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Context Matters: The Use of Algorithmic Management Mechanisms in Platform, Hybrid, and Traditional Work Contexts

Isabell Lippert
Technische Universität Dresden
isabell.lippert@tu-dresden.de

Kathrin Kirchner
Technical University of Denmark
kakir@dtu.dk

Martin Wiener
Technische Universität Dresden
martin.wiener@tu-dresden.de

Abstract

Emerged from platform organizations, algorithmic management (AM) refers to a data-driven approach in which intelligent algorithms are employed to automate managerial functions. Given its organizational benefits (e.g., efficiency gains), AM is also increasingly used in other work contexts, including traditional organizations (with permanent employees). Against this backdrop, our study investigates what AM mechanisms are used in different organizational work contexts and to what extent, and why, these mechanisms translate to other contexts. We do so by systematically analyzing and synthesizing knowledge from 45 studies. Our results point to seven usage patterns regarding the contextual translatability of AM mechanisms. For example, while we find that some mechanisms are used across contexts but with differing intentions, we also identify several context-specific AM mechanisms that are not (easily) translatable. We conclude by discussing factors that help explain the identified usage patterns (e.g., worker status and skill level) and promising avenues for future research.

Keywords: Algorithmic management (mechanisms), control/matching, platform vs. traditional work contexts

1. Introduction

Algorithmic management (AM), defined as "learning algorithms that carry out coordination and control functions traditionally performed by managers" (Möhlmann et al., 2021, p. 2001), represents an integral ingredient of the highly artificial intelligence (AI)-driven future of work (Scheiber, 2017). Emerged from platform organizations, such as Uber or Upwork, AM is a cutting-edge approach that has been characterized by "faceless management" (Möhlmann & Henfridsson, 2019) and is used to manage a large number of freelance workers and to achieve organizational goals efficiently. Based on AI techniques, AM has been described as a key facilitator for the success and seemingly infinite scalability of many platform-based business models (Bucher et al., 2021; Jabagi et al., 2020). Due to its potential for dramatic efficiency enhancements (Möhlmann et al., 2021), AM is gaining traction beyond platform organizations, especially in traditional organizations with a centralized management philosophy. For example, major banks (e.g., Bank of America) (Cram & Wiener, 2020), logistics firms (e.g., DHL) (Pignot, 2021) or retail (e.g., Amazon) (Delfanti, 2021) rely on AM-based solutions to improve the operations of their call centers, delivery processes or warehouse labor, respectively. The growing contextual scope of AM is in line with Parent-Rocheleau and Parker (2021, p. 3), who state that the execution of AM is "not contingent on the type of organization". While we generally agree with this statement, we still argue that many specific AM mechanisms used in platform-based work contexts cannot be easily transferred to, and thus do not necessarily translate to, traditional work contexts. Among other things, this is because of major structural differences between traditional and platform organizations (Duggan et al., 2020). For example, in platform organizations, AM is used to substitute human managers, whereas, in traditional organizations, AM is used along organizational hierarchies to complement human managers (Jarrahi et al., 2021), or as Delfanti (2021, p. 43) aptly puts it: "human managers whose work is augmented by technical and cultural rationalities rather than fully outsourced to algorithms". Another obvious difference between platform organizations and traditional organizations is that workers in the former are considered as freelancers, whereas the latter employ permanent employees (Duggan et al., 2020). With regard to AM mechanisms commonly used in the platform economy, such as algorithmic replacing (Kellogg et al., 2020), a direct employment (i.e., a regular employer-employee relationship) has the effect that these mechanisms are not applicable in the work context of traditional organizations (Adams-Prassl, 2019). Given its far-reaching implications for the future of work, along with its increasing use across different work contexts, the AM phenomenon has already sparked considerable interest in the information systems (IS) literature and beyond. In particular, since the term "algorithmic management" was coined by Lee et al.

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(2015), we were able to identify a total of 45 studies with an exclusive focus on the use of AM in various work contexts. As such, we argue that the time is ripe to analyze existing literature and to develop a more nuanced, context-specific understanding of the AM mechanisms used in platform and traditional organizations. More specifically, this study sets forth to address the following two research questions: *(1) What specific AM mechanisms are being used in different work contexts (i.e., platform vs. traditional organizations)? (2) To what extent do these mechanisms translate to other work contexts, and why?* To answer our research questions, we conduct a systematic review of existing AM and AI literature, following the approach by Webster and Watson (2002) and the suggested structure by Schryen (2015) in order to contribute to novel insights into the work context-specific use of AM and its mechanisms. The remainder of this study is structured as follows: After framing the conceptual foundations of AM in the second section, we outline the methodology steps in the third section. In the fourth section, we synthesize the results of the literature review and particularly interpret the observed usage patterns regarding the use of AM in different work contexts. Finally, we discuss the usage patterns, as well as implications and limitations of this study, and point to promising avenues for future research.

2. Conceptual foundations

2.1. Algorithmic management (AM)

According to Möhlmann et al. (2021, p. 2005), management "is generally concerned with coordinating and controlling organizational resources and activities to achieve defined organizational goals and objectives". The adaption of this general concern of management to *algorithmic* management results in the definition of AM being the "large-scale collection and use of data to develop and improve learning algorithms that carry out coordination and control functions traditionally performed by managers" (Möhlmann et al., 2021, p. 2005). Generally, AM, as a part of sophisticated AI techniques, has been conceptualized in terms of two dimensions: algorithmic control and algorithmic matching (Möhlmann et al., 2021).

Algorithmic control (AC) refers to the use of intelligent algorithms to "align worker behaviors with organisational objectives" (Wiener et al., 2021, p. 1; cf. Möhlmann et al., 2021). To conceptualize AC, we rely on the "6R" framework, which Kellogg et al. (2020) introduced. Besides being frequently cited in current AM research, a key strength of this framework is that it draws on the broader control literature, thereby ensuring theoretical consistency with this literature. In particular, following Edwards' (1979) perspective on organizational control, Kellogg et al. (2020) distinguish between six AC forms (all starting with an "R"), which are structured along the three basic steps of the generic control process (direction, evaluation, and discipline). First, algorithms are used for the direction of workers by *algorithmic restricting* and *algorithmic recommending*. Second, *algorithmic recording* and *algorithmic rating* is used to evaluate workers. Third, workers are disciplined by using *algorithmic replacing* or *algorithmic rewarding*. (Kellogg et al., 2020). Please refer to Table 1 for a short description of the six AC forms.

Table 1. Conceptualization of AM and its sub-forms (based on Möhlmann et al., 2021; Kellogg et al. 2020).

AM	Forms	**Short description** (including *sub-forms*)
Algorithmic control	**Recommending**	Use of algorithms to provide workers with *implicit* recommendations "intended to prompt [them] to make decisions preferred by the choice architect" (Kellogg et al., 2020, p. 372) or *explicit* recommendations (i.e., specific courses of action)
	Restricting	Using algorithms to intentionally restrict workers' access to *information* and/or their *behavioral* options, by presenting narrowly confined choices of action (Kellogg et al., 2020)
	Recording	Organizations use *passive monitoring* for surveillance and recording of workers' behavior and providing *real-time feedback* on the gathered data (Kellogg et al., 2020)
	Rating	Using online ratings and rankings for *real-time* evaluation of workers' behavior and performance and generating rankings. Further, *predictive analytics* are used to estimate future performance, based on current ratings (Kellogg et al., 2020)
	Rewarding	Rewarding high-performing workers with *non-monetary* rewards, including gamification approaches and *monetary* rewards (Kellogg et al., 2020)
	Replacing	Using algorithms to automatically or immediately *dismiss* workers (Kellogg et al., 2020)
Algo.: matching	**Market-level matching**	Algorithms *match market demand (= customers) vs. supply (= workers)* and continuously search for the "most beneficial matches for both sides" (Möhlmann et al., 2021, p. 2005)
	Worker-level matching	Algorithms *match customers vs. workers* based on their attributes, e.g., their real-time location, aiming at the best worker-to-customer fit (Möhlmann et al., 2021)

Algorithmic matching, also referred to as algorithmic coordination, "involves a market-like coordination of human resources" (Möhlmann et al., 2021, p. 2005). It thus pertains to "the algorithmically mediated coordination of interactions between demand and supply" (Möhlmann et al., 2021, p. 2005) of labor. In the specific context of the platform economy, successful algorithmic matching typically requires the availability of both worker and customer data. On this basis, algorithmic matching is the result of a complex algorithmic calculation of worker-related and market-related data in order to seek "for the most beneficial matches for both sides" (Möhlmann et al., 2021, p. 2005) by providing just-in-time staffing to satisfy customers on-demand based on the economies of scale. While market-related data are the predominant source for algorithmic matching calculations within the platform-based work, worker-related data also play an integral role in traditional organizations and related work contexts. Here, algorithms compare data and attributes of workers with properties of customers in order to assign workers to specific tasks, aiming at the best worker-to-customer fit (Parent-Rocheleau & Parker, 2021). Table 1 summarizes the conceptual foundations regarding AM and its constituents (AC and algorithmic matching). The concepts introduced in this table will serve as a 'guiding' basis for our literature analysis.

2.2. AM-related work contexts

As indicated above, economic work arrangements can be broadly distinguished into two basic work contexts (cf. Cappelli & Keller, 2013; Duggan et al., 2020), namely, platform-based and traditional contexts.

Platform-based work context (PWC). In this context, work can be categorized as freelance work, which is characterized by the fact that a traditional "employment relationship does not exist" (Duggan et al., 2020, p. 117). Freelance work includes, among others, gig work arrangements, which are defined as an "indirect relationship involving a minimum of three parties: intermediary online platform, worker and customer" (Duggan et al., 2020, p. 117). Within the PWC, the online platform completely substitutes the human manager, i.e., organizations delegate coordination and control mechanisms to algorithms (Jarrahi et al., 2021). The PWC covers all forms of gig work, including capital platform work (e.g., Airbnb), crowdwork (e.g., Amazon Mechanical Turk), and app-based work (e.g., Uber, Deliveroo) (Duggan et al., 2020).

Traditional work context (TWC). Here, work can be categorized as direct employment, meaning a "direct relationship involving two parties: employer and employee" (Cappelli & Keller, 2013, p. 577) along an organizational hierarchy. The difference from the earlier use of algorithms in management is that AM is not used to support managers in the execution of their tasks but to *partially delegate* managerial tasks to algorithms (Giermindl et al., 2022). Examples of TWCs where AM is already used are manufacturing, retail or hospitality (Parent-Rocheleau & Parker, 2021).

Hybrid work context (HWC). In addition, a third work context that has emerged more recently, which we refer to as HWC, is a mixture of the two arrangements described above. Specifically, while the overarching organizational logic of this context follows a platform logic, the employment relationship corresponds to the TWC with a permanent employment contract. This has the effect that there is often an either substitutive or complementary implementation of AM. Hybrid work (e.g., Gorillas, Lieferando) is often found within the quick commerce sector (q-commerce), where goods ordered by customers, e.g., food are delivered by drivers via bike, car or scooter in less than one hour (Huang & Yen, 2021). Moreover, due to European legislation, especially within European countries, hybrid work is often found in countries such as Germany or Denmark. Please refer to Table 2 for an overview of the AM-reltated work contexts and their characteristics.

Table 2. Characteristics of relevant work contexts and the corresponding usage of AM

<table>
<tr><th></th><th colspan="2">Platform-based work context (PWC)</th><th colspan="2">Hybrid work context (HWC)</th><th>Traditional work context (TWC)</th></tr>
<tr><td>Type of employment</td><td colspan="2">Self-employed, no employment contract</td><td colspan="3">Direct employment, based on a permanent contract</td></tr>
<tr><td>Organizational logic</td><td colspan="4">Platform-based</td><td>Organizational hierarchy</td></tr>
<tr><td>Role of AM vs. manager</td><td colspan="3">AM as substitute for human managers</td><td colspan="2">AM coexists with human managers</td></tr>
<tr><td>Application fields (examples)</td><td>Driving service, programming</td><td colspan="3">Food delivery, courier service</td><td>Manufacturing, warehouses, hospitality</td></tr>
</table>

3. Methodology

Since the seminal work by Lee et al. (2015), a considerable body of literature on the use of AM in various work contexts, ranging from PWC to TWCs, has emerged. Against this backdrop, our study aims to investigate what specific AM mechanisms are being used in different work contexts and to what extent these mechanisms translate to other contexts by synthesizing and interpreting existing knowledge in extant literature (Schryen, 2015). For this purpose, we conduct a systematic review of the AM literature following the guidelines provided by Webster and Watson (2002) and Schryen (2015). First, to search for literature, we derived the following search terms from our research questions: *Algorithmic (management OR control OR matching) AND (work* OR organization* OR employ* OR platform*).* To ensure comprehensiveness, we followed an iterative search approach (Webster & Watson, 2002), consisting of five steps, searching the title and the abstract in the following databases: (1) Manual search of each journal in the "Senior Scholars' Basket of Eight". (2) Searching the most prominent Association for Information Systems (AIS) conferences, namely, the European Conference on Information Systems (ECIS), the International Conference on Information Systems (ICIS) and the Hawaii International Conference on System Sciences (HICSS). (3) We then conducted a backward search by screening the references of the studies identified in steps (1) and (2). (4) This was followed by a forward search, for which we used *Google Scholar* to find literature citing the articles from all previous steps. (5) Lastly, a database search in *Business Source Complete* ensured that we did not miss any key studies. Please refer to Figure 1 in terms of the resulting number of studies from the search steps and the selection process.

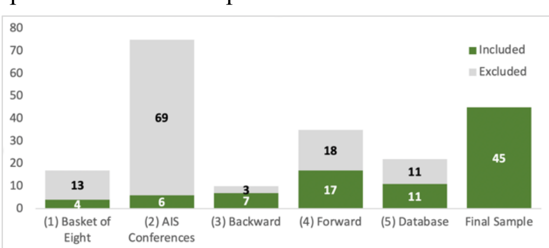

Figure 1. Identified studies along the search process.

Second, within the literature assessment (Schryen, 2015), we included studies published since 2015, the year in which Lee et al. (2015) initially coined the term AM. Using this definition, we were able to clearly identify which studies addressed AM and accordingly potentially qualified for our sample. Moreover, we also included studies on AM-related topics, such as people analytics (e.g., Giermindl et al., 2022), or AI at work (e.g., Adams-Prassl, 2019), as long as it became clear that workers had to interact *directly* with the algorithmic or AI technologies. In contrast, we excluded literature, in which algorithms were used to support managerial tasks, e.g., for decision support. Adding to this, we excluded non-peer reviewed articles, research-in-progress papers, and conference papers resulting in journal articles (in order to avoid any redundancies).

The above-described search procedures led to a review sample of 45 studies, including 32 journal articles, 11 conference papers, and 2 dissertations. In terms of research disciplines, about 42% of the studies in our review sample originated from the IS literature, 32% from work sociology, and the remaining 26% from strategy, organization, management, and human resources. To analyze our review sample, we used the qualitative analysis software *MAXQDA* to conduct a combination of top-down and bottom-up coding approaches (Saldaña, 2021). In a first round, we coded for attributes of the three work contexts described in section 2.2. On this basis, we classified 26, 14, and 5 studies as focusing on platform-based, traditional, and hybrid work contexts, respectively. In a second coding, our focus shifted toward the specific AC mechanisms described in the reviewed studies. Here, we relied on the AM concepts introduced in section 2.1 (top-down coding), while remaining open for novel AM concepts emerging from our data (bottom-up coding). For example, we assigned the code "algorithmic recording" (see Table 1 above) for statements such as the following one: "Uber drivers are tracked via the Uber app. Their whereabouts are transmitted at all times." (Möhlmann & Zalmanson, 2017, p. 8). To capture the specific AC mechanism described in this statement, this code was then further refined with the sub-code "behavioral recording". For algorithmic matching, we followed the same process. Here, however, bottom-up coding played a more prominent role, given the lack of an established framework that helps distinguish among different matching forms. For instance, we assigned the code "algorithmic matching" for statements like "rather than choosing the tasks themselves, workers were assigned tasks algorithmically based on their skills" (Lehdonvirta, 2018, p. 20) and refined it with "skill-based matching". Based on our coding procedures, we identified a total of 7 usage patterns across 12 distinct AC and 6 algorithmic matching sub-forms. The following synthesis of the literature includes an elaboration of various examples of AM mechanisms in the three different work contexts, as well as a summary about the identified usage patterns.

4. Results

In the following, we present our review results along the forms and sub-forms of algorithmic control and matching (see Table 1). Based on an illustration of specific manifestations of AM mechanisms used in the three work contexts introduced in Table 2 (i.e., PWC, HWC, TWC), we particularly focus on identifying usage patterns across these contexts.

4.1. Mechanisms of algorithmic control

Regarding **algorithmic recommending**, the literature synthesis indicates that mechanisms for the sub-form *implicit recommending*, also referred to as *algorithmic nudging* (i.e., persuading workers to perform a previously prioritized behavior without explicitly asking them to do so), are used exclusively in the PWC (e.g., Möhlmann et al., 2021; Cameron, 2020; Shapiro, 2018). At Uber, for instance, when a driver is about to end his shift, a message with the following content appears: "Are you sure you want to go offline?" (Rosenblat & Stark, 2016, p. 3769). Drivers then must confirm these messages with "Keep driving" or reject them with "Go offline" (Rosenblat & Stark, 2016, p. 3769). While implicit recommending is used exclusively in the PWC, mechanisms for *explicit recommending* are used in all three work contexts. Uber, as an example for the PWC, automatically sends emails to workers, including a general guidance for workers on how to improve their rating, for instance, by offering a free bottle of water to customers (Wiener et al., 2021). In the HWC, at the food delivery service Lieferando (former Foodora), the worker app explicitly recommends a path to the restaurant and subsequently to the customer (Ivanova et al., 2018) and similarly to Uber, Lieferando workers regularly receive emails with instructions on how to cycle safely on the road (Schreyer, 2021). Explicit recommending in the TWC is based on the analysis of employees' email, calendar, or video conferencing activity data and appropriately visualizing it in productivity dashboards. Simultaneously, employees receive automated messages, such as: "your calendar is usually less than 30% booked when the week starts; make sure to plan time for focused work into your calendar" (Gal et al., 2020, p. 8).

In terms of **algorithmic restricting**, we observe that mechanisms for the sub-form *restricting access to information* are used in all three work contexts. At the PWCs Uber and Lyft, information on destinations are intentionally withheld before drivers accept a ride (e.g., Griesbach et al., 2019; Rosenblat & Stark, 2016; Kuhn & Maleki, 2017). Likewise, the food delivery service Lieferando, as part of the HWC, hides order-related information from riders, such as the amount of included items and whether the customer tipped them via the app, until the order is delivered (Ivanova et al., 2018). In the TWC, for example, in a supermarket distribution center, access to information is restricted by communicating only two main figures to employees: "a percentage figure based on the company's hourly pick targets, and a cases per minute (CPM) rate" (Gent, 2018, p. 126). Another sub-form of algorithmic restricting, namely *restricting behavior*, is used within the PWC and the HWC, i.e., in organizations with platform logic. Especially within delivery services, when workers receive an order via push message the only option is to confirm the message by swiping "Accept" (Ivanova et al., 2018, p. 23) on the smartphone screen (Griesbach et al., 2019; Schreyer, 2021).

Our analysis results suggest that mechanisms for both sub-forms of **algorithmic recording** (passive monitoring and real-time feedback) are used in all three work contexts. An example of *passive monitoring* in the PWC is outlined by Jabagi et al. (2020) and Kuhn and Maleki (2017) at Upwork, where algorithms are monitoring workers' keystrokes and taking screenshots of their work. In the HWC, such as food delivery, in addition to passively monitoring workers' location and delivery speed via Global Positioning System (GPS) (Ivanova et al., 2018), worker behavior is monitored via front-facing Closed-Circuit Television (CCTV) and their braking behavior is measured via telematics (Gent, 2018). In terms of passive monitoring in the TWC, we find two examples: First, in a call center, the tone of an employee's voice is monitored and analyzed by voice algorithms to determine whether they show enough empathy toward customers (Park et al., 2021; Jarrahi et al., 2021; Parent-Rocheleau & Parker, 2021). Second, in an Amazon fulfillment center, scanners for picking items are also used for behavioral monitoring of employees (Faraj et al., 2018; Gent, 2018; Delfanti, 2021). Concerning *real-time feedback*, Upwork, as an example of the PWC, sends automated messages, such as: "make sure that you don't work outside of Upwork" (Jarrahi et al., 2020, p. 16), when workers share contact data with clients. In the HWC, Ivanova et al. (2018) point to an example of the food delivery service Lieferando, where workers are promted to continue their work via push messages if they stay in the same place for too long during working hours. Building on the example of passively monitoring the voice of employees in call centers of the TWC, Parent-Rocheleau and Parker (2021) give an example for real-time feedback: "As a result of this [voice] assessment, the system shows instant instructions about particular emotional cues" (p. 5).

The literature indicates that **algorithmic rating** is only used in the PWC and the TWC. In PWCs, such as Uber, UberEats or DoorDash, we observed, that *real-time rating and ranking* as one sub-form of algorithmic rating, is implemented as follows: Either by means of customers' positive or negative ratings for workers, or by means of organization-specific metrics, such as acceptance and cancellation ratings (Lee et al., 2015; Möhlmann et al., 2021; Griesbach et al., 2019) or by means of worker-related attributes, such as "punctuality, reliability, and participation during peak activity" (Galiere, 2020, p. 362) in order to determine an overall performance score for workers (Jarrahi et al., 2020). Specifically, in terms of using algorithms for ranking, Jarrahi et al. (2020) point to an example from Upwork, where an freelancers' rating is used to list those with a particularly high rating at the top of the clients' search results. A similar approach is used in the TWC, where the performance of employees is measured via customer ratings, for instance, in a news editorial office, where a journalist's performance is measured and subsequently ranked based on click rates of online articles (Faraj et al., 2018). The use of *predictive analytics*, i.e., "predictive artificial intelligence algorithms, like the famous IBM Watson" (Parent-Rocheleau & Parker, 2021, p. 6), which we find in the TWC exclusively, anticipates the future performance of employees based on their current rating data and subsequently identifies career and training opportunities for high-performing employees.

In terms of **algorithmic rewarding**, we identify mechanisms for both sub-forms, i.e., non-monetary rewarding, and monetary rewarding in all three work contexts. In the PWC and HWC, *non-monetary rewarding* is implemented, for example, by granting certain privileges, such as early access to the so-called shift picker system. Another mechanism for providing non-monetary rewards is to use gamification approaches, such as virtual badges (Galiere, 2020; Jabagi et al., 2019), which we find in the PWC and TWC, but not in the HWC. As such, Uber drivers, for instance, receive badges like "Expert Navigation" or "Great Conversation" (Pignot, 2021, p. 217). In the TWC, we find an example by Schafheitle et al. (2020), where employees are granted a "knowledge expert" badge (p. 5) by an AI-augmented software when they regularly share their knowledge with colleagues on internal collaboration platforms. Mechanisms for *monetary rewarding* in the PWC are implemented, for example, at Uber, by algorithmically granting financial rewards for completing an above-average number of rides within a predefined time period, such as "50 rides in the next 5 days for an extra $50" (Cameron, 2020, p. 129) or, for example, at Instacart, where workers receive a bonus of $3 for every five-star rating. Similarly to the PWC, employees in the HWC receive a bonus of 100€ for delivering at least 100 orders during weekends (Ivanova et al., 2018). Park et al. (2021) outline an example of monetary rewarding in the TWC, where a bonus for employees of an IT consulting firm is calculated based on their predicted contribution to a project's success, as well as on their past performance and gained experience in previous projects.

Mechanisms for **algorithmic sanctioning,** which we consider as a new form of AC in the literature, and **algorithmic replacing,** share the same pattern: They are used in the PWC exclusively. Algorithmic sanctioning includes mechanisms for *temporarily denying workers' access* to the app. At Uber or Deliveroo, for example, workers are being deactivated for and by the app for up to two days for non-compliant or impolite behavior (Galiere, 2020; Möhlmann et al., 2021) or for below-average acceptance rates (Griesbach et al., 2019; Cameron, 2020). Another example of algorithmic sanctioning can be observed at Upwork, where freelancers with a low ranking are sometimes not listed in the client-side search queries (Jarrahi et al., 2020). As an extreme form of punishing workers in the PWC, particularly at Uber and Caviar, algorithmic replacing, i.e., *dismissing* workers, is practiced by deactivating them automatically by and for the worker app if they reject too many assignments or if their overall-rating score falls below a predefined threshold (Cameron, 2020; Galiere, 2020; Verelst et al., 2022; Shapiro, 2018).

4.2. Mechanisms of algorithmic matching

For **market-based matching**, we find evidence for two sub-forms that contrast each other. First, a sub-form we identify exclusively in the PWC is "*surge pricing*", mainly observed at Uber (Möhlmann & Zalmanson, 2017). Especially algorithms of platform organizations continuously assess supply and demand, to strive for market equilibrium (e.g., Griesbach et al., 2019; Lee et al., 2015; Duggan et al., 2020), which works as follows: During surge periods, riders receive push messages and in-app visualizations of surge price areas (as heat maps) in the Uber driver app (Lee et al., 2015). Second, another sub-form of market-focused matching, we find in the TWC exclusively, is *prediction-based scheduling,* for which Lee (2018) provides an example at Starbucks: There, predictive algorithms "determined when café baristas would be called into work based on the predicted number of customers in the café at a given time" (p. 5).

In line with Möhlmann et al. (2021), we find several instances of using intelligent algorithms for **worker-level matching**, aimed at determining the 'optimal' match between workers and customers (Schreyer, 2021; Parent-Rocheleau & Parker, 2021; Jarrahi et al., 2021; Schildt, 2017). One sub-form for worker-level matching is *skill-based matching*, which is used in PWC and TWC. At Upwork (= PWC) freelancers receive, based on their provided skillset, recommendations through automated notifications with job requests from clients matching their skill profile (Jarrahi et al., 2020). Lehdonvirta (2018) describes within the outsourcing platform MobileWorks that "rather than choosing the tasks themselves, workers were assigned tasks algorithmically based on their skills" (p. 20). Regarding skill-based matching in the TWC, Lee et al. (2021) also consider employee interest in the underlying task, task-related stress, and job-related growth opportunities as crucial input components for mechanisms of skill-based matching, particularly within high-skilled work. We observe that the mechanisms for *location-based matching,* as a further sub-form of worker-level matching range across all three work contexts. Thereby, the mechanisms for location-based matching in the PWC and the HWC, e.g., ride-hailing or food delivery services, work exactly in the same way: Workers from the PWC, respectively employees from the HWC, are located via the GPS feature in their smartphones and automatically assigned to pick up a customer or an order nearby (Parent-Rocheleau & Parker, 2021; Cameron, 2020; Schreyer, 2021). Gent (2018) points to a mechanism of location-based matching in the TWC: In an Amazon fulfillment center, employees are equipped with scanners on which locations of an orders' items are displayed step by step according to their distance to each other in the shelves, thus reducing walking times. In addition to the sub-forms of worker-level matching described above, we find *performance-based scheduling* and *preference-based scheduling* as further sub-forms used in HWC and TWC, i.e., in work contexts with employment contracts, exemplified by the following mechanisms: In a distribution center of the HWC, for instance, an employee receives a "text message, prior to the start of the shift, which tells him [or her] whether the shift is confirmed or canceled based on his [or her] productivity the previous day" Gent (2018, p. 122). Schaupp (2021) provides an example of performance-based scheduling within the TWC, where workers at a chemical company are automatically assigned to additional tasks when production machines detected a drop in human labor utilization. For preference-based scheduling, we note, that the mechanisms for this sub-form of worker-level matching are mainly worker-induced. Employees within the HWC, for example at Lieferando, select their time preferences in a shift booking system once a week. An algorithm then compares the preferences of all employees and subsequently assigns the employees to shifts. Within the TWC, an example for a preference-based scheduling mechanism is described in Lee et al. (2021), where workers' preferred types of tasks and working times are considered, with the ultimate goal of enhancing their well-being.

4.3. Summary of the identified usage patterns

In our literature synthesis, we outline 25 examples for AM mechanisms along the 6 introduced AC forms and 1 new sub-form of AC. Further, we find 11 examples for AM mechanisms along the 2 forms for algorithmic matching and concretize algorithmic matching through 6 additional sub-forms. Our literature synthesis leads us to 7 different usage patterns regarding the use of AM mechanisms in the respective work contexts (see Table 2 for an overview). The corresponding usage patterns of applying AM mechanisms in all three work contexts (= P4) occurs most frequently (seven times), with regard to the mechanisms *explicit recommending*, *restricting access to information*, *location-based matching*, as well as to all forms of algorithmic recording and all forms of algorithmic rewarding. This context-spanning use is mainly determined by the fact that these mechanisms in the PWC, HWC and TWC can be implemented in a similar way. However, we find that the mechanisms are used with different intentions, which we discuss more detailed in Section 5. While some AM mechanisms are used context-spanning, some are context-specific, such as *recommending*, *sanctioning* and *replacing, and surge-pricing* in the PWC (= P1) or *predictive analytics* and *predictive scheduling* in the TWC (= P3). The exclusive use of mechanisms is explained by the work context characteristics, to which only certain AM mechanisms fit, such as *replacing* in the PWC due to the type of employment, i.e., self-employment, or using *predictive analytics* due to the complementary role of algorithms vs. mangers in the TWC. Notably, no AM mechanism is used exclusively in HWC (= P2) but always in co-occurence with either the PWC (= P5) or the TWC (= P7), or both (= P4). For P5, which refers to the platform-based organizational logic and P7, which attributes to the same type of employment, i.e., employment contract, it is remarkable that the AM mechanisms used there, consisting of *restricting of behavior* and *performance-based* and *preference-based scheduling,* are used in the same fashion. However, as P5 and P7 occur in a low frequency, more data would be needed in order to draw a firm conclusion regarding this co-occurrence and to support these usage patterns. We also note the occurrence of two times in the contrasting contexts of PWC and TWC (= P6), determined by the implementation of *skill-based matching* and *real-time ranking and rating*. Regarding skill-based matching, we assume that this occurs as a shared usage pattern since the outlined examples concern a similar application field, i.e., high-skilled work. Regarding real-time rating and ranking, based on the underlying data, we assume that this mechanism is likely to be used in the HWC as well and thus corresponds to usage pattern P4.

			Working contexts			
AM	**Forms**	*Sub-forms*	**PWC**	**HWC**	**TWC**	**Usage Pattern**
AC	**Recommending**	*Implicit recommending*	X			P1
		Explicit recommending	X	X	X	P4
	Restricting	*Restricting access to information*	X	X	X	P4
		Restricting behavior	X	X		P5
	Recording	*Passive monitoring*	X	X	X	P4
		Real-time feedback	X	X	X	P4
	Rating	*Real-time (online) rating and ranking*	X		X	P6
		Using predictive analytics			X	P3
	Rewarding	*Non-monetary rewarding*	X	X	X	P4
		Monetary rewarding	X	X	X	P4
	Sanctioning[new]	*Temporarily withdrawing access or benefits*	X			P1
	Replacing	*Dismissing workers*	X			P1
Algo. Matching	**Market-level matching**	*Surge pricing*	X			P1
		Prediction-based scheduling			X	P3
	Worker-level matching	*Skill-based matching*	X		X	P6
		Location-based matching	X	X	X	P4
		Performance-based scheduling		X	X	P7
		Preference-based scheduling		X	X	P7
			14	10	13	∑

Patterns: P1 = PWC; P2 = HWC; P3 = TWC; P4 = All Working Contexts; P5 = PWC & HWC; P6 = PWC & TWC; P7 =HWC & TWC

Usage Pattern	Frequency
P4	7
P1	4
P3	2
P6	2
P7	2
P5	1
P2	0

Figure 2. Sub-forms of AM mechanisms and occurring usage patterns (left), ordered by frequency (right).

5. Discussion and conclusion

The study at hand set out to analyze the use of AM mechanisms in three different work contexts (PWC, HWC, TWC), as well as to shed light on the extent to which these mechanisms translate across contexts. In this regard, our study reveals several usage patterns, ranging from context-spanning to context-specific AM mechanisms. In addition to the reasons stemming from the work context characteristics already described in Section 4.3., the identified usage patterns can, from our point of view, be attributed to the following factors: First, although we find that some mechanisms are used in all three work contexts (=P4), our results indicate that they are used with *context-dependent intentions*. For example, explicit algorithmic recommending is used in PWC, HWC, and TWC; however, while such recommending is often perceived as concrete (i.e., binding) work instructions in the PWC, they are commonly perceived as 'loose' suggestions in the two other contexts. Second, we find that the context-specific use of AM mechanisms (=P1 and P3) is closely related to the *status of workers*. For example, since freelancers are not protected by a legal work contract, mechanisms for nudging, replacing, and sanctioning are found to be used exclusively in PWC, which is in stark contrast to the frequently highlighted work autonomy in this work context (Wood et al., 2019). In turn, these mechanisms are not applicable in the HWC and TWC, as employment contracts protect employees, e.g., regarding algorithmic replacement. Conversely, predictive scheduling algorithms are only used in the HWC and TWC (i.e., in contexts with direct employment), given the general unpredictability of platform-based work (Wood et al., 2019) and making the use of pre-planned shifts obsolete. Third, another factor that seems to determine the extent to which AM mechanisms are transferable, as well as how they are implemented, is the workers' *skill level*, ranging from high-skilled (e.g., programming) to low-skilled work (e.g., food delivery). For instance, real-time feedback and passive monitoring are used context-spanning, as part of usage pattern P4, but primarily in low-skilled work, such as call centers and delivery services.

To conclude, our study results make three main contributions to extant literature. First, they contribute to a more detailed and nuanced understanding of AM mechanisms in different work contexts. Second, by uncovering different usage patterns, our results shed light on the transferability of AM mechanisms, and point to an initial set of factors that help explain the observed differences. Third, our identified usage patterns can serve as a guiding framework for researchers (and practitioners), e.g., in the context of case studies. These contributions should however be interpreted with the following limitations in mind: First, through our search strategy, we attempted to include as many relevant studies as possible in our analysis. However, we cannot exclude the possibility that some published studies, including mechanisms supporting our usage patterns, were missed. Second, besides an imbalance of the literature regarding the work contexts (see Section 3), there is also an imbalance in the application fields of the PWC, where many examples of Uber appear, potentially biasing the results. Third, considering that a literature review does not capture all real-world applications (especially in TWC), we believe that the results of the observed patterns are not fully generalizable and further research, as well as practical insights, are needed.

Thus, the research area would benefit from future research with a particular focus on HWCs, TWCs and further application fields of the PWC—preferably with qualitative research methods (e.g., case studies or ethnography)—in order to uncover rich insights and potentially new, context-specific AM mechanisms and further advance our understanding of the phenomenon. Such future research can also provide deeper insights regarding the factors that determine a context-spanning or context-specific use of AM, including factors ranging from the organizational and managerial to the individual level. Considering our study as a framework for future AM research, it is also conceivable to establish links between different countries by comparing, for example, country-specific labor regulations. We hope our study helps guiding and inspiring such research on AM and AI.

6. References[1]

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[1] Due to space constraints, not all 45 studies included in our review sample are listed here. The complete list is available upon request.

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