymmetrical human-AI systems, in which distributed delegation is largely driven by algorithms that rely heavily on human data. This is evident in systems like HireVue (https://www.hirevue.com), an AI video interviewing system where job candidates are interviewed and evaluated by a collective of algorithms instead of a human. In these systems, the complexity of operations requires a collective of various algorithms to work together. These include simple-reflex algorithms that gather data and apply what-if rules as well as model-based algorithms. Similar to the Uber case studied here, these mechanisms rely heavily on human data that, for example, allow algorithms to be trained, be adjusted in real time, make predictions, or generate responses to human activities (in the example of HireVue this would be previous video-recorded interactions with job candidates that are used to train the AI interviewing system). We conclude that many human-AI interactions in multi-agent settings that are dependent on human data may exhibit collective hybrid appraisal, distribution, and coordination, as theorized here. Nevertheless, considering that delegation among agents can be pictured as a continuum, the specific positioning of humans and algorithmic collectives along the continuum is a determinant of whether our findings can be fully applied to a particular scenario. For instance, in different contexts, algorithms may be more or less reliant on human input compared to the Uber case studied here. For example, ChatGPT assistants and the Google search engine probably require more human input compared to the Uber case (given that humans can provide written instructions that can be adjusted based on the chatbot's response—in the form of follow-up prompts), while self-driving cars may require less so (given that human input may mainly be limited to sharing information about the desired destination address).

Limitations and Future Research

We encourage future researchers to build on and extend our work. We identify several areas of future research in Table 4. One important area emerges from our findings addressing collective hybrid appraisal. We invite future researchers to extend our findings and investigate how diverse agents can be appraised accurately and effectively, and what happens if there is limited opportunity for high-quality appraisal. Another promising direction for future research stems from our findings addressing collective hybrid distribution. Given that some agents may be more dominant than others, it would be an important area for future research to investigate how power and control points affect distribution, and how to distribute more "fairly" to different humans. We encourage research addressing what hybridity means for liabilities in case a process results in undesirable outcomes. Further, we believe that our findings concerning collective hybrid coordination would be a good starting point for future research focusing on how to optimize and coordinate in constantly changing hybrid settings in which algorithms and human input form a symbiosis that needs to be adjusted to a changing environment. Finally, we call for research focusing on how to design distributed delegation ethically to allow human users interacting with multiple algorithms to feel empowered and workers to feel valued and find meaning in their work.

Given that we did not conduct a longitudinal study, we cannot make any claims about how algorithm-to-human delegations and their hybridity in multi-agent settings evolve over time. We hope that future research will address this topic. As an important limitation, our study concerns a multi-agent setting that relies heavily on human data. However, there are many possible multi-agent settings and algorithms that do not concern data from or about humans. Of course, our findings do not extend to such contexts as we only study multi-agent settings where algorithms and humans interact. Furthermore, we did not assess the role of Uber's data engineers and the interaction with the algorithms they developed. Instead, this paper focuses on humans who provide data while interacting with an app: drivers and riders in the Uber case. We encourage future research to unpack this important aspect of human-algorithm interaction in multi-agent settings.

Table 4. Avenues for Future Research	
Collective hybrid appraisal	● How can diverse agents be appraised accurately and effectively? What if there is limited opportunity for high-quality appraisal? ● How should distributed delegation be designed? Which attributes, skills, and capabilities are needed in which contexts?
Collective hybrid distribution	● Are some agents more dominant than others? Are they being distributed to more frequently? How do power and control points moderate distributed delegation? How can distribution be done fairly? ● What does hybridity mean for liability? How do jurisdictions deal with this new reality? How should they?
Collective hybrid coordination	● How is it possible to optimize and coordinate in hybrid settings in which algorithms and human input form a symbiosis? How can it be done in changing environments? ● How can the distribution of authority be managed between primary and less central agents?
Overall framework	● How would distributed delegation play out differently in other contexts (such as different industries or non-platform contexts)? ● How do algorithm-to-human delegations and their hybridity evolve over time? ● How does the configuration of agents in the continuum of delegation change depending on differences in multi-agent settings? ● How can distributed delegation be designed ethically, allowing human workers to feel valued and see meaning in their work and users to feel empowered?

Managerial Implications and Conclusion

In light of perceived increased algorithmic autonomy, many organizations are assessing whether employing model-based algorithms to automate key processes would best support their organizational objectives. Some of them are reflecting on whether human labor is needed at all. Our findings suggest that it could be worthwhile to shift the focus toward humans and algorithms working together in collective, hybrid, and relational delegation settings. We hope that our theorization of distributed delegation proves helpful for developers and managers, as it indicates situations in which algorithms still require different human inputs, such as in situations of delegation breakdowns in which humans can engage in delegation repairs. It also highlights the fact that some multi-agent settings rely on delegation on a continuum, where some rights and responsibilities can be delegated between different configurations of algorithmic collectives and multiple humans. Cognizant of the limits of autonomy, managers can make better-informed decisions regarding the specific configurations of humans and algorithms working together that are best suited to their contexts. At the same time, our theorization of distributed delegation brings to the forefront the fact that the more IS and humans work together in distributed arrangements, the more difficult it will be to assign rights and responsibilities for outcomes. For example, future regulatory frameworks will have to address questions of responsibility and liability in the case of unintended consequences of actions taken in such configurations.

In this paper, we theorize delegation from algorithms to humans as a collective, hybrid, and relational effort that unfolds when algorithms work together and draw on human inputs to delegate to humans in multi-agent settings. Our research presents initial insights into this novel and important research agenda and we encourage others to build on our work.

Acknowledgments

We would like to thank the senior editor, associate editor, and the reviewers, who provided constructive and developmental feedback on previous versions of this manuscript. We received helpful comments on an earlier version of this manuscript from Aleksi Aaltonen. This work was partly supported by the Innovation Fund Denmark for the project DIREC (9142-00001B). The W. Michael Hoffman Center for Business Ethics (HCBE) at Bentley University provided financial support to cover the open access fees for this paper.

References

Abbas, A., Zhang, L., & Khan, S. U. (2014). A literature review on the state-of-the-art in patent analysis. *World Patent Information, 37,* 3-13. https://doi.org/10.1016/j.wpi.2013.12.006

Anthony, C., Bechky, B. A., & Fayard, A.-L. (2023). "Collaborating" with AI: Taking a system view to explore the future of work. *Organization Science, 34*(5), 1672-1694. https://doi.org/10.1287/orsc.2022.1651

Baird, A., & Maruping, L. M. (2021). The next generation of research on IS use: A theoretical framework of delegation to and from agentic IS artifacts. *MIS Quarterly*, *45*(1), 315-341. https://doi.org/10.25300/MISQ/2021/15882

Barad, K. (2003). Posthumanist performativity: Toward an understanding of how matter comes to matter. *Gender and Science: New Issues, Spring*, 801-831. https://doi.org/10.1086/345321

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing artificial intelligence. *MIS Quarterly*, *45*(3), 1433-1450. https://doi.org/10.25300/MISQ/2021/16274

Butler, A. E., Copnell, B., & Hall, H. (2018). The development of theoretical sampling in practice. *Collegian*, *25*(5), 561-566. https://doi.org/10.1016/j.colegn.2018.01.002

Cecez-Kecmanovic, D., Galliers, R. D., Henfridsson, O., Newell, S., & Vidgen, R. (2014). The sociomateriality of information systems. *MIS Quarterly*, *38*(3), 809-830. https://doi.org/10.25300/MISQ/2014/38:3.3

Constantiou, I., Marton, A., & Tuunainen, V. K. (2017). Four models of sharing economy platforms. *MIS Quarterly Executive*, *16*(4), 231-251.

Eisenhardt, K. M. (1989). Agency theory: An assessment and review. *Academy of Management Review*, *14*(1), 57-74. https://doi.org/10.2307/258191

Ekbia, H., & Nardi, B. (2017). *Heteromation, and other stories of computing and capitalism*. MIT Press.

Emirbayer, M., & Mische, A. (1998). What is agency? *American Journal of Sociology*, *103*(4), 962-1023. https://doi.org/10.1086/231294

Fadel, K. J., & Brown, S. (2010). Information systems appraisal and coping: The role of user perceptions. *Communications of the Association for Information Systems*, *26*(1), 107-126. https://doi.org/10.17705/1CAIS.02606

Faraj, S., & Pachidi, S. (2021). Beyond Uberization: The co-constitution of technology and organizing. *Organization Theory*, *2*(1). https://doi.org/10.1177/2631787721995205

Fügener, A., Grahl, J., Gupta, A., & Ketter, W. (2021). Will humans-in-the-loop become borgs? Merits and pitfalls of working with AI. *MIS Quarterly*, *45*(3), 1527-1556. https://doi.org/10.25300/MISQ/2021/16553

Fügener, A., Grahl, J., Gupta, A., & Ketter, W. (2022). Cognitive challenges in human-artificial intelligence collaboration: Investigating the path toward productive delegation. *Information Systems Research*, *33*(2), 678-696. https://doi.org/10.1287/isre.2021.1079

Ge, R., Zheng, Z., Tian, X., & Liao, L. (2021). Human-robot interaction: When investors adjust the usage of robo-advisors in peer-to-peer lending. *Information Systems Research*, *32*(3), 774-785. https://doi.org/10.1287/ISRE.2021.1009

Glaser, B. G. (1978). *Theoretical sensitivity: advances in the methodology of grounded theory*. Sociology Press.

Glaser, B. G., & Strauss, A. L. (1967). *The discovery of grounded theory: Strategies for qualitative research*. Aldine.

Glaser, V. L., Pollock, N., & D'Adderio, L. (2021). The biography of an algorithm: Performing algorithmic technologies in organizations. *Organization Theory*, *2*, 1-27. https://doi.org/10.1177/26317877211004609

Grønsund, T., & Aanestad, M. (2020). Augmenting the algorithm: Emerging human-in-the-loop work configurations. *Journal of Strategic Information Systems*, *29*(2), Article 101614. https://doi.org/10.1016/j.jsis.2020.101614

Hutchins, E. (1995). *Cognition in the wild*. MIT Press.

Jain, H., Padmanabhan, B., Pavlou, P. A., & Raghu, T. S. (2021). Editorial for the special section on humans, algorithms, and augmented intelligence: The future of work, organizations, and society. *Information Systems Research*, *32*(3), 675-687. https://doi.org/10.1287/ISRE.2021.1046

Jain, H., Padmanabhan, B., Pavlou, P. A., & Santanam, T. (2018). Call for papers—Special issue of information systems research: Humans, algorithms, and augmented intelligence: The future of work, organizations, and society. *Information Systems Research*, *29*(1), 250-251. https://doi.org/10.1287/isre.2018.0784

Jennings, N. R. (2000). On agent-based software engineering. *Artificial Intelligence*, *117*, 277-296. https://doi.org/10.1016/S0004-3702(99)00107-1

Jussupow, E., Spohrer, K., Heinzl, A., & Gawlitza, J. (2021). Augmenting medical diagnosis decisions? An investigation into physicians' decision-making process with artificial intelligence. *Information Systems Research*, *32*(3), 713-735. https://doi.org/10.1287/ISRE.2020.0980

Latour, B. (1987). *Science in action: how to follow scientists and engineers through society*. Harvard University Press.

Lebovitz, S., Lifshitz-Assaf, H., & Levina, N. (2022). To engage or not to engage with AI for critical judgments: How professionals deal with opacity when using AI for medical diagnosis. *Organization Science*, *33*(1), 126-148. https://doi.org/10.1287/ORSC.2021.1549

Leonardi, P. M. (2011). When flexible routines meet flexible technologies: Affordance, constraint, and the imbrication of human and material agencies. *MIS Quarterly*, *35*(1), 147-167. https://doi.org/10.2307/23043493

Leontief, W. (1983). National perspective: The definition of problems and opportunities. In *The Long-Term Impact of Technology on Employment and Unemployment: A National Academy of Engineering Symposium* (pp. 3-8). The National Academy Press.

Lyytinen, K., Nickerson, J. V., & King, J. L. (2021). Metahuman systems = humans + machines that learn. *Journal of Information Technology*, *36*(4), 427-445. https://doi.org/10.1177/0268396220915917

Mahdawi, A. (2018). Uber developing technology that would tell if you're drunk. *The Guardian*. https://www.theguardian.com/technology/2018/jun/11/uber-drunk-technology-new-ai-feature-patent.

Malone, T. W., & Crowston, K. (1994). The interdisciplinary study of coordination. *ACM Computing Surveys*, *26*(1), 87-119. https://doi.org/10.1145/174666.174668

Marabelli, M., Newell, S., & Handunge, V. (2021). The lifecycle of algorithmic decision-making systems: Organizational choices and ethical challenges. *Journal of Strategic Information Systems*, *30*(3), Article 101683. https://doi.org/10.1016/j.jsis.2021.101683

Moehrle, M. G., Walter, L., Bergmann, I., Bobe, S., & Skrzipale, S. (2010). Patinformatics as a business process: A guideline through patent research tasks and tools. *World Patent Information*, *32*(4), 291-299. https://doi.org/10.1016/j.wpi.2009.11.003

Möhlmann, M., Zalmanson, L., Henfridsson, O., & Gregory, R. (2021). Algorithmic management of work on online labor platforms: When matching meets control. *MIS Quarterly*, *45*(4), 1999-2022. https://doi.org/10.25300/MISQ/2021/15333

Möhlmann, M., Salge, C., & Marabelli, M. (2023). Algorithm sensemaking: How platform workers make sense of algorithmic management, *Journal of the Association of Information Systems*, *24*(1), 35-64. https://doi.org/10.17705/1jais.00774

Murray, A., Rhymer, J., & Sirmon, D. (2021). Humans and technology:

Forms of conjoined agency in organizations. *Academy of Management Review*, *46*(3), 552-571. https://doi.org/10.5465/amr.2019.0186

Noh, H., Song, Y. K., & Lee, S. (2016). Identifying emerging core technologies for the future: Case study of patents published by leading telecommunication organizations. *Telecommunications Policy*, *40*(10-11), 956-970. https://doi.org/10.1016/j.telpol.2016.04.003

Orlikowski, W. J. (2007). Sociomaterial practices: Exploring technology at work. *Organization Studies*, *28*(9), 1435-1448. https://doi.org/10.1177/0170840607081138

Rai, A., Constantinides, P., & Sarker, S. (2019). Editor's comments: Next-generation digital platforms: toward human-AI hybrids. *MIS Quarterly*, *43*(1), iii-ix.

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation-augmentation paradox. *Academy of Management Review*, *46*(1), 192-210. https://doi.org/10.5465/amr.2018.0072

Ransbotham, S., Fichman, R. G., Gopal, R., & Gupta, A. (2016). Special section introduction: Ubiquitous IT and digital vulnerabilities. *Information Systems Research*, *27*(4), 834-847. https://doi.org/10.1287/isre.2016.0683

Russell, S. (2019). *Human compatible: Artificial intelligence and the problem of control*. Viking.

Russell, S. J., & Norvig, P. (2016). *Artificial intelligence: A modern approach*. Pearson.

Schuetz, S., & Venkatesh, V. (2020). Research perspectives: The rise of human machines: How cognitive computing systems challenge assumptions of user-system interaction. *Journal of the Association for Information Systems*, *21*(2), 460-482. https://doi.org/10.17705/1jais.00608

Shaikh, M., & Vaast, E. (2023). Algorithmic interactions in open source work. *Information Systems Research*, *34*(2), 744-765. https://doi.org/10.1287/isre.2022.1153

Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. *California Management Review*, 66-83. https://doi.org/10.1177/0008125619862257

Susskind, R. E., & Susskind, D. (2015). *The future of the professions: How technology will transform the work of human experts*. Oxford University Press.

Tarafdar, M., Page, X., & Marabelli, M. (2023). Algorithms as co-workers: Human algorithm role interactions in algorithmic work. *Information Systems Journal*, *33*(2), 232-267. https://doi.org/10.1111/isj.12389

Trippe, A. J. (2003). Patinformatics: Tasks to tools. *World Patent Information*, *25*(3), 211-221. https://doi.org/10.1016/S0172-2190(03)00079-6

Tseng, Y.-H., Lin, C.-J., & Lin, Y.-I. (2007). Text mining techniques for patent analysis. *Information Processing and Management*, *43*, 1216-1247. https://doi.org/10.1016/j.ipm.2006.11.011

Urquhart, C. (2023). *Grounded theory for qualitative research*. SAGE.

Yin, R. K. (2018). *Case study research and applications: Design and methods*. SAGE.

Yoo, Y., Henfridsson, O., & Lyytinen, K. (2010). The new organizing logic of digital innovation: An agenda for information systems research. *Information Systems Research*, *21*(4), 724-735. https://doi.org/10.1287/isre.1100.0322

Wiener, M., Cram, W. A., & Benlian, A. (2023). Algorithmic control and gig workers: A legitimacy perspective of Uber drivers. *European Journal of Information Systems*, 32(3), 485-507. https://doi.org/10.1080/0960085X.2021.1977729

Zhang, Z., Lindberg, A., Lyytinen, K., & Yoo, Y. (2021). The unknowability of autonomous tools and the liminal experience of their use. *Information Systems Research*, *32*(4), 1192-1213. https://doi.org/10.1287/isre.2021.1022

About the Authors

Marta Stelmaszak is an assistant professor of information systems at the Isenberg School of Management at the University of Massachusetts Amherst. She holds a Ph.D. from the London School of Economics and Political Science and an M.Sc. in data science from Birkbeck, University of London. Marta's research interests concern digital data and their responsible, sustainable, and ethical management in organizations. Her research has appeared in, among other sources, *MIS Quarterly*, *Information Systems Research*, and *Journal of the Association for Information Systems*. ORCID: https://orcid.org/0000-0003-3173-7470

Mareike Möhlmann is an associate professor in the Department of Computer Information Systems (Business) at Bentley University. Her major research interests include human-AI interaction, algorithmic management, the future of work, the ethical use of AI in organizations, and (sharing economy) platforms. Her research has been published in academic journals such as *MIS Quarterly, Research Policy* and *Journal of the Association for Information Systems*. Additionally, her work has appeared in major practitioner outlets like *Harvard Business Review* and *MIT Sloan Management Review*. She holds a Ph.D. from the University of Hamburg and an M.Sc. from the London School of Economics and Political Science. ORCID: https://orcid.org/0000-0003-3338-5050

Carsten Sørensen holds the DIREC Chair of Digital Transformation in the Department of Digitalization at Copenhagen Business School. He has a B.Sc. in mathematics, an M.Sc., and a Ph.D. in computer science from Aalborg University, Denmark. Since 1989, Carsten has been affiliated with several Danish, Swedish, and British institutions, and he worked at The London School of Economics and Political Science for 25 years. He studies the digital transformation of enterprises, e.g., how digital platforms and infrastructures form the foundation of contemporary business. Carsten has published in *MIS Quarterly, Information Systems Research, Journal of Information Technology, Journal of Management Information Systems, Journal of Strategic Information Systems, Information Systems Journal,* and *European Journal of Information Systems,* among other outlets. He has extensive experience as a principal investigator on several national, EU, and industry research grants in the U.K. and Sweden. Since 1991, Carsten has consulted and conducted executive teaching with a range of large international firms and public organisations. ORCID: https://orcid.org/0000-0002-2002-9383

Appendix A

Qualitative Patent Analysis Example

As an example of the level of insight that qualitative patent analysis can offer, consider U.S. patent number 10762441, granted to Uber Technologies, Inc. by the patent office on 2020-09-01 for predicting the user state using machine learning.[6] The application for this patent was filed on 2016-12-01, and the patent was published on 2018-06-07. These and other administrative details, such as applicant name and inventors, are listed at the top of the patent. The abstract provides a summary of the invention that is protected by the patent:

> *A system coordinates services between users and providers. The system trains a computer model to predict a user state of a user using data about past services. The prediction is based on data associated with a request submitted by a user. Request data can include current data about the user's behavior and information about the service that is independent of the particular user behavior or characteristics. The user behavior may be compared against the user's prior behavior to determine differences in the user behavior for this request and normal behavior of prior requests. The system can alter the parameters of a service based on the prediction about the state of the user requesting the service*. (Patent P.28)

At the beginning of a patent, the images relevant to the patent are shown and are also referred to later in the text, as they contain diagrams and drawings of the technology. In our case, we were able to obtain detailed representations of how algorithms worked from these images. The body of a patent starts with a background statement that introduces the general field—in this case, machine learning used to predict the user state—and provides a brief description of the technology to be patented, outlining the context for the invention and the need for it. The summary that follows provides a description of how the invention works—in our case, describing in plain English how machine learning is used to predict user behavior on Uber and account for these predictions in matching passengers with drivers to minimize safety and satisfaction risks. The summary contains descriptions, for instance, of what data is collected: "For example, text input characteristics may include the number of typographical errors entered by a user or the number of characters erased by a user while entering a search query"; how it is analyzed: "To predict user state, the system compares data associated with the trip request to data about past trip requests submitted by the user"; and how the algorithm makes decisions: "For example, when the likelihood [of unusual behavior] is comparatively very high, the user may not be matched with any provider, or limited to providers with experience or training with users having an unusual state." This part of the patent usually contains a few paragraphs on one page, consisting of around 1,000 words.

The summary description is expanded upon in the brief description of the drawings and detailed description sections that follow, which include detailed explanations of how the technology works with references to images. This part of the paper stretches over many paragraphs and can contain between 6,000 and 8,000 words. In terms of protecting intellectual property, the most important part of the paper is the claims section, which starts from a formulaic "What is claimed is:" and contains a number of specific points that describe the exact technology that is to be protected—e.g.: "2. The computer-implemented method of claim 1, wherein the activity data comprises one or more of: data input accuracy, data input speed, interface interaction behavior, device angle, or walking speed."

As shown above, consisting of over around 10,000 words, each patent offers unique insights into how algorithms work that are useful not only for researchers but also for journalists—who, in the case of Patent 10762441, reported that Uber is "developing technology that would tell if you're drunk" (Mahdawi, 2018).

[6] Patent US 10762441 is available at: https://patentimages.storage.googleapis.com/c7/cd/0d/d0b34fb47cc499/US20180157984A1.pdf. We recommend that interested readers open the patent file and browse it along with our description in this section of the paper for a more in-depth understanding.