Rising like a Phoenix: Emerging from the Pandemic and Reshaping Human Endeavors with Digital Technologies ICIS 2023

Digital Technologies and the Future of Work

Dec 11th, 12:00 AM

# A Taxonomy of Algorithmic Control Systems

Armin Alizadeh
*Technical University of Darmstadt*, alizadeh@ise.tu-darmstadt.de

Felix Hirsch
*Dresden University of Technology*, felix.hirsch@tu-dresden.de

Jennifer Jiang
*Technical University Dresden*, jennifer.jiang@tu-dresden.de

Martin Wiener
*TU Dresden*, martin.wiener@tu-dresden.de

Alexander Benlian
*Technical University of Darmstadt*, benlian@ise.tu-darmstadt.de

# A Taxonomy of Algorithmic Control Systems

*Completed Research Paper*

**Armin Alizadeh**
TU Darmstadt
Karolinenplatz 5,
64289 Darmstadt, Germany
alizadeh@ise.tu-darmstadt.de

**Felix Hirsch**
TU Dresden
Helmholtzstr. 10,
01069 Dresden, Germany
felix.hirsch@tu-dresden.de

**Jennifer Jiang**
TU Dresden
Helmholtzstr. 10,
01069 Dresden, Germany
jennifer.jiang@tu-dresden.de

**Martin Wiener**
TU Dresden
Helmholtzstr. 10,
01069 Dresden, Germany
martin.wiener@tu-dresden.de

**Alexander Benlian**
TU Darmstadt
Karolinenplatz 5, 64289 Darmstadt, Germany
benlian@ise.tu-darmstadt.de

## Abstract

*Algorithmic control (AC) uses digital technologies and advanced algorithms to control workers and is rapidly becoming a central component of modern work environments. While previous research has explored the implications of AC by examining its specific forms, mechanisms, or functions, this research argues for a broader understanding of AC as socio-technical systems, explicitly considering the technological and organizational characteristics of AC. The overarching goal of this study is to identify and conceptualize the core dimensions and respective characteristics of AC systems. To achieve this goal, we develop a taxonomy based on a review of prior literature and an analysis of 21 empirical examples. Furthermore, we demonstrate the application and usefulness of the derived taxonomy by applying it to three real-world AC systems. By adopting a holistic system perspective and developing a validated taxonomy, our study contributes to the theoretical understanding of AC systems and sets the stage for deeper exploration in future research.*

**Keywords**: Algorithmic control (AC), AC systems, taxonomy development, future of work.

## Introduction

As digital technologies have become more prevalent in the workplace, organizations have sought to leverage them to exert greater control over employee behavior. One way they have done so is by implementing algorithmic systems that monitor, evaluate, and direct worker activities (Lee et al. 2015; Möhlmann et al. 2021). This practice, termed algorithmic control (AC), has gained significant attention in recent years as more and more organizations adopt these technologies. Frequently cited examples are online labor platforms such as Uber or Upwork. These and similar platforms use AC to monitor and manage more than

180 million platform workers in the U.S. and Europe alone without human manager supervision but exclusively via digital technologies (Benlian et al. 2022; Cram & Wiener 2020). However, AC is also gaining traction in more traditional organizations (i.e., organizations where workers are permanent employees, as opposed to independent gig workers). For example, logistics companies like Amazon collect extensive data on the behavior of their workers and direct them almost entirely through digital devices such as barcode scanners or wearables (Delfanti 2021; Vallas et al. 2022). In more office-heavy jobs, AC is exercised through smart company badges, which record and evaluate employee interactions (Cram & Wiener 2020). These examples provide a glimpse into how AC has fundamentally changed how work is organized and will continue to do so, affecting millions of workers in one way or another.

A defining characteristic of AC is that control instructions originate from an information system rather than a human manager and that the control instructions are delivered through digital interfaces (Wiener et al. 2020). AC relies on mass data collection through digital sensors and real-time analytics through advanced algorithms. As such, AC is considered more comprehensive, instantaneous, interactive, and opaque than earlier forms of organizational control (Kellogg et al. 2020). Although the implementation of AC is often driven by economic imperatives, such as the need for increased efficiency and competitiveness, its positive and negative implications for workers, organizations, and society are complex and far-reaching (Baiocco et al. 2022; Meijerink & Bondarouk 2023; Spiekermann et al. 2022; Wesche & Sonderegger 2019).

When examining the potential benefits and apparent drawbacks of AC for organizations and workers, previous research has mainly considered specific AC *forms* (e.g., Cram et al. 2022; Wiener et al. 2023), *mechanisms* (e.g., Kellogg et al. 2020), or *functions* (e.g., Parent-Rocheleau & Parker 2021). These concepts proved valuable as they provided significant insights into how organizations use, and workers experience AC. However, AC is by no means limited to differences in specific isolated forms (respectively, mechanisms or functions); rather, it differs in a range of technological characteristics, including the types of digital devices utilized, data sources accessed, and analytical capabilities. Additionally, AC differs in relevant organizational characteristics such as the organizational type, worker involvement, and the specific areas within the organization where AC is implemented (Cameron et al. 2023; Schafheitle et al. 2020). This heterogeneous use of AC is particularly evident in traditional organizations (Jarrahi et al. 2021). In contrast to platform-based organizations such as Uber, where AC was part of the architecture from the beginning, AC is now being introduced in a variety of existing organizational settings. In this light, existing AC concepts seem to fall short of adequately capturing the diverse range of real-world applications of AC.

The inadequate conceptual coverage of technological and organizational characteristics of AC also hampers comparability and generalizability in existing research. For instance, studies on AC have been conducted in the gig economy, where workers receive directives solely through smartphones or websites, without human supervisors or traditional employment relationships (e.g., Duggan et al. 2020; Wiener et al. 2023; Zheng & Wu 2022). Conversely, research on AC has also been conducted in logistics warehouses, where workers receive directives through digital devices such as barcode scanners, with the presence of human supervisors and traditional employment relationships (e.g., Delfanti 2021; Wood 2021). Despite falling under the broad umbrella of AC, the similarities between these research contexts are limited, making it challenging to transfer research results across different contexts. Therefore, a more comprehensive AC framework, including technological and organizational characteristics, is urgently needed to establish a common frame of reference for AC research.

Motivated by the need to grasp the complex nature of AC and to provide a foundation for AC research, our study proposes the broader concept of AC *systems*. This concept emphasizes that AC is used in a specific technological and organizational system that is instrumental in understanding this phenomenon. Based on a working definition of AC systems and following established methodology (Nickerson et al. 2013), we develop a taxonomy of AC systems, including three technological and four organizational dimensions that can be used to differentiate different systems. To derive these dimensions, we draw on a review of previous literature, along with an analysis of 21 real-world AC systems. Further, we illustrate the applicability and usefulness of the taxonomy by classifying three empirical examples along the taxonomy dimensions.

Our study advances AC research in two key aspects. First, we extend and shift the previous literature's predominant focus on isolated forms of AC to a broader perspective on the phenomenon by introducing the notion of AC systems. Second, by presenting a comprehensive taxonomy, we provide AC researchers with a tool to classify AC systems along their defining dimensions, allowing meaningful comparisons of similarities and differences between them. This, in turn, enhances the comparability and generalizability of research findings related to the effects of AC systems on specific organizational and individual outcomes. Additionally, the taxonomy serves as a valuable resource for practitioners, policymakers, and organizations in understanding and managing the complexities of AC systems in various domains. Ultimately, our study enhances the understanding of AC as a distinctive form of organizational control, providing a foundation for future research in this emerging and critical area of study.

## Conceptual Foundations

### *Organizational and Algorithmic Control*

Organizational control is broadly defined as any attempt to intentionally influence the behavior of workers (or a group of workers) to act in accordance with the organization's objectives (Cardinal et al. 2017; Kirsch 1996; Smith & Tannenbaum 1963; Wiener et al. 2016). This definition implies a dyadic relationship between controllers and controlees, in which the former use different mechanisms to influence the behavior of the latter. These mechanisms do not exist in isolation but are embedded in a broader organizational context, such as organizational structure and organizational culture (Flamholtz et al. 1985; Schafheitle et al. 2020).

Over time, the way organizations control their workers has evolved (Edwards 1979): Early 'simple' forms of control typically involved direct supervision and oversight by a human manager, with little reliance on formal procedures or technology. In contrast, the use of structural control introduced more formalized mechanisms for monitoring and regulating work processes. This can include technical control, where the pace of work is determined by machinery and automated systems, as well as bureaucratic control, which involves adherence to company policies, procedures, and rules. In this context, AC represents the latest type of organizational control, where data-driven algorithms and advanced technologies are used to direct, evaluate, and discipline workers. AC is characterized by its ability to adapt control procedures to individuals based on data insights, making it a more sophisticated and dynamic form of organizational control (Kellogg et al. 2020).

As the role of technology in organizational control has evolved, so has the focus within the IS research community. Initially, IS control research focused on *how to manage information technology* efficiently, specifically in the context of IS project control (Saunders et al. 2020; Wiener et al. 2016). However, with the changing role of information technology in shaping organizations (Orlikowski and Scott 2008) and the amount of observational data organizations collect (Bernstein 2017; Zuboff 2015), the way information technology is viewed within the control process is also changing. Attention is now shifting to how *information technology alters the control process itself (Cram & Wiener 2020)*, both in the information systems (IS) (e.g., Adam et al. 2023; Benlian et al. 2022; Cameron et al. 2023; Zheng & Wu 2022) and related management literature (e.g., Cardinal et al. 2017; Kellogg et al. 2020; Parent-Rocheleau & Parker 2021; Power 2022; Wesche & Sonderegger 2019).

### *Algorithmic Control Concepts*

Past research has drawn on various theories and concepts to examine the nature, effects, and dynamics of AC use in organizations (see Table 1 for an overview of key AC concepts). In their seminal paper, Kellogg et al. (2020) picture AC as a new "contested terrain" of control. Drawing on labor process theory, they identify six *mechanisms* managers employ to exert control over workers. Subsequently, they discuss how each mechanism may lead to potential (negative) worker experiences. Although the study reviews a wide range of AC systems, there is no extensive discussion on the specific characteristics, similarities, or differences of these systems. Wiener et al. (2023) examine how workers judge the legitimacy of two predominant *forms* of AC in their study of Uber drivers. They find that workers' legitimacy judgments are positively correlated with AC that is used to instruct workers on how to conduct their daily work (guiding AC). In contrast, they find that AC used to regulate who is allowed to work on a platform (gatekeeping AC) negatively correlates with workers' legitimacy perceptions. The study is limited to Uber as an extreme case of AC, and the proposed concept of AC forms does not include any further characteristics of the AC system. In a similar study design, Cram et al. (2020) investigate the effect of three different AC *modes* on workers' well-being. Finally, Parent-Rocheleau and Parker (2021) investigate how six management *functions* that algorithms currently perform affect key job resources (e.g., job autonomy) and job demands (e.g., workload). Notably, the study incorporates sociotechnical moderators in its conceptual model, focusing primarily on subjective perceptions such as system transparency and fairness, rather than observable system properties.

| **Concept** | **Subconcept** | **Definition/Description** |
|---|---|---|
| **Forms**<br>Wiener et al. (2023) | Gatekeeping AC | Use of AC to screen/vet and monitor workers in order to control who is allowed to commence, or to continue, working for a given company. |
| | Guiding AC | Use of AC to oversee and guide worker behavior, as well as to provide feedback on performance, in order to control how workers conduct their daily work. |
| **Functions**<br>Parent-Rocheleau and Parker (2021) | Monitoring | Algorithms used in systems aiming to collect and report any data on employees during their work. |
| | Goal setting | Algorithms assigning tasks or rides, organizing employees' work, or setting performance or productivity targets. |
| | Performance management | Algorithms carrying out and/or displaying employees' performance ratings or providing automated performance feedback. |
| | Scheduling | Algorithms carrying out employee's schedules or sending nudges for suggested working times. |
| | Compensation | Automated calculation of pay based on algorithmically managed conditions and metrics. |
| | Job termination | Algorithmic termination decision making and/or announcement. |
| **Mechanisms**<br>Kellogg et al. (2020) | Recommending | Entails employers using algorithms to offer suggestions intended to prompt the targeted worker to make decisions preferred by the choice architect. |
| | Restricting | Entails the use of algorithms to display only certain information and allow specific behaviors while preventing others. |
| | Recording | Entails the use of computational procedures to monitor, aggregate, and report, often in real time, a wide range of finely grained data from internal and external sources. |
| | Rating | Managers [...] using computational technologies to gather ratings and rankings to calculate some measure of workers' performance, as well as predictive analytics to predict measures of their future performance. |
| | Replacing | Entails rapidly or even automatically firing underperforming workers from the organization and replacing them with substitute workers. |
| | Rewarding | Entails using algorithms to reward high-performing workers interactively and dynamically (e.g., with work privileges, higher pay, and promotions). |
| **Modes**<br>Cram et al. (2020) | Input control | The use of gatekeeping and screening criteria to determine the workers who are granted access to an online platform. |
| | Behavior control | Managerial monitoring of worker behavior for adherence to rules and procedures. Rewards or sanctions are granted, depending on compliance. |
| | Output control | Establishing output requirements and targets, which are evaluated by the online platform. Workers are rewarded or sanctioned, depending on the outputs. |

**Table 1. Overview of Algorithmic Control Concepts**

This summary of current AC concepts demonstrates that past research has exclusively examined isolated parts of AC and (at least conceptually) neglected the characteristics of the system in which AC is embedded. This is in stark contrast to recent developments in practice, where AC is used in increasingly heterogeneous ways (e.g., Benlian et al. 2022). In particular, while considering AC as a homogeneous phenomenon in platform-based contexts might have been feasible (though debatable), this does not hold true for traditional organizations, where AC is "not the primary means of organizing work" and "adds to pre-existing power dynamics and regimes of control." (Jarrahi et al. 2021, p. 4). To avoid being left behind by real-world developments, we contend it is necessary and timely to broaden the previously isolated concepts and introduce a comprehensive conceptualization of AC.

## *Algorithmic Control Systems*

Recognizing the significance of AC in contemporary organizational environments, a comprehensive understanding of AC as an integrated sociotechnical system becomes paramount. We propose the concept of AC *systems*, which we define as the deliberate combination and integrated design of hardware, software, and data resources, as well as related digital capabilities and procedures enacted by an organization to align worker behavior with organizational goals. At the heart of this definition is the understanding that when considering information technology in an organizational context, the concrete characteristics (i.e., the specific combination of hardware and software) are relevant to examine its impact on organizations (Srinivasan et al. 2005). In the case of AC systems, the intended design purpose is to control employees' behavior. We recognize that such a system does not have AC as its sole purpose but that the AC system may be part of a superordinate IS. In addition, our working definition emphasizes that the system is embedded in a specific organizational context. Therefore, we follow Flamholtz et al. (1985) described perspective of organizational control, which defines a "core control system" embedded in a wider organizational "control context." This transfers to our understanding of an AC system, where the integrated design of hardware, software, data resources, as well as digital capabilities and procedures, represent the core control system, and the organizational context represents the control context. Figure 1 illustrates our understanding of an AC system.

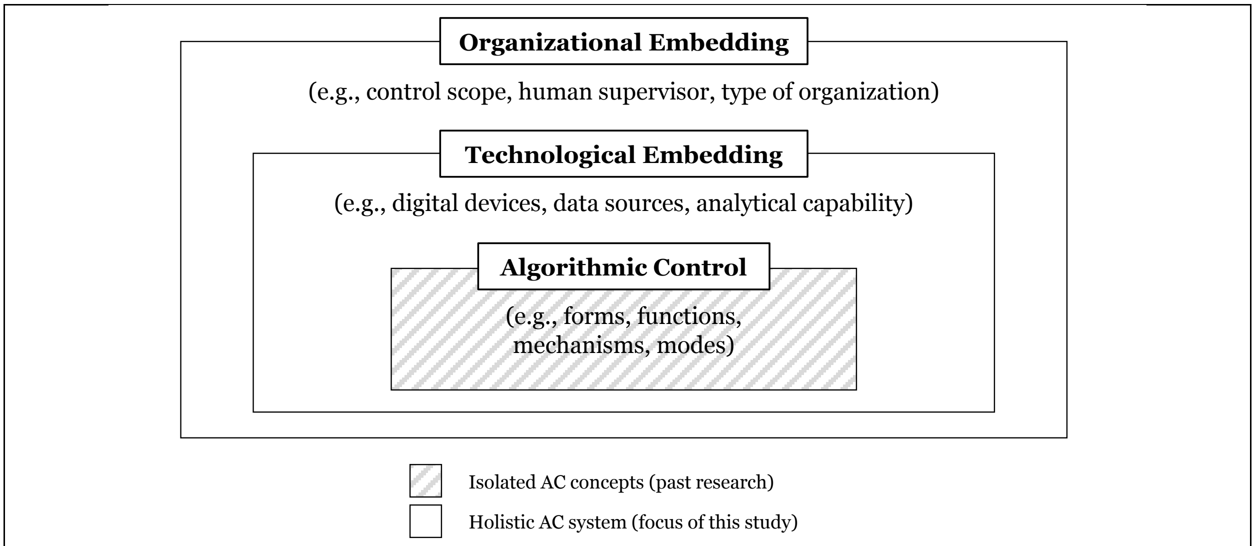


**Figure 1. Algorithmic Control System**

The focus and limitations of the proposed construct must be carefully articulated. First, it is distinct in its emphasis on organizations, setting it apart from other established concepts like "algocracy" (Danaher 2016), "algorithmic regulation" (Ulbricht & Yeung 2022), and "algorithmic governance" (Katzenbach & Ulbricht 2019), which target the role of algorithms in steering political processes and broader societal structures. Second, building on organizational control literature, our approach focuses on interaction, i.e., the processes through which the AC system attempts to align workers' behavior with organizational goals, rather than algorithmic decision making as such (Kirsch 1996; Wiener et al. 2023). And third, it focuses on the dyadic relationship between the AC system and the worker. While other actors, like customers providing ratings, integrate into this system, their significance within our theoretical lens emerges solely based on their impact on the interactions between the AC system and the worker.

By shifting the focus from isolated components to the intricate interplay between organizational and technological characteristics, researchers can better comprehend the nuanced effects on worker behavior and the alignment of such behaviors with organizational objectives. It should be noted that the AC concepts introduced in the preceding section may be extended to a systems perspective if needed. That is, each of the previous concepts can move to the very center of the AC system understanding (shaded box in Figure 1), by incorporating the technological and organizational dimensions of the encompassing system. We empirically derive the key technological and organizational dimensions in the subsequent section.

## Methodology

In the following sections of this study, we aim to identify the main technological and organizational dimensions of AC systems. We do so by developing a taxonomy of AC systems that researchers and practitioners can use to describe and classify AC systems. The relevance of taxonomies is commonly recognized in the IS literature because “the classification of objects helps researchers and practitioners understand and analyze complex domains” (Nickerson et al. 2013, p. 1). Here, the purpose of a taxonomy goes beyond classification. It can help to identify similarities and differences among objects, and understand relationships. They help researchers and practitioners communicate on a shared basis and can thus also support theory-building efforts (Glass & Vessey 1995; Schöbel et al. 2020). It should be noted that the goal of taxonomy development efforts is not to provide a detailed description of all possible characteristics but to reduce complexity and highlight the characteristics that are pivotal for distinguishing the objects of interest (Nickerson et al. 2013).

To develop the AC systems taxonomy, we followed Nickerson et al. (2013) approach, as it is well established in the IS literature (Kundisch et al. 2022) and provides a systematic, step-by-step process for taxonomy development. In short, the process involves defining a meta-characteristic from which all other characteristics are derived. Then, the taxonomy dimensions are iteratively derived and refined until a point of theoretical saturation is reached, indicated by a set of ending conditions. A detailed overview of the entire process can be found in Nickerson et al. (2013).

## *Meta-Characteristic and Ending Conditions*

The taxonomy development process begins with defining a meta-characteristic (Nickerson et al. 2013). This meta-characteristic serves as the point of reference for deriving all other characteristics in the taxonomy and, at the same time, helps researchers to identify and eliminate irrelevant characteristics. The meta-characteristic should be derived from the taxonomy’s purpose, which is determined by the intended user group and their anticipated use of the taxonomy.

The user of the taxonomy we develop are researchers interested in studying AC. Typically, this user group is interested in various technological and organizational characteristics of the AC system that might impact how AC is perceived, evaluated, and reacted to in organizations and beyond. However, they often do not have an “inside view” of the system; instead, they gather their information from public sources or through conducting interviews. Based on this information, researchers want to characterize and classify the AC system along its critical dimensions. Therefore, the purpose of the AC systems taxonomy is to distinguish among AC systems based on observable technological and organizational characteristics. Consequently, we define our meta-characteristic as *AC systems’ observable technological and organizational characteristics*.

Next, a set of objective and subjective ending conditions must be defined. These ending conditions indicate when a taxonomy has reached a steady state appropriate to its purpose (i.e., theoretical saturation), and further developmental iterations are no longer necessary.As for this study, we adopt five of the objective and five subjective ending conditions proposed by Nickerson et al. (2013, p. 9): Specifically, the five objectives ending conditions were (1) that at least one object is classified under every characteristic of every dimension (2), that no new dimensions or characteristics were added in the last iteration (3), that no dimensions or characteristics were merged or split in the last iteration, (4) that every dimension is unique and not repeated, and (5) that every characteristic is unique within its dimension. The five subjective ending conditions where that the developed taxonomy is (1) concise (i.e., five to nine dimensions), (2) robust, (3) comprehensive, (4) extendible, and (5) explanatory.

## *Taxonomy Development Iterations*

Each taxonomy development iteration follows either a conceptual-to-empirical or an empirical-to-conceptual approach. In conceptual-to-empirical iterations, existing concepts along with the researchers’ experiences and judgments are used to derive new dimensions. In contrast, in empirical-to-conceptual iterations, researchers examine empirical objects to validate existing and derive additional dimensions. Researchers identify common dimensions that possess discriminative characteristics among objects during each iteration. All derived dimensions must align logically with the meta-characteristic. New dimensions can be discovered, and existing ones can be adjusted or removed in each iteration. After each iteration, the fulfillment of the ending conditions is verified. If satisfied, the taxonomy development process concludes; otherwise, another iteration commences (Nickerson et al. 2013). A summary of our taxonomy development process is provided in Figure 2.

**Iteration 1.** We followed the advice by Nickerson et al. (2013, p. 10) to start with a conceptual-empirical approach if "the researcher has significant understanding of the domain." We searched for and selected articles that AC and related concepts on a conceptual level. The selection of the paper is, by its nature, based to some extent on a subjective evaluation by the researcher, as Nickerson acknowledges, and reflects the researcher's expertise on the subject (Nickerson et al. 2013). More specifically, we analyzed Duggan et al. (2020); Jarrahi et al. (2020); Kalischko and Riedl (2021); Kellogg et al. (2020); Parent-Rocheleau and Parker (2021); Schafheitle et al. (2020); Wiener et al. (2023).

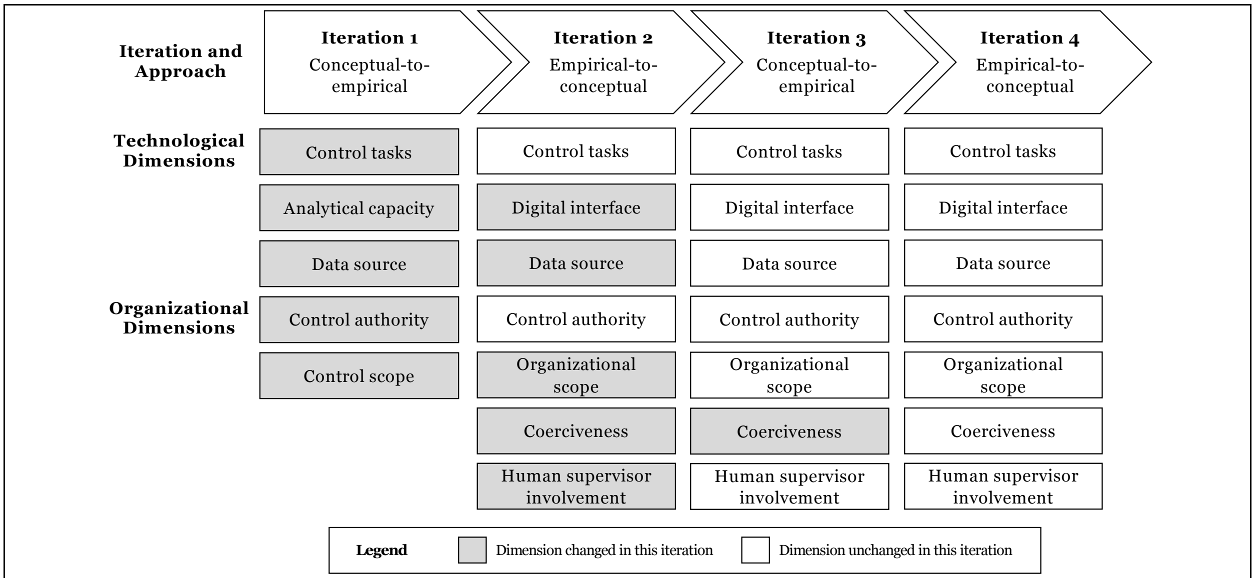


**Figure 2. Overview of Taxonomy Dimensions Across Iterations**

We then proceeded in four steps: First, we gathered all relevant dimensions (and characteristics), including their definitions. This resulted in a list of 19 dimensions and 67 characteristics. Second, we screened each dimension for its relation to our meta-characteristic. In this step, several dimensions were dropped because they lacked observability, as our meta-characteristic demanded. For instance, the dimension *data visibility* (i.e., who can access the system's data) (Schafheitle et al. 2020) is not observable without knowing the system's internal mechanisms and thus does not align with our meta-characteristic. However, this step also led to eliminating the dimension *data sources* (Schafheitle et al. 2020). Here, we replaced the previous unobservable characteristics (structured and unstructured data) with characteristics researchers can obtain through investigation (e.g., GPS, communications data, vital data, and others). Third, we assessed the similarity of the dimensions and considered a second-level grouping, which led to one additional dimension, *control task*. Fourth, through discussions within the author team, we ranked the dimensions by their importance and uniqueness. This four-step process led to an initial version of the taxonomy entailing three technological and two organizational dimensions (see left column in Figure 2).

**Iteration 2.** To test the conceptually derived dimensions gathered in the first iteration and to identify additional characteristics, we chose an empirical-to-conceptual approach for the second iteration. Following the recommendation of Nickerson et al. (2013), we identified objects (AC systems) by conducting an extensive review of relevant literature. Our objective was to encompass a diverse range of platform-based and traditional work settings, as well as various technological design configurations. In total, we selected 12 gig-work platforms frequently mentioned in the related literature: Amazon Mechanical Turk, Airbnb, DoorDash, Ele.me, Fiverr, Instacart, Meituan, Lyft, Swiggy, TaskRabbit, Uber, UberEats, Upwork, Zomato. Regarding more traditional work contexts (i.e., organizations where workers are permanent or part-time employees), we selected five organizations: Amazon Fulfillment Centers, Gorillas, Humanyze, Lieferando, and UPS. In addition, we included four software tools available on the market and the literature referred to as AC: Rationalizer, Viva Insights, Genome, and Preactor. Initially, we collected descriptions of each AC system from the available literature. We supplemented these descriptions with additional online sources such as developer blogs, corporate websites, news articles, and reports. This way, we gathered a total of 21 detailed descriptions of AC systems, which served as a pool of objects for empirical-to-conceptual iterations.

In the second iteration, we selected a random sample from our collection of empirical objects. Classifying only a subset during empirical-conceptual iterations is a common procedure, as it allows for swift initial insights into the empirical data (Nickerson et al. 2013; Passlick et al. 2021; Scharfe & Wiener 2020). We then proceeded in two steps: First, we classified the selected AC systems using the initial taxonomy. We found that the dimensions of *analytical capacity* and *control scope* (Schafheitle et al., 2020) were fuzzy and despite our efforts to collect comprehensive descriptions of the systems we lacked sufficient information to clearly differentiate them. We therefore decided to exclude these dimensions. We also observed a requirement for additional modifications to the *data sources* dimension and refined the dimension accordingly. Second, we examined the empirical objects to identify additional dimensions aligned with the meta-characteristic. We identified the dimensions of *digital interface, organizational scope, coerciveness,* and *human supervisor involvement* and consequently incorporated them into the second version of the taxonomy. As a result, the taxonomy encompassed four organizational and three technological dimensions (see the second column from the left in Figure 2).

**Iteration 3.** In the third iteration, we used a conceptual-to-empirical approach and conducted a targeted literature review for individual taxonomy dimensions. In particular, we focused on the dimensions added in the previous two empirical-to-conceptual iterations (digital interface, types of processed data, organizational scope, and voluntariness). For each dimension, we derived a set of keywords (e.g., ‘digital interface' AND ('taxonomy' or 'classification' or 'typology' or 'categories')), searched for, and analyzed relevant literature. This process led to adjustments in the dimension of *coerciveness*. However, although we found relevant literature for the other dimensions, such as types of data, the concepts did not fit our purpose of the taxonomy, and therefore we decided to stick with the characteristics derived from the empirical objects.

**Iteration 4.** Since the taxonomy was already close to a stable state in the third iteration (i.e., only one of the dimensions was adjusted), we decided to conduct another empirical-to-conceptual iteration in which we classified the remaining objects collected in iteration two. In this iteration, the classification process did not result in any changes to the taxonomy. Since the other objective and subjective ending conditions were also met, the taxonomy development process ended at this point. An overview of how the dimensions changed through the iterations is depicted in Figure 2. The final iteration comprises three technological and four organizational dimensions with 21 characteristics.

## A Taxonomy of Algorithmic Control Systems

This section presents the AC systems taxonomy (dimensions and respective characteristics) resulting from the above-described development process. Table 2 gives an overview of all dimensions and characteristics.

### *Organizational Embedding*

Concerning the organizational embedding of AC systems, we have identified four dimensions that are central to distinguishing AC systems. The organizational scope of the AC system, the control authority the system can exercise, the presence or absence of a human supervisor, and the system’s coerciveness.

**Organizational scope of the AC system.** This dimension refers to the extent to which the AC system is used in the organization. In the broadest organizational scope, an AC system entails the *full control* over an organization’s operations. Prominent examples of AC, such as Uber, align with this extensive scope, wherein the AC system controls the company’s core function, specifically the drivers. Conversely, this does not mean the system controls all workers in the organization without exception. As Wiener et al. (2020) illustrate, even in a scenario where all operations are controlled through the system, there are still managers and programmers who configure the system. In a narrower organizational scope, the AC system can be employed for *partial operational control*. When an AC system exercises partial operational control, it still oversees the working processes of the employed. However, it does so in only one defined part of the organization (e.g., one function, one factory, one site). For example, an AC system may be used in the warehouse of a manufacturing company but not in the production area. In the narrowest organizational scope, the AC system exercises *task-specific* control. An example is the Microsoft Viva Insights system, which analyzes the individual usage behavior of office software and derives behavioral recommendations to increase the worker’s well-being (Microsoft 2022a).

**Control authority of the AC system.** This dimension refers to the amount of authority a system can exercise over workers, or in other words, the extent to which the system relies on the worker's consent. If an AC system is granted *full authority*, it is free (at least formally) to dispose of a worker's working time and capacity. Consider the AC system used to instruct workers in Amazon Warehouses. Here, employees are prompted to perform the following task using digital scanners. There is no possibility to reject this instruction. In contrast, if the AC system is granted *partial authority*, it relies on the worker's initial consent to exercise control. For instance, in the case of an Uber driver, they must initially accept and confirm each ride. Yet, once accepted, the system can make adjustments to the route and destination without requiring the driver's consent (e.g., Rosenblat & Stark 2016). If an AC system is *advisory*, it relies on the continuous consent of the worker to follow its suggestions. In other words, the system issues recommendations but has no executive power to enforce them. Take the case of Microsoft Viva Insights, which offers suggestions but lacks any authoritative control.

**Human supervisor involvement.** This dimension focuses on the presence or absence of a human supervisor within the organizational embedding of AC systems. While AC systems assume tasks previously handled by human managers, this does not automatically result in the replacement of human supervisors. We identified the human supervisor as a significant distinguishing factor in the organizational integration of AC systems. Examples of AC systems with *no supervisor involvement* can be found in the gig economy, where AC was always part of the organizational architecture. However, it may be surprising to learn that this is not mandatory. For example, Li (2021) describes the role of human supervisors in the Chinese ride-hailing service Didi. Unlike platform-based organizations, *human supervisor involvement* is typical when existing, traditional organizations introduce AC into their organizational structure. In this scenario, role conflict may arise when the worker must appease both the "algorithmic boss" and the human boss.

**Coerciveness of the AC system.** This dimension addresses the degree of coerciveness the organization imposes on workers to engage with the AC system. We adopted this dimension (and characteristics) from the Datafication Technology Control Configuration-framework proposed by Schafheitle et al. (2020) and confirmed them using our empirical examples. Regarding their coerciveness, AC systems can be divided into three categories. First, organizations may provide *opt-in options*, where workers actively choose to use the AC system or its specific components. Chinese food-delivery platform Meituan allows riders to opt into an order assignment mode rather than the typical pick mode (van Doorn & Chen 2021). Second, there may be *opt-out options* for an AC system or specific components of it. Microsoft Viva Insights serves as an example, as it is typically activated by default with office software provision, but workers retain the ability to opt out of the service. The third category comprises AC systems with *no opt-out options*. This commonly occurs in organizations utilizing AC extensively for worker management or where AC is deemed indispensable for the work process.

## *Technological Embedding*

We have identified three vital technological dimensions to differentiate AC systems. The digital interface through which the control instructions are passed from the system to the worker, the type of data sources the system taps, and the control tasks implemented.

**Digital interface.** The digital interface dimension refers to the various means through which workers interact with the AC system, enabling the system to provide control instructions. We have identified three overarching types of digital interfaces that AC systems leverage to control workers. First, *websites* serve as the primary means of AC for gig and crowd workers, with the specific end device being less relevant. Examples include online labor platforms like Fiverr, Upwork, Twine, TaskRabbit, and Amazon Mechanical Turk, where AC is employed to shape worker-client relationships (e.g., Bucher et al. 2021; Curchod et al. 2020; Jarrahi et al. 2020). Second, *dedicated software* is required to be installed on digital devices, such as smartphones, in organizations like Uber and Lyft. This software extends beyond mere website display, enabling intended control functionalities like driver GPS tracking (e.g., Rosenblat & Stark 2016). Last, AC can be facilitated through *dedicated devices*, such as handheld scanners in logistics warehouses (e.g., Jarrahi et al. 2021; Kellogg et al. 2020; Schaupp 2022) or wearables like augmented reality glasses and wristbands (e.g., Ajunwa 2020; Cram & Wiener 2020; Maltseva 2020).

**Data sources.** This dimension describes the types of data collected and analyzed by AC systems to control workers in real time. Four overarching types of data sources have been identified: First, the AC system may collect and evaluate *process data*. This type includes data inputs necessary to monitor the progress of the work process itself digitally. For example, it involves confirming the completion of process steps, such as a food courier confirming receipt of the meal (e.g., Huang 2022) or a warehouse worker scanning a barcode to record package receipt (e.g., Delfanti 2021; Vallas et al. 2022). The second type is *behavioral data*. This type of data is not essential for monitoring the work process but is evaluated by AC systems to assess and control the overall work behavior of employees. Behavioral data is collected by monitoring interactions between colleagues through "smart badges" (Cram & Wiener 2020), by monitoring conversations in call centers (Parent-Rocheleau & Parker 2021), or by monitoring and evaluating GPS data to detect speeding violations (Zheng & Wu 2022). The third type of evaluation data is *customer data* related to the worker's work results or behavior. Prime examples are the various rating systems implemented in many online labor platforms (Rahman 2021). The last type of data evaluated is data from *external sources*. This type includes a wide range of data sources external to the organization, such as publicly available weather data (van Doorn & Chen 2021), automated screening of workers' public criminal records (Wiener et al. 2023), or, in extreme cases, a direct data connection to government surveillance (Huang 2022). Overall, the data sources dimension highlights the diverse types of data collected and analyzed by AC systems, including process data, behavioral data, customer data, and data from external sources. These data sources play a crucial role in enabling real-time control of workers.

<table>
<tr><th></th><th>Dimensions<br>(n)e = (not) mutually exclusive</th><th colspan="12">Characteristics</th></tr>
<tr><td rowspan="4">Organizational</td><td>Organizational scope e</td><td colspan="4">Full operational control</td><td colspan="4">Partial operational control</td><td colspan="4">Task-specific control</td></tr>
<tr><td>Control authority e</td><td colspan="4">Full authority</td><td colspan="4">Partial authority</td><td colspan="4">Advisory</td></tr>
<tr><td>Human supervisor involvement e</td><td colspan="6">Human supervisor involved</td><td colspan="6">No human supervisor involved</td></tr>
<tr><td>Coerciveness e</td><td colspan="4">No Opt-out options</td><td colspan="4">Opt-out options</td><td colspan="4">Opt-in options</td></tr>
<tr><td rowspan="3">Technological</td><td>Digital interface e</td><td colspan="4">Website</td><td colspan="4">Dedicated software</td><td colspan="4">Dedicated device</td></tr>
<tr><td>Data sources ne</td><td colspan="3">Process data</td><td colspan="3">Behavioral data</td><td colspan="3">Customer data</td><td colspan="3">External data</td></tr>
<tr><td>Control tasks ne</td><td colspan="3">Algorithmic gatekeeping</td><td colspan="3">Algorithmic directing</td><td colspan="3">Algorithmic steering</td><td colspan="3">Algorithmic disciplining</td></tr>
</table>

**Table 2. Taxonomy of Algorithmic Control Systems**

**Control tasks.** The control tasks dimension refers to the different types of control activities AC systems perform. On the basis of previous conceptual work and empirical examples, we have identified four control tasks of which a system can execute one or more. The first control task AC systems may perform termed *algorithmic gatekeeping*. This control task is executed before the actual work process and controls "who is allowed to commence, or to continue, working for a given company" (Wiener et al. 2023, p. 4). This involves AC recruiting new workers (Kellogg et al. 2020), or AC practices to ensure sufficient spatial-temporal labor supply for day-to-day operations (Li 2021; Zheng & Wu 2022). The second control task AC systems may execute termed *algorithmic directing*. Here, the AC system specifies the (intermediate) goals of the work process. Examples of algorithmic directing are instructing workers which parcel to pick up in a warehouse (Vallas et al. 2022), defining an upcoming pick-up location of a customer (Rosenblat & Stark 2016), or specifying the next task of a click worker (Bucher et al. 2021). The third task AC systems can perform is *algorithmic steering*. This includes all control attempts that are not necessarily integral to finishing the work process but are related to general work behavior. For example, AC systems can recommend specific behaviors toward customers (Rosenblat & Stark 2016; van Doorn & Chen 2021), ensure that workers remain productive during the day by monitoring their screens and keystrokes (Jarrahi et al. 2021; Wood et al. 2019), and warn against increased emotionality in trading (Cram & Wiener 2020). The fourth task, *algorithmic disciplining*, refers to the algorithmically automated rewarding and sanctioning of the worker's work process and behavior. Control systems incorporating algorithmic disciplining use a wide range of non-monetary rewards and sanctions, often implemented through gamification elements such as badges and leaderboards (Mollick & Rothbard 2014; van Doorn & Chen 2021). Additionally, a variety of controls can also increase or decrease pay based on job performance and work behavior or provide financial incentives to control the worker (Huang 2022; Rosenblat & Stark 2016).

## *Empirical Illustrations*

To showcase the applicability and usefulness of the developed taxonomy, we exemplify its application through three empirical instances of AC systems in real-world settings. The choice of Uber, Amazon Warehouse, and Microsoft Viva Insights as case studies is intentional, chosen to highlight distinct types of AC systems that are illustrative for similar organizations or tools. Uber exemplifies an extreme case of AC in the gig economy (Möhlmann et al. 2021; Wiener et al. 2023). Amazon Warehouse offers insights into the application of AC in traditional workplaces. Microsoft Viva Insights represents a softer, more suggestive form of AC, focusing on enhancing worker productivity through recommendations rather than mandates. A classification of the presented AC systems along the dimensions of the AC system taxonomy and the list of references used can be found in Table 3.

**Uber.** The AC system employed by Uber exercises control over all drivers throughout the organization's complete operations (organizational scope: full operations). Its primary objective is to efficiently allocate requested rides to drivers. However, given that Uber drivers are typically independent contractors, the system can only propose rides that drivers are free to accept or decline (control authority: partial authority). The AC system operates entirely through the platform, eliminating the need for human supervisors (human supervisor involvement: none). Drivers working for Uber do not have the option to opt-out of the AC system or its components (coerciveness: no opt-out options). In terms of technology, Uber mandates the installation of a dedicated application on drivers' smartphones (digital interface: dedicated software). The AC system of Uber processes diverse data sources, including accepted ride counts (process data), vehicle speed (behavioral data), customer ratings (customer data), and external data on upcoming events that may impact ride demand. Uber's AC system executes control functions across the board, such as screening driver licenses and public criminal records (algorithmic gatekeeping), guiding the ride-hailing process (algorithmic directing), recommending customer interactions (algorithmic steering), and incentivizing drivers for accepting rides in specific areas. In summary, Uber's AC system demonstrates a comprehensive approach to control.

**Amazon Warehouses.** The Amazon Warehouse (Fulfillment Center, FC) is considered a prime example of AC in traditional organizations. Alongside distribution centers and delivery drivers, they are a central component of Amazon's logistics chain. Different AC systems are used in the respective process steps; in this case study, we focus on the AC system used in fulfillment centers (organizational scope: partial operational control). The AC system in the fulfillment center utilizes dedicated devices, such as digital barcode scanners, to communicate task instructions to workers (digital interface: dedicated device, control authority: full authority), and as this is the only way to receive tasks, there is no option to opt-out (coerciveness: no opt-out option). Although the AC system limits human oversight, human managers, called "process assistants," still oversee the work process (human supervisor involvement: human supervisor involved). Amazon FC's AC system mainly relies on process data and, to a lesser extent, on behavioral data to control workers. Based on this data, the system executes two control tasks, algorithmic directing, as described above, and algorithmic steering.

**Microsoft Viva Insights.** Viva Insights, a workplace analytics platform developed by Microsoft, offers recommendations to enhance worker productivity and well-being without exerting full control over the work process (organizational scope: task-specific control, control authority: advisory). While organizations using Viva Insights typically operate within traditional hierarchical structures involving human supervisors (human supervisor involvement: human supervisor involved), the tool is also available for personal use. While the system is activated by an administrator, opting out is generally an option for workers (coerciveness: opt-out options). The platform can be accessed through a web version, eliminating the mandatory requirement of dedicated software (digital interface: website). Behavioral data collected from office software usage informs the system, independent of specific work processes (data sources: behavioral data). Process, customer, and external data are not utilized. The derived recommendations are intended to influence worker behavior (control task: algorithmic steering).

| | | Uber | Amazon Warehouses | Microsoft Viva Insights |
|---|---|---|---|---|
| | **References** | Chan and Humphreys (2018); Cram and Wiener (2020); Pignot (2021); Rosenblat and Stark (2016); Wiener et al. (2023) | Altenried (2022); Beverungen (2021); Delfanti (2021); Struna and Reese (2020); Vallas et al. (2022) | John et al. (2022); Microsoft (2022a), 2022b) |
| **Organizational** | **Organizational scope** | Full operational control | Partial operational control | Task-specific control |
| | **Control authority** | Partial authority | Full authority | Advisory |
| | **Human supervisor involvement** | No human supervisor involved | Human supervisor involved | Human supervisor involved |
| | **Coerciveness** | No opt-out options | No opt-out options | Opt-out options |
| **Technological** | **Digital interface** | Dedicated software (Uber App) | Dedicated Hardware (digital scanners) | Website |
| | **Data sources** | Behavioral data<br>Process data<br>Customer data<br>External data | Behavioral data<br>Process data | Behavioral data |
| | **Control tasks** | Algorithmic gatekeeping<br>Algo. directing<br>Algo. steering<br>Algo. disciplining | Algorithmic directing<br>Algorithmic steering | Algorithmic steering |

**Table 3. Empirical Illustrations of the Algorithmic Control System Taxonomy**

## Discussion

Starting point of this research was our concern that existing AC concepts are no longer sufficient to grasp the nature of the increasingly heterogeneous landscape of real-world AC applications. We proposed the concept of an AC system, which emphasizes the relevance of specific technological and organizational characteristics of the broader system that enacts AC. In a taxonomy development effort, we reviewed existing concepts of AC along with 21 AC systems from a range of organizational contexts. We identified four organizational and three technological dimensions that characterize AC systems. In addition, we demonstrated the heterogeneity of current real-world AC systems by classifying three empirical examples along the identified dimensions.

### *Research Contributions and Practical Implications*

We believe that this contributes to the AC literature in two specific ways. First, whereas past AC research has focused on specific forms, mechanisms, or functions when examining the effects of AC, what has been missing were concepts that reflect the critical differences in the broader sociotechnical system in which AC is embedded. This study introduces the broader concept of AC systems. Specifically, we distinguish technological embedding (i.e., the integrated design of hardware, software, and data resources, as well as digital capabilities and procedures) and organizational embedding (i.e., the organizational context) as core conceptual dimensions of AC systems. In doing so, we connect established AC concepts and the widely accepted perspective in organizational control literature, that the impact of control is intricately tied to the distinct attributes of the control system, including its contextual factors, rather than individual control mechanisms (Cardinal et al. 2010; Flamholtz et al. 1985). With this understanding, we pave the way for future theoretical and empirical research that explores a broader perspective on the impact of AC systems in organizations.

Second, the existing AC research lacked a common frame of reference to consider similarities and differences in AC-dominated workplaces. Particularly when it comes to transferring research results from the heavily studied platform-based gig context to more traditional work contexts, where AC is "not the primary means of organizing work" and "adds to pre-existing power dynamics and regimes of control." (Jarrahi et al. 2021, p. 4), there is a high risk of comparing apples and oranges. We address this issue by presenting a comprehensive taxonomy of AC systems, consisting of three technological and four organizational dimensions along which AC systems can be classified. Our research thus sits within a series of conceptual studies that have attempted to capture how digital technology is changing the nature of organizational control (e.g., Kalischko & Riedl 2021; Parent-Rocheleau & Parker 2021; Schafheitle et al. 2020; Wesche & Sonderegger 2019). However, conceptualizing AC systems in the form of a taxonomy stands from existing conceptual efforts in multiple ways. First, to the best of our knowledge, this is the first effort to describe and structure the characteristics of AC systems, including technological and organizational dimensions. Second, the purpose of a taxonomy is to provide a helpful means of classifying empirical objects. While previous concepts require researchers to obtain an "inside view" of the AC system (e.g., Schafheitle et al. 2020), we ensure that for applying the AC systems taxonomy, researchers can use available information from public sources or workers. Third, we made sure to limit the taxonomy to the most important dimensions for classification, rather than an exhaustive list of every system characteristic, to increase the applicability of the taxonomy (Nickerson et al. 2013). In summary, our AC system taxonomy can serve as a comprehensive reference framework for the research community. It facilitates the identification of commonalities and distinctions among AC systems, enhances the comparability and generalizability of existing AC research, and provides a structured foundation for future AC studies.

The proposed taxonomy is highly beneficial for workers, organizations, and policymakers. It outlines the breadth of choices organizations face when adopting AC, highlighting that there's significant room for decision-making and, consequently, stakeholder negotiation upon the introduction of such systems. In this vein, the taxonomy can guide internal organizational dialogues, encompassing collective decision-making processes with involved workers. Policymakers can also benefit from the taxonomy by using it as a tool to facilitate the implementation of requested and effective AC regulations, as it enables a structured analysis of how regulatory proposals may impact specific AC system types.

## *Limitations and Future Research*

As with any research, our study has some limitations that can inform future research efforts. The first limitation refers to our conceptualization of AC systems. By focusing on isolated systems, we neglected that multiple AC systems may coexist in parallel and might be connected within an organization. For example, in our understanding, Amazon Warehouses employs multiple AC systems for different steps of the work process (one for picking and one for stowing). Future research might consider how multiple AC systems relate to each other on a broader organizational scope. The second limitation relates to the collection of empirical examples of AC. We included as wide a range of AC systems from platform-based and traditional organizations as possible in the taxonomy development. Although we are confident that we captured the key characteristics, we cannot fully ensure that our sample of 21 AC systems entailed all existing manifestations of real-world AC. Future research may validate the taxonomy using an even more comprehensive sample. In general, it should be noted that taxonomies are never considered final but allow for new dimensions or characteristics to be added if new objects appear (Nickerson et al. 2013). Given the rapid advancements in AC, we encourage future researchers to view this taxonomy as a preliminary framework and continuously expand upon it.

Besides these limitations, our study provides several additional directions for future, our taxonomy may serve as a reference point for future theory-building efforts. For example, the taxonomy could be used as a basis to derive a typology of AC systems. research. First, researchers could examine the interplay between specific dimensions of AC systems and other AC concepts, such as depicted in Table 1. For example, some AC mechanisms might be perceived as legitimate by workers in some organizational embeddings while others are not (Wiener et al. 2020). Building on this foundation, researchers could delve deeper into configurations perceived by workers as especially coercive or empowering (Cardinal et al. 2017). Understanding these perceptions is academically intriguing and may be pivotal for shaping regulations surrounding these technologies within the workplace. Second, it's evident that AC systems are dynamic rather than static, continuously evolving due to human interventions and self-learning algorithms (Meijerink & Bondarouk 2023). Understanding how the behavior of stakeholders, rendered into input data for the AC system, affects how these systems evolve seems crucial to understand the long-term effects AC will have on people and organizations. Third, typologies "identify multiple ideal types, each of which represents a unique combination of the organizational attributes that are believed to determine the relevant outcome(s)" (Doty & Glick 1994, p. 232). Fourth, as the taxonomy provides a framework for comparing AC systems, it may be leveraged to synthesize and systemize prior research AC on AC systems. Future research may use the taxonomy to conduct a meta-analysis (Jeyaraj & Dwivedi 2020) on the effects of specific AC system dimensions on the organizational and worker-level outcomes of AC.

## Conclusion

Given that AC is likely to become an essential ingredient of the future workplace, it is vital to advance our understanding of its organizational and, perhaps more importantly, its worker-level implications. In light of the growing heterogeneity of AC in practice, we argue that there is a pressing need for AC research to keep up with these developments. With this study, we introduce the notion of AC systems and propose a shift from studying isolated AC concepts toward studying holistic AC systems from a socio-technical perspective. We offer a conceptual and empirically derived taxonomy of AC systems, including three technological and four organizational dimensions. In doing so, we emphasize the need to examine AC with specific technical design and organizational embedding. Ultimately, we hope that our research will contribute to a more reflective use of this technology in the future, where AC should contribute to better working conditions and benefit society.

## Acknowledgements

The authors gratefully acknowledge the funding support by the German Research Foundation (DFG) as part of the project *AlgoWork* (project number 461985572) and the Center for Responsible Digitality (ZEVEDI).

## References

Adam, M., Croitor, E., Werner, D., Benlian, A., & Wiener, M. (2023). Input control and its signalling effects for complementors' intention to join digital platforms. *Information Systems Journal*, *33*(3), 437-466. **https://doi.org/https://doi.org/10.1111/isj.12408**

Ajunwa, I. (2020). The "black box" at work. *Big Data & Society*, *7*(2). **https://doi.org/10.1177/2053951720938093**

Altenried, M. (2022). *The Digital Factory: The Human Labor of Automation*. University of Chicago Press.

Baiocco, S., Fernández-Macías, E., Rani, U., & Pesole, A. (2022). *The Algorithmic Management of Work and its Implications in Different Contexts* (2022/02). (JRC Working Papers Series on Labour, Education and Technology). **https://joint-research-centre.ec.europa.eu/publications/algorithmic-management-work-and-its-implications-different-contexts_en**

Benlian, A., Wiener, M., Cram, W. A., Krasnova, H., Maedche, A., Möhlmann, M., Recker, J., & Remus, U. (2022). Algorithmic Management. *Business & Information Systems Engineering*, *64*(6), 825–839. **https://doi.org/10.1007/s12599-022-00764-w**

Bernstein, E. S. (2017). Making Transparency Transparent: The Evolution of Observation in Management Theory. *Academy of Management Annals*, *11*(1), 217-266. **https://doi.org/10.5465/annals.2014.0076**

Beverungen, A. (2021). Remote Control: Algorithmic Management of Circulation at Amazon. In M. Burkhardt, M. Shnayien, & K. Grashöfer (Eds.), *Explorations in Digital Cultures*. (pp. 5-18). Lüneburg: meson press. **https://doi.org/10.14619/1716**

Bucher, E. L., Schou, P. K., & Waldkirch, M. (2021). Pacifying the algorithm – Anticipatory compliance in the face of algorithmic management in the gig economy. *Organization*, *28*(1), 44-67. **https://doi.org/10.1177/1350508420961531**

Cameron, L., Lamers, L., Leicht-Deobald, U., Lutz, C., Meijerink, J., & Möhlmann, M. (2023). Algorithmic Management: Its Implications for Information Systems Research. *Communications of the Association for Information Systems*, *52*, 518-537. **https://doi.org/10.17705/1CAIS.05221**

Cardinal, L. B., Kreutzer, M., & Miller, C. C. (2017). An Aspirational View of Organizational Control Research: Re-invigorating Empirical Work to Better Meet the Challenges of 21st Century Organizations. *Academy of Management Annals*, *11*(2), 559-592. **https://doi.org/10.5465/annals.2014.0086**

Cardinal, L. B., Sitkin, S. B., & Long, C. P. (2010). A configurational theory of control. In K. M. Bijlsma-Frankema, L. B. Cardinal, & S. B. Sitkin (Eds.), *Organizational Control* (pp. 51-79). Cambridge University Press. **https://doi.org/10.1017/CBO9780511777899.004**

Chan, N. K., & Humphreys, L. (2018). Mediatization of Social Space and the Case of Uber Drivers. *Media and Communication*, *6*(2), 29-38. **https://doi.org/10.17645/mac.v6i2.1316**

Cram, W. A., & Wiener, M. (2020). Technology-mediated Control: Case Examples and Research Directions for the Future of Organizational Control. *Communications of the Association for Information Systems*, *46*, 70-91. **https://doi.org/10.17705/1CAIS.04604**

Cram, W. A., Wiener, M., Tarafdar, M., & Benlian, A. (2020). Algorithmic Controls and their Implications for Gig Worker Well-being and Behavior. *ICIS 2020 Proceedings*, 1. **https://aisel.aisnet.org/icis2020/is_workplace_fow/is_workplace_fow/1**

Cram, W. A., Wiener, M., Tarafdar, M., & Benlian, A. (2022). Examining the Impact of Algorithmic Control on Uber Drivers' Technostress. *Journal of Management Information Systems*, *39*(2), 426-453. **https://doi.org/10.1080/07421222.2022.2063556**

Curchod, C., Patriotta, G., Cohen, L., & Neysen, N. (2020). Working for an Algorithm: Power Asymmetries and Agency in Online Work Settings. *Administrative science quarterly*, *65*(3), 644-676. **https://doi.org/10.1177/0001839219867024**

Danaher, J. (2016). The Threat of Algocracy: Reality, Resistance and Accommodation. *Philosophy and Technology*, *29*, 245-268. **https://doi.org/10.1007/s13347-015-0211-1**

Delfanti, A. (2021). *The Warehouse: Workers and Robots at Amazon*. Pluto Press. **https://doi.org/10.2307/j.ctv2114fnm**

Doty, D. H., & Glick, W. H. (1994). Typologies as a Unique Form of Theory Building: Toward Improved Understanding and Modeling. *The Academy of Management Review*, *19*(2), 230-251. **https://doi.org/10.2307/258704**

Duggan, J., Sherman, U., Carbery, R., & McDonnell, A. (2020). Algorithmic management and app-work in the gig economy: A research agenda for employment relations and HRM. *Human Resource Management Journal*, *30*, 114-132. **https://doi.org/10.1111/1748-8583.12258**

Edwards, R. C. (1979). *Contested Terrain*. Basic Books, Inc.

Flamholtz, E. G., Das, T. K., & Tsui, A. S. (1985). Toward an integrative framework of organizational control. *Accounting, Organizations and Society*, *10*(1), 35-50. **https://doi.org/10.1016/0361-3682(85)90030-3**

Glass, R. L., & Vessey, I. (1995). Contemporary Application-Domain Taxonomies. *IEEE Software*, *12*(4), 63–76. **https://doi.org/10.1109/52.391837**

Huang, H. (2022). Algorithmic management in food-delivery platform economy in China. *New Technology, Work and Employment*, 1-21. **https://doi.org/10.1111/ntwe.12228**

Jarrahi, M. H., Newlands, G., Lee, M. K., Wolf, C. T., Kinder, E., & Sutherland, W. (2021). Algorithmic management in a work context. *Big Data & Society*, *8*(2). **https://doi.org/10.1177/20539517211020332**

Jarrahi, M. H., Sutherland, W., Nelson, S. B., & Sawyer, S. (2020). Platformic Management, Boundary Resources for Gig Work, and Worker Autonomy. *Computer Supported Cooperative Work*, *29*(1), 153-189. **https://doi.org/10.1007/s10606-019-09368-7**

Jeyaraj, A., & Dwivedi, Y. K. (2020). Meta-analysis in information systems research: Review and recommendations. *International Journal of Information Management*, *55*, 102226. **https://doi.org/10.1016/j.ijinfomgt.2020.102226**

John, B., Alsamarra'i, Z., & Panteli, N. (2022). Enhancing Employee Experience in the Era of Hybrid Work: The Case of Microsoft Viva. *IEEE Software*, *40*(2), 70-79. **https://doi.org/10.1109/MS.2022.3229956**

Kalischko, T., & Riedl, R. (2021). Electronic Performance Monitoring in the Digital Workplace: Conceptualization, Review of Effects and Moderators, and Future Research Opportunities. *Frontiers in Psychology*, *12*. **https://doi.org/10.3389/fpsyg.2021.633031**

Katzenbach, C., & Ulbricht, L. (2019). Algorithmic governance. *Internet Policy Review*, *8*(4), 1-18. **https://doi.org/10.14763/2019.4.1424**

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at Work: The New Contested Terrain of Control. *Academy of Management Annals*, *14*(1), 366-410. **https://doi.org/10.5465/annals.2018.0174**

Kirsch, L. J. (1996). The Management of Complex Tasks in Organizations: Controlling the Systems Development Process. *Organization Science*, *7*(1), 1-21. **https://doi.org/10.1287/orsc.7.1.1**

Kundisch, D., Muntermann, J., Oberländer, A. M., Rau, D., Röglinger, M., Schoormann, T., & Szopinski, D. (2022). An Update for Taxonomy Designers. *Business & Information Systems Engineering*, *64*(4), 421-439. **https://doi.org/10.1007/s12599-021-00723-x**

Lee, M. K., Kusbit, D., Metsky, E., & Dabbish, L. (2015). Working with Machines: The Impact of Algorithmic and Data-Driven Management on Human Workers. *CHI '15: Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 1603-1612. **https://doi.org/10.1145/2702123.2702548**

Li, A. K. (2021). Beyond algorithmic control: flexibility, intermediaries, and paradox in the on-demand economy. *Information, Communication & Society*, 1-16. **https://doi.org/10.1080/1369118X.2021.1924225**

Maltseva, K. (2020). Wearables in the workplace: The brave new world of employee engagement. *Business Horizons*, *63*(4), 493-505. **https://doi.org/10.1016/j.bushor.2020.03.007**

Meijerink, J., & Bondarouk, T. (2023). The duality of algorithmic management: Toward a research agenda on HRM algorithms, autonomy and value creation. *Human Resource Management Review*, *33*, 100876. **https://doi.org/10.1016/j.hrmr.2021.100876**

Microsoft. (2022a). *Microsoft Viva Insights*. https://adoption.microsoft.com/files/viva/insights/how_Microsoft_uses_Viva_Insights.pdf

Microsoft. (2022b). *Viva Insights Home*. https://support.microsoft.com/en-gb/topic/viva-insights-home-tab-6e7d28b2-6b0e-4367-9b52-1999a86eb391

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**

Mollick, E. R., & Rothbard, N. (2014). Mandatory Fun: Consent, Gamification and the Impact of Games at Work. *The Wharton School Research Paper Series*. **https://doi.org/10.2139/ssrn.2277103**

Nickerson, R. C., Varshney, U., & Muntermann, J. (2013). A method for taxonomy development and its application in information systems. *European Journal of Information Systems*, *22*(3), 336-359. **https://doi.org/10.1057/ejis.2012.26**

Parent-Rocheleau, X., & Parker, S. K. (2021). Algorithms as work designers: How algorithmic management influences the design of jobs. *Human Resource Management Review*, *32*(3), 100838. **https://doi.org/10.1016/j.hrmr.2021.100838**

Passlick, J., Dreyer, S., Olivotti, D., Grützner, L., Eilers, D., & Breitner, M. H. (2021). Predictive maintenance as an internet of things enabled business model: A taxonomy. *Electronic Markets*, *31*(1), 67-87. **https://doi.org/10.1007/s12525-020-00440-5**

Pignot, E. (2021). Who is pulling the strings in the platform economy? Accounting for the dark and unexpected sides of algorithmic control. *Organization*, *30*(1), 140-167. **https://doi.org/10.1177/1350508420974523**

Power, M. (2022). Theorizing the Economy of Traces: From Audit Society to Surveillance Capitalism. *Organization Theory*, *3*(3). **https://doi.org/10.1177/26317877211052296**

Rahman, H. A. (2021). The Invisible Cage: Workers' Reactivity to Opaque Algorithmic Evaluations. *Administrative Science Quarterly* *66*(4), 945-988. **https://doi.org/10.1177/00018392211010118**

Rosenblat, A., & Stark, L. (2016). Algorithmic labor and information asymmetries: A case study of Uber's drivers. *International Journal of Communication* *10*, 3758-3784. **https://doi.org/10.2139/ssrn.2686227**

Saunders, C., Benlian, A., Henfridsson, O., & Wiener, M. (2020, November 23). IS Control & Governance *MIS Quarterly Research Curations*, **https://www.misqresearchcurations.org/blog/2020/11/23/is-control-amp-governance**

Schafheitle, S., Weibel, A., Ebert, I., Kasper, G., Schank, C., & Leicht-Deobald, U. (2020). No Stone Left Unturned? Toward a Framework for the Impact of Datafication Technologies on Organizational Control. *Academy of Management Discoveries*, *6*(3), 455-487. **https://doi.org/10.5465/amd.2019.0002**

Scharfe, P., & Wiener, M. (2020). A Taxonomy of Smart Machines in the Mechanical Engineering Industry: Toward Structuring the Design Solution Space. *ICIS 2020 Proceedings*, 1. **https://aisel.aisnet.org/icis2020/iot_smart/iot_smart/1**

Schaupp, S. (2022). Cybernetic proletarianization: Spirals of devaluation and conflict in digitalized production. *Capital and Class*, *46*(1), 11-31. **https://doi.org/10.1177/03098168211017614**

Schöbel, S. M., Janson, A., & Söllner, M. (2020). Capturing the complexity of gamification elements: a holistic approach for analysing existing and deriving novel gamification designs. *European Journal of Information Systems*, *29*(6), 641-668. **https://doi.org/10.1080/0960085X.2020.1796531**

Smith, C. G., & Tannenbaum, A. S. (1963). Organizational control structure: A comparative analysis. *Human Relations*, *16*, 299-316. **https://doi.org/10.1177/001872676301600401**

Spiekermann, S., Krasnova, H., Hinz, O., Baumann, A., Benlian, A., Gimpel, H., Heimbach, I., Köster, A., Maedche, A., Niehaves, B., Risius, M., & Trenz, M. (2022). Values and Ethics in Information Systems. *Business & Information Systems Engineering*, *64*(2), 247-264. **https://doi.org/10.1007/s12599-021-00734-8**

Srinivasan, A., March, S., & Saunders, C. (2005). Information technology and organizational contexts: Orienting our work along key dimensions. *ICIS 2005 Proceedings*, 84. **https://aisel.aisnet.org/icis2005/84**

Struna, J., & Reese, E. (2020). Automation and the Surveillance-Driven Warehouse in Inland Southern California. In E. Reese & J. Alimahomed-Wilson (Eds.), *The Cost of Free Shipping* (pp. 85-101). Pluto Press. **https://doi.org/10.2307/j.ctv16zjhcj.12**

Ulbricht, L., & Yeung, K. (2022). Algorithmic regulation: A maturing concept for investigating regulation of and through algorithms. *Regulation & Governance*, *16*(1), 3-22. **https://doi.org/https://doi.org/10.1111/rego.12437**

Vallas, S. P., Johnston, H., & Mommadova, Y. (2022). Prime Suspect: Mechanisms of Labor Control at Amazon's Warehouses. *Work and Occupations*, *49*(4), 421-456. **https://doi.org/10.1177/07308884221106922**

van Doorn, N., & Chen, J. Y. (2021). Odds stacked against workers: datafied gamification on Chinese and American food delivery platforms. *Socio-Economic Review*, *19*(4), 1345-1367. **https://doi.org/10.1093/ser/mwab028**

Wesche, J. S., & Sonderegger, A. (2019). When computers take the lead: The automation of leadership. *Computers in Human Behavior*, *101*, 197-209. **https://doi.org/10.1016/j.chb.2019.07.027**

Wiener, M., Cram, W., & 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**

Wiener, M., Cram, W. A., & Benlian, A. (2020). Technology-Mediated Control Legitimacy in the Gig Economy: Conceptualization and Nomological Network. In R. Hirschheim, A. Heinzl, & J. Dibbern (Eds.), *Information Systems Outsourcing: The Era of Digital Transformation* (pp. 387-410). Springer International Publishing. **https://doi.org/10.1007/978-3-030-45819-5_16**

Wiener, M., Mähring, M., Remus, U., & Saunders, C. (2016). Control Configuration and Control Enactment in Information Systems Projects: Review and Expanded Theoretical Framework. *MIS Quarterly*, *40*(3), 741-774. **https://doi.org/10.25300/MISQ/2016/40.3.11**

Wood, A. J. (2021). *Algorithmic Management: Consequences for Work Organisation and Working Conditions* (2021/07). (JRC Working Papers Series on Labour, Education and Technology). **https://joint-research-centre.ec.europa.eu/publications/algorithmic-management-consequences-work-organisation-and-working-conditions_en**

Wood, A. J., Graham, M., Lehdonvirta, V., & Hjorth, I. (2019). Good Gig, Bad Gig: Autonomy and Algorithmic Control in the Global Gig Economy. *Work, Employment and Society*, *33*(1), 56-75. **https://doi.org/10.1177/0950017018785616**

Zheng, Y., & Wu, P. F. (2022). Producing speed on demand: Reconfiguration of space and time in food delivery platform work. *Information Systems Journal*, *32*(5), 973-1004. **https://doi.org/10.1111/isj.12377**

Zuboff, S. (2015). Big other: Surveillance Capitalism and the Prospects of an Information Civilization. *Journal of Information Technology*, *30*(1), 75-89. **https://doi.org/10.1057/jit.2015.5**