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COVERT RESISTANCE AGAINST ALGORITHMIC CONTROL ON ONLINE LABOR PLATFORMS – A SYSTEMATIC LITERATURE REVIEW

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Research Paper

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Abstract

Online labor platforms (OLPs) such as Uber or Upwork heavily rely on algorithms instead of human managers to control workers' behavior. While algorithmic control (AC) allows platform providers to control their workers efficiently, it is often perceived by workers as a tighter control (compared to human-based control) which increases their motivation to resist. Especially covert resistance (i.e., workers' hard-to-observe oppositional actions) provides essential insights into how workers deal with AC that affect platforms' longevity. In this study, we conducted a systematic literature review to develop a theoretical framework showing how and why workers perform covert resistance against AC. Further, our analysis reveals the enabling role of sensemaking for diverse forms of covert resistance. Overall, our study expands the literature on AC by shedding light on the formation of workers' covert resistance. Therefore, we offer platform providers and policymakers crucial insights to create fairer working environments for workers under AC.

Keywords: Algorithmic Control, Covert Resistance, Online Labor Platforms, Literature Review.

1 Introduction

In recent years, online labor platforms (OLPs) such as Uber, Upwork, and Deliveroo have significantly changed labor markets around the world by offering platform-based work arrangements. OLPs offer freelance, short-term employment relationships where workers take on work assignments in a specific area (Galliers et al., 2017). Currently, we observe a rising popularity of work on OLPs: In 2021, 16% of the U.S. working-age population had already worked for an OLP, and 9% of them did some work on an OLP during the past year (Anderson et al., 2021). Moreover, OLPs are mostly responsible for the increase of 34% of freelancers in the U.S. between 2020 and 2021 (Little, 2022).

One key characteristic of OLPs is their usage of algorithmic control (AC), where intelligent algorithms are used instead of human managers to control worker behavior (Wiener et al., 2021). On the one hand, AC is valuable for platform providers to improve efficiency and scalability in management tasks by automatically guiding workers' behavior, monitoring their activities, and deciding to reward or sanction them based on their performance (Lee et al., 2015). On the other hand, AC allows tighter control over workers' behavior (compared to human-based control) due to algorithms' comprehensive, instantaneous, interactive, and opaque characteristics (Kellogg et al., 2020). Thus, workers under AC face new organizational dynamics with increased power and information asymmetries in favor of the platform provider (e.g., Curchod et al., 2020), which can have negative consequences for individual workers, ranging from social isolation and distress to precarity (Petriglieri et al., 2018).

In response to the tight control, workers can comply with AC (e.g., Martin et al., 2014), but they can also resist it (e.g., Newlands, 2021). This study focuses on worker resistance since it can significantly reshape organizational structures, thus substantially impacting organizations (e.g., Hodson, 1995). In addition, we examine workers' resistance in the context of OLPs because they rely heavily on AC, and their workers are less legally bound to the platform due to their freelancer status, which gives them more freedom to develop resistance practices (compared to traditional organizations). Besides various types of resistance (e.g., overt resistance like strikes, unwitting resistance like daydreaming at work), our study investigates workers' covert resistance (e.g., circumvent control instructions) (e.g., Cameron & Rahman, 2022; Morrill et al., 2003). Covert resistance refers to a worker's intentional, oppositional action that is less obvious to the platform provider (Hollander & Einwohner, 2004). This type of resistance is particularly important for OLPs as it can constantly occur in the day-to-day business (e.g., compared to event-based strikes), significantly influence organizational dynamics (e.g., compared to daydreaming at work with less impact) (e.g., Hodson, 1995), and is more difficult for platform providers to detect (Scott, 1968). Especially in the context of AC, the disintermediation of human managers leads to a spatial separation between the platform provider and workers (Kellogg et al., 2020), which creates greater room for workers to develop covert resistance. Thus, it is crucial to discover how workers perform covert resistance against AC to enable platforms' longevity. On the other hand, workers' covert resistance can also be seen as a symptom of AC, where workers continue to work under AC but try to mitigate existing information and power asymmetries. In this regard, covert resistance is a way how workers can deal with the tight control through algorithms. By understanding the triggers of workers' covert resistance, we can derive implications for a sustainable work environment for workers under AC.

Drawing from the management and organizational literature, the target of workers' covert resistance can be either organizational change (e.g., introducing self-managing work teams) (e.g., Knights & McCabe, 2003) or organizational control (e.g., managerial influence tactics) (e.g., Falbe & Yukl, 1992). However, existing information systems (IS) literature mainly focuses on one of these two targets, namely workers' covert resistance against organizational change which is induced by IS implementation (e.g., Lapointe & Rivard, 2005). While there are many similarities between those two resistances, we observe several key differences: First, covert resistance against organizational change aims to maintain the status quo (e.g., Kim & Kankanhalli, 2009), whereas covert resistance against organizational control tries to change the status quo (e.g., Edwards, 1979). In addition, while one way to covertly resist IS implementation (i.e., organizational change) is often the non-usage of the particular IS (Ferneley & Sobreperez, 2006), such avoidance of AC (i.e., organizational control) would indicate exclusion from work which is only possible to a limited extent. Overall, the rising phenomenon of AC enables us to enrich the IS literature with studies about workers' covert resistance against organizational control through algorithms.

Current research on workers' covert resistance against AC on OLPs (many outside of IS literature) is highly context-specific, rather isolated from each other, and spread across several research disciplines. For example, the ride-hailing OLP Uber offers a service called UberPool, which organizes customers to travel in the same direction in one trip at reduced prices (Uber, 2022a). Vasudevan & Chan (2022) discover how drivers accept the first customer on UberPool and then log off the app to avoid the pickup of further customers. This finding is highly specific to the ride-hailing context and less adaptable to other OLPs. Hence, there is still a lack of an overall conceptual framework for different forms of covert resistance and how they emerge. Therefore, we intend to answer the following research question:

RQ: How and why do platform workers perform covert resistance against AC?

To address this research question, we conducted a systematic literature review to leverage existing individual and context-specific findings for developing a generalizable theoretical framework. Following the guidelines from Paré et al. (2015) and Webster & Watson (2002), we identified 30 relevant articles which were analyzed using a qualitative coding approach (Saldaña, 2021). We examined what different forms of covert resistance workers perform, if there are preparatory steps to engage in covert resistance (*how*), as well as antecedents triggering workers' covert resistance (*why*).

With this study, we offer three theoretical contributions to the literature on AC on OLPs. First, we provide a holistic understanding of different forms of covert resistance against AC on OLPs by integrating previous findings into a theoretical framework. Second, we offer a nuanced understanding of the triggers of covert resistance shedding more light on what experience may lead to such resistance against AC. Third, we explain how covert resistance is formed with sensemaking (i.e., the process of deriving deep knowledge about the algorithms) as a crucial activity to enable diverse forms of covert resistance. Additionally, we discover literature gaps based on the insights of our theoretical framework and offer directions for future research on this basis.

2 Conceptual Foundations

2.1 Algorithmic Control

Platform providers have a high interest in controlling their workers to ensure that worker behaviors are aligned with organizational goals (Tiwana, 2015; Saunders et al., 2020). While in the past, human managers were mainly responsible to control workers (Liu et al., 2010; Ouchi, 1979), algorithms increasingly take over this role (Kellogg et al., 2020; Benlian et al., 2022). Algorithms can be defined as computer-based procedures that convert input data into desired outputs (e.g., control instructions) (Gillespie, 2014). In recent years, advanced big data and machine learning technologies have enabled algorithms not only to support decision-making but also to take over the task of controlling workers in organizations (Constantiou & Kallinikos, 2015). This phenomenon is called AC, which we refer to as "the managerial use of intelligent algorithms and advanced digital technology as a means to align worker behaviors with organizational objectives" (Wiener et al., 2021, p. 1). In this regard, algorithms are mainly responsible for the enactment and delivery of control instructions to workers (Cram & Wiener, 2020; Wiener et al., 2016). Additionally, they play an increasingly important role in the design and implementation of control configurations based on machine-learning approaches (Wiener et al., 2021). A prominent example of AC is the ride-hailing company Uber which heavily relies on algorithms to control drivers' behaviors (Cram et al., 2022). There, the performance of drivers is measured based on collected data that are aggregated into certain metrics (e.g., acceptance rates of ride assignments) (Uber, 2022b), and based on these metrics drivers are rewarded (e.g., bonus pay) or punished (e.g., account deactivation) (Lee et al., 2015).

AC allows much tighter control of workers compared to previous human-based control due to the increased comprehensive, instantaneous, interactive, and opaque characteristics of algorithmic technologies (Kellogg et al., 2020). For example, the comprehensiveness of algorithms allows widespread data collection (e.g., GPS, communication messages) to gather detailed information about workers and their activities, thus increasing the surveillance of workers (Anteby & Chan, 2018). These characteristics lead to increased power and information asymmetries between the platform provider and workers in favor of the platform provider (Curchod et al., 2020). Further, with the absence of human managers, workers have little to no opportunities to appeal to the empathy of managers, making contextually necessary exceptions no longer possible (Newlands, 2021). Such circumstances can result in more isolation, precarity, and distress for workers under AC (Petriglieri et al., 2018), making them potentially ripe for resistance.

2.2 Covert Resistance Against Organizational Control

Drawing on studies from the management and organizational literature, organizational control can be seen as a contested terrain (Kellogg et al., 2020; Edwards, 1979), where, on the one hand, platform providers try to maximize the value created by workers through organizational control (Braverman, 1974), and on the other hand, workers resist organizational control to defend their identity and dignity (Thompson & Vincent, 2010). In this regard, worker resistance can be defined as the action of a worker to produce alternative forms of power that are different from those dictated to them (Baikovich & Wasserman, 2020; Courpasson & Vallas, 2016). There are different types of worker resistance which all have in common that they involve an action that is performed in opposition to organizational control (Hollander & Einwohner, 2004). The different types of worker resistance can be distinguished based on the intention to resist and if the action is recognized as resistance by the platform provider or by the observer (e.g., researcher) (see Table 1 for an overview of different types of resistance). For example, while overt resistance is intended as resistance by the worker and is recognized by the platform provider and observer, covert resistance is intended by the worker but is recognized only by the observer as resistance. If a worker's oppositional action does not meet any of these three criteria, it is not defined as resistance (Hollander & Einwohner, 2004).

Resistance type	Intention to resist	Recognized as resistance by platform provider	Recognized as resistance by observer
Overt resistance	Yes	Yes	Yes
Covert resistance	Yes	No	Yes
Unwitting resistance	No	Yes	Yes
Target-defined resistance	No	Yes	No
Externally-defined resistance	No	No	Yes
Missed resistance	Yes	Yes	No
Attempted resistance	Yes	No	No
Not resistance	No	No	No

Table 1. Types of resistance based on Hollander & Einwohner (2004).

In this study, we focus on covert resistance which we define as workers' hard-to-observe oppositional action against organizational control that can take place within the everyday life of organizations (Cameron & Rahman, 2022; Prasad & Prasad, 2000). Investigating covert resistance is particularly important: First, covert resistance can occur in the day-to-day business which indicates that platform providers face it frequently (Scott, 1968). In addition, covert resistance can have a significant impact on organizational dynamics as workers challenge existing power structures to advance their interests (Hodson, 1995). Third, covert resistance is more difficult for platform providers to detect, leaving platform providers with uncertain consequences (Prasad & Prasad, 2000). In the context of AC, it is even more crucial to investigate covert resistance since the disintermediation of human managers leads to an increased spatial separation between the platform provider and workers (Kellogg et al., 2020). This greater distance allows more (creative) room for workers to develop diverse forms of covert resistance since it is more difficult for platform providers to detect such resistance. Given that covert resistance can be very harmful to an organization's business, it is crucial to discover how workers perform covert resistance against AC to enable the longevity of platforms. On the other hand, workers' covert resistance can also be seen as a symptom of AC, where workers continue to work under AC but try to mitigate the power and information asymmetries to reduce their suffering. By understanding the triggers of workers' covert resistance we can derive implications for a sustainable work environment for workers under AC.

There are several reasons why workers engage in covert resistance against organizational control. For example, Gill (2019) uses compatibility and coherence to explain workers' response to organizational control: While compatibility describes the fit between workers' personality and their subjective experience of organizational control, the degree of coherence tells how consistent workers perceive different control instructions by the organization. In the case of low compatibility, workers suffer because of perceived threats to dignity and identity (Hodson, 1995; Thompson, 1989; Willmott, 1993), which, in turn, can lead to (covert) resistance. If, in addition to low compatibility, workers experience a high degree of coherence between multiple control modes, they may increase the resistance intensity, while, on the other hand, a low coherence may weaken workers' (covert) resistance (Gill, 2019).

Existing literature on AC argues that it is much more difficult for workers to covertly resist AC compared to human-based control (e.g., Curchod et al., 2020; Lee et al., 2015). For example, the opaque characteristic of AC limits workers' understanding of the control strategies of platform providers making it more challenging to resist. Further, the comprehensiveness and instantaneousness of AC via extensive and personalized nudges and penalties can also diminish workers' room for resistance because of social isolation and individualization of control instructions. The interactivity of AC can lead to the use of internal and external data sources to monitor performance, which also makes it more difficult for workers to contest their performance measurements due to the increased complexity (Kellogg et al., 2020). Therefore, workers under AC need to develop new and more subtle ways to covertly resist AC. These significant differences between AC and human-based control for workers make it necessary to develop a deeper knowledge of workers' covert resistance against AC to understand the effects of AC on workers, their resistance behavior, and the resulting organizational dynamics.

3 Methodology

For the systematic literature review, we conducted a theoretical review that is used for explanation building (Paré et al., 2015). The goal of this theoretical review is to synthesize existing research findings into an overarching theoretical structure and develop a theoretical framework for workers' covert resistance against AC (Schryen et al., 2020; Schryen et al., 2017). Therefore, we implemented the search strategy by Webster & Watson (2002): First, we searched for "resist*" in the abstract, title, and keywords in leading management, organizational, and IS journals, as well as leading IS conferences (see Appendix A for details). Thereafter, we screened the abstracts of the resulting articles to check if they were about worker resistance. In this regard, we excluded non-resistance articles, articles that are not about workers who resist (e.g., organizations that resist), and non-peer-reviewed articles. Afterward, we screened the full text to filter those articles which are about covert resistance against AC. Therefore, we excluded all articles that are not about covert resistance (e.g., only about strikes and protests). From this first step, we found six articles for our potential review sample. Second, we did a backward search by screening citations from the six articles found in the previous step and identified the relevant ones (i.e., potentially about covert worker resistance against AC). Those articles were then screened by abstract and full-text, where we additionally found 11 articles for our potential review sample. Third, we carried out a forward search using Google Scholar to examine articles that cited those articles identified from the previous two steps. These articles were screened by abstract and full-text, where we found 22 articles for our potential review sample. Finally, from the 39 articles found in the previous steps, we only kept empirical studies and excluded conference papers that resulted in journal articles. Thus, our final review sample contains 30 articles (see Figure 1).

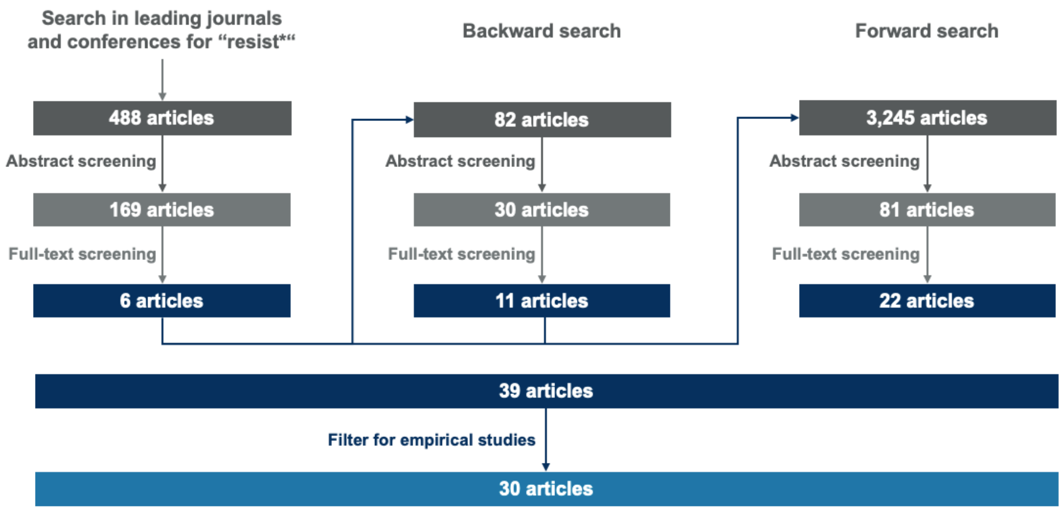


Figure 1. Literature review process.

20 out of 30 articles from our review sample are published in journals (thereof four from IS journals) and ten are conference articles (thereof five IS conferences). In sum, two-thirds of the articles in the review sample are from outside of the IS literature (see Appendix B for more details). Most articles in our review sample apply qualitative analysis methods on interviews and/or forum posts (25). Only a few articles applied quantitative methods with survey data (3) or conducted a mixed-method study with interview and survey data (2). Regarding the study context, our review sample includes four types of OLPs. Ride-hailing platforms (e.g., Uber) have a particularly high frequency in our review sample (18), followed by knowledge-based work (e.g., Upwork) (5), food delivery (e.g., Meituan) (3), and online marketplace (e.g., eBay) (1). In terms of the publication year, most articles in our review sample are published in 2021 (12), indicating the rising popularity of AC (see Appendix C for more details).

To analyze our review sample, we applied a qualitative coding approach (Saldaña, 2021). Therefore, we first identified excerpts from our review sample that are relevant to answer our research question. In this step, we searched for descriptions of covert resistance against AC and examined whether there are preparatory steps to be able to engage in covert resistance. In addition, we looked for antecedents of covert resistance to understand why workers engage in such resistance. We found 107 excerpts about different forms of covert resistance, 21 excerpts about preparatory steps for covert resistance, and 60 excerpts about triggers of covert resistance. For example, one excerpt about a trigger of covert resistance is provided by Lee et al. (2015) where they describe that "these numeric systems that made drivers accountable for all interactions were sometimes seen as unfair and ineffective and created negative psychological feelings in drivers" (p. 1608). In the next step, we aggregated the excerpts into categories which are further summarized into higher-level themes. For example, we coded the excerpt from Lee et al. (2015) in the previous example as "unfairness" and aggregated it together with the other categories "low autonomy," "pressure," and "low privacy" into the theme "low compatibility." Finally, we summarized all categories, themes, and their relationships into a theoretical framework (see Figure 2). During the process, these codes are refined over several iterations during discussions with two other researchers until we reached a consensus about the final categories and dimensions (Saldaña, 2021).

4 Results

To answer our research question of how and why workers on OLPs perform covert resistance against AC, we developed a theoretical framework (see Figure 2). This framework describes what forms of covert resistance are performed and their triggers. Further, we discovered that workers might engage in sensemaking as a preparatory step that enables them to develop diverse forms of covert resistance. In the first three sections of this chapter, we describe our theoretical framework in detail. Afterward, we propose future research directions based on the key insights from the framework.

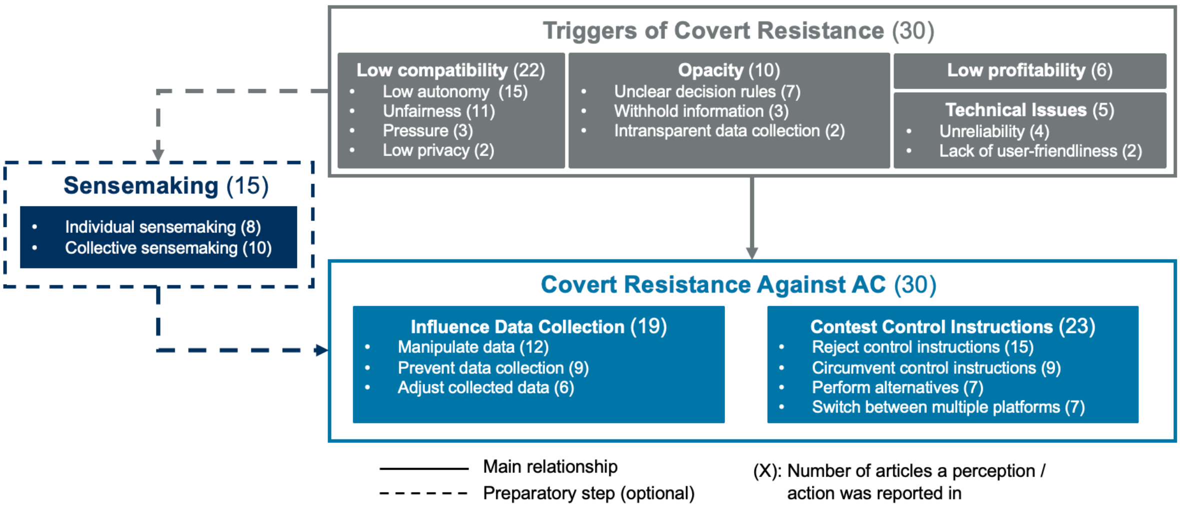


Figure 2. Covert resistance formation against AC.

4.1 Triggers of Covert Resistance

One of the most frequent triggers of covert resistance is **low compatibility** between workers' personhood (physical, psychological, and social qualities) and their subjective experience of AC (e.g., Gill, 2019). We found in our review sample that low compatibility can be characterized by four categories. First, the tight control through AC lets workers feel *low autonomy* because they are unable to direct and control important aspects of their work (Bucher et al., 2021; Gutiérrez Crocco & Atzeni, 2022; Reid-Musson et al., 2020; Wiener et al., 2021). For example, they have few to no opportunities to justify and correct themselves when they experience an unjustified decision from AC (e.g., Cameron & Rahman, 2022; Jiang et al., 2021). Second, workers perceive *unfairness* through AC (e.g., Lee et al., 2015; Wiener et al., 2021). For example, workers believe that customer reviews are important for their success, but they are also fundamentally flawed because customers can submit unjustified reviews and are not held accountable for them (e.g., Curchod et al., 2020; Kinder et al., 2019). Third, workers also feel *pressure* from AC during their work. They constantly receive automated messages about their performance metrics and are instructed to maintain or improve them (e.g., Mosseri, 2022). The high pressure from AC can lead to distress because workers are not able to deal with such pressure (Cram et al., 2022). Last, workers feel they have *low privacy* when working under AC (e.g., Wiener et al., 2021). The widespread surveillance and continuous collection of data (e.g., GPS, customer reviews) lead to the fear that AC can seriously threaten their privacy (Sannon et al., 2022). Overall, the low compatibility between a worker's personality and the experienced AC is a trigger for workers to mitigate the tight control that platforms exert over them (Curchod et al., 2020; de la Vega et al., 2021). Thereby covert resistance is performed to increase autonomy, fairness, and privacy on the one hand and decrease the perceived pressure from AC on the other hand (Ferrari & Graham, 2021; Walker et al., 2021).

Another frequently mentioned trigger for workers' covert resistance is the highly **opaque** working environment under AC (Jarrahi & Sutherland, 2019; Möhlmann & Zalmanson, 2017). We found that this opaqueness can be expressed via three categories. First, the control instructions from AC are based on *unclear decision rules* for the workers. For example, workers are suspended from their accounts without knowing the particular reason (Jiang et al., 2021). When they try to ask their platform provider for the deactivation reason, they do not receive an answer (Pregenzer, Wieser, et al., 2021). Such unclear decision rules used by AC lead to workers' unpredictability of control instructions (Vasudevan & Chan, 2022). Another form of opaqueness is that AC *withholds information* from workers, which is often crucial for them to make their business decisions. For example, ride-hailing drivers do not know the destination of a ride until they accept that ride (Rosenblat & Stark, 2016). Therefore, drivers cannot make an accurate decision on how profitable that particular ride will be. Third, workers do *not know what data is collected* about them and which data is used for AC decisions, making it difficult for them to access, for example, how their privacy may be affected by AC (Sannon et al., 2022). In sum, the highly opaque working environment leads to great uncertainty for workers regarding their working conditions with missing information about their earnings and job security (Pregenzer, Wieser, et al., 2021).

Low profitability and the resulting precarity can also be a trigger of covert resistance against AC (Gutiérrez Crocco & Atzeni, 2022). In ride-hailing, for example, fare rates have declined in recent years, and promotions are less lucrative than in the past, leading to significant dissatisfaction among workers (Pregenzer, Remus, et al., 2021). In this case, covert resistance is a means to increase profitability (Vasudevan & Chan, 2022) and to alleviate the precarity of workers (de la Vega et al., 2021).

Last but not least, the current literature describes how **technical issues** can motivate workers' covert resistance. First, workers report that they receive *unreliable* control instructions from AC (Sun, 2019; Vasudevan & Chan, 2022). For example, Uber uses surge pricing to lure drivers with higher fares than usual to drive to areas with high demand. As a result, one driver reported that the areas with increased price levels changed unexpectedly within a few seconds (Lee et al., 2015). Second, there can be a *lack of user-friendliness* in the way how AC delivers the control instructions to workers (Rosenblat & Stark, 2016). For example, a ride-hail driver complained that the color coding of the maps based on the number of ride requests is confusing, leading him to find other ways to extract this information (Karanović et al., 2021). Hence, such technical problems may motivate workers to engage in covert resistance to reduce their reliance on AC and thus experience fewer technical complications (Möhlmann et al., 2021).

4.2 Sensemaking

In half of the articles in our review sample, we observed that workers first make sense of AC before engaging in covert resistance. Most articles describe sensemaking as a process of deriving deep knowledge about the algorithms by discovering patterns about what kind of input data leads to what kind of control instructions (Curchod et al., 2020; Jarrahi & Sutherland, 2019; Sun, 2019). Therefore, workers put a high effort into **individual sensemaking** by guessing, deciphering, or reverse-engineering AC from their personal experience with AC. Based on the derived knowledge, workers can develop covert resistance (Cameron & Rahman, 2022; Möhlmann & Zalmanson, 2017; Yu et al., 2022). For example, a freelancer on Upwork experiments with different contract lengths and different setups to close contracts with customers to find out how this behavior affects his or her performance score (Rahman, 2021). Besides individual sensemaking through their personal experience with AC, workers can also engage in **collective sensemaking**. In this regard, they can use, for example, online forums or social media groups to communicate with each other and share their knowledge (Bucher et al., 2021; Ferrari & Graham, 2021; Vasudevan & Chan, 2022). This knowledge exchange can lead to further insights, where workers can either verify their previously gained knowledge from individual sensemaking or collectively derive new patterns of AC (Arubayi, 2021; Jiang et al., 2021; Kinder et al., 2019). Overall, sensemaking is an optional preparatory step to enable diverse forms of covert resistance. Especially regarding covert resistance that influences data collection (see chapter 4.3), workers must understand how the collected data (i.e., input of AC) impacts control instructions (i.e., output of AC). Only with this knowledge workers can actively shape the control instructions to achieve their desired outcome.

4.3 Covert Resistance Against AC

Workers can covertly resist AC in two ways. First, they can **influence the data collection** (i.e., input for AC) which in turn has a direct impact on the control instructions (i.e., output of AC). In this regard, workers can *manipulate data*, where they modify the collected data to their advantage. For example, on Upwork, freelancers split one project into multiple smaller projects to receive for each smaller project a separate customer rating. Therefore, they can inflate the number of ratings to improve their performance score (Cameron & Rahman, 2022; Jarrahi & Sutherland, 2019). Another way to manipulate the ratings is to directly contact the customer to change the already submitted ratings in exchange for extra work for free (Bucher et al., 2021; Kinder et al., 2019). In the ride-hailing context, Uber drivers want to take a break but also benefit from an hourly promotion. Therefore, they can manipulate the data by staying online and parking between other Uber drivers to avoid getting ride requests (Lee et al., 2015). Drivers also learned how they can take advantage of surge pricing by manipulating the supply data. Therefore, they log out of the app, hoping that AC will recognize that the supply is tight. In this case, AC would increase the fare rate and provide a surge. When the surge is high enough, the drivers will go online and take rides with the high surges (Arubayi, 2021; Karanović et al., 2021). Workers also manipulate data to protect their privacy. In this regard, workers enter fake personal information or use VPNs to make it difficult for their platform provider to track their location and related information (Sannon et al., 2022).

Another approach to influence data collection is to *prevent data from being collected*, especially those data that would negatively impact the worker. For example, freelancers on knowledge-based platforms require customers to promise them a perfect score in advance otherwise, they will not start the contract (Cameron & Rahman, 2022). Some freelancers avoid features from the platform such as a time tracker to prevent data collection (Sannon et al., 2022). In the context of ride-hailing, drivers turn off the app or deactivate their GPS data to avoid getting ride requests from undesirable neighborhoods (Jiang et al., 2021; Lee et al., 2015). A further way to prevent unwanted data collection is to ask customers to cancel trips that drivers do not want to take so that drivers' cancellation rate is not affected (Cameron & Rahman, 2022; Möhlmann & Zalmanson, 2017). At online marketplaces, some sellers use offline (personal) communication to influence their buyers (instead of online communication over the platform) increasing the probability of a higher rating (Curchod et al., 2020).

Workers can also attempt to *adjust the already collected data* to influence data collection. Therefore, they try to contact the platform provider of AC to complain about collected data that does not reflect reality and becomes a disadvantage to them. For example, workers file disputes with their platform providers about unfair customer ratings or claims against false customer accusations (Cameron & Rahman, 2022; Mosseri, 2022). To underline that the collected data is indeed not justified and unfair to the worker, workers collect their own data and send it to their platform provider as proof. For example, ride-hailing drivers install dashcams in their cars and offer video materials from the dashcam to Uber in the case of unfair customer accusations (Pregenzer, Remus et al., 2021). To keep track of their performance metrics (e.g., acceptance rate, cancellation rate), drivers track their rides with manual logs or in the form of screenshots of the app (Rosenblat & Stark, 2016; Sannon et al., 2022). Sometimes it is also possible to adjust the collected customer ratings by directly contacting the customer to withdraw it. In the case of an online marketplace, some sellers contacted buyers who had left a negative review and sought to encourage them to remove it (Curchod et al., 2020).

Second, workers can directly **contest the control instructions** (i.e., output of AC) to covertly resist AC. Therefore, workers *reject control instructions* by disobeying recommendations and nudges provided by AC (Cram et al., 2022; Jiang et al., 2021; Wiener et al., 2021). For example, ride-hailing drivers decline unfavorable ride recommendations from the algorithm (Lee et al., 2015; Pregenzer, Remus, et al., 2021; Vasudevan & Chan, 2022), cancel already assigned customers in the app (Möhlmann & Zalmanson, 2017), not following navigation instructions which are suboptimal (Tarafdar et al., 2022), and ignore messages about surge pricing (Karanović et al., 2021; Rosenblat & Stark, 2016). In this regard, workers can even use bot apps to automatically reject unfavorable ride recommendations (Chen, 2018).

Workers can also contest control instructions by *circumventing* them. One approach is to avoid using the platform as much as possible. Therefore, workers try to establish long-term relationships with customers where the customer can directly contact the worker instead of finding one over the platform (Rahman, 2021). For example, ride-hailing drivers hand out their phone numbers to customers and encourage them to request a ride via a phone call instead of using Uber (Lee et al., 2015). Similarly, Upwork freelancers use the platform to link potential customers to their professional homepage and try to establish relationships with customers outside of the Upwork platform (Kinder et al., 2019). In the case where workers can work for multiple platforms at the same time, workers try to convince customers to move to the platform with a less strict AC for future requests (Maffie, 2022). Moreover, workers can also create a new profile and start from scratch after maintaining a low-performance score on the previous profile (Kinder et al., 2019). There is even a market among workers who sell their profiles to those workers who have been banned by AC (Gutiérrez Crocco & Atzeni, 2022). While the previous two approaches are mainly taking place outside of the platform, some resistances can be performed within the platform. For example, Uber uses AC to withhold the destination of a ride to the driver. Hence, drivers call the customers to ask them about their destination and decide afterward whether to pick up the customers or not (Cameron & Rahman, 2022). In the case of knowledge-based work, where the displays of freelancers are under constant surveillance of AC (e.g., the platform takes every few minutes a screenshot of the display interface to check if the freelancer is working properly), some freelancers set up a second display that is not monitored (Ferrari & Graham, 2021).

Workers can also *perform alternatives* to the control instructions. Instead of simply rejecting a control instruction and passively waiting for the next one, they can use their experience and knowledge to self-organize their work (Lee et al., 2015). For example, when ride-hailing platforms do not provide clear information about the route, drivers try to search for alternatives to accomplish the ride with a better route (Karanović et al., 2021; Tarafdar et al., 2022; Yu et al., 2022). This covert resistance has positive consequences for the ride-hailing platform provider as it allows for more efficient fulfillment of the ride request, which is also in the platform's best interest. Further, instead of relying on the platform, drivers can learn by themselves about when surges are likely to appear. Therefore, they used knowledge about bigger events (e.g., concerts) to anticipate where and when a high demand could occur and relocate themselves based on this knowledge (Vasudevan & Chan, 2022).

Last, workers can *switch between multiple platforms* to contest the control instructions from AC. By switching between different platforms, workers can diversify their earning opportunities and distribute the risks of precarity by suddenly being deactivated from one particular platform (Möhlmann & Zalmanson, 2017; Sun, 2019; Yu et al., 2022). For example, freelancers on knowledge-based platforms try to maintain high visibility for potential customers by registering on multiple platforms (Kinder et al., 2019). Similarly, ride-hailing drivers can register their vehicles via several accounts and devices to pick and choose from different requests recommended by multiple platforms (Chen, 2018; Möhlmann et al., 2021). In the case of account deactivation (threats), workers can avoid a loss of income by (temporally) working for another platform (de la Vega et al., 2021).

4.4 Future Research Directions

Based on our theoretical framework, we identified several important gaps in the existing literature that could be promising future research directions (see Table 2 for an overview). First, we summarized several triggers for covert resistance from existing articles. In the current literature, these triggers are considered in isolation from each other. Preliminary studies show how these triggers may influence each other to strengthen or weaken workers' motivation to resist. For example, Pregenzer, Wieser, et al. (2021) find that low transparency can be a catalyst for resistance when workers experience low profitability in their work. Moreover, we noticed that the most frequent trigger of workers' covert resistance is low compatibility (e.g., low autonomy, unfairness). While compatibility can be a significant reason for worker resistance, Gill (2019) proposed a framework where the extent to which workers perceive two or more control instructions as logical and consistent (i.e., coherence) can also heavily impact worker resistance. While there is some initial research that also considers the coherence of multiple control instructions of AC as a trigger to explain worker resistance (Pregenzer, Remus, et al., 2021), future research may expand our knowledge of how AC can elicit different perceptions of coherence and how they may affect workers' covert resistance. To investigate the interrelations among different triggers of covert resistance as well as the impact of control coherence on workers' covert resistance intensity, researchers could apply a factorial survey (Dülmer, 2016) to study the effects and effect sizes of the different triggers on covert resistance intensity. Additionally, besides various forms of negative resistance (i.e., hinder platform providers from achieving their goals), we also observed that some forms of covert resistance can be positive for organizations (i.e., help platform providers to achieve their goals). For example, ride-hailing drivers find better routes than suggested by AC to get customers to their destination faster (i.e., perform alternatives). Future research could investigate which triggers produce positive resistance and which lead to negative resistance, for example, by using a fuzzy set qualitative comparative analysis (Mikalef & Pateli, 2017) on interviews with platform workers.

Second, the current literature describes several forms of covert resistance against AC but does not distinguish how covert resistance can systematically differ based on different AC mechanisms (e.g., algorithmic recommending, algorithmic restricting) (Kellogg et al., 2020). One could dive deep into the different mechanisms of AC and workers' covert resistance to understand the relationship between control and resistance in the context of AC. For example, workers have much more latitude for resistance against algorithmic recommendations where they can choose whether to follow them or not. On the other hand, it is much more difficult for workers to covertly resist algorithmic restrictions (e.g., restricting workers' access to information) where AC enforces a particular work environment that leaves less room for workers to resist. Similarly to Cameron & Rahman (2022), researchers could apply a grounded theory approach on trace data to study such relationships between AC and covert resistance. Moreover, future research could also investigate how covert resistance against AC differs from human-based control because of the characteristics of algorithms (i.e., comprehensive, instantaneous, interactive, and opaque), for example, by conducting a case study with workers who previously worked primarily under human-based control but now work a significant amount under AC.

Third, our literature review revealed that sensemaking plays an enabling role in covert resistance, especially for those forms where workers influence data collection. There is already preliminary research on algorithm sensemaking (Möhlmann et al., 2022) and about how workers use it as a preparatory step for covert resistance, but it is still unclear how workers leverage their knowledge from algorithm sensemaking for their covert resistance and how the interplay between sensemaking activities and covert resistance looks like (e.g., linear process or iterative). To investigate this interplay, researchers could conduct a narrative analysis (Pentland, 1999) on interview data from platform workers who engage in sensemaking and covert resistance to uncover the temporal dynamics between sensemaking activities and covert resistance practices.

Last, we discovered that most articles (over 80%) in our review sample used qualitative research methods. Further, ride-hailing is by far the most common study context of covert resistance against AC. Thus we encourage future research to diversify this literature by developing more quantitative studies (Alizadeh et al., 2023) and investigating contexts outside of ride-hailing (Lippert et al., 2023).

Future research directions	Sample research questions
Triggers of covert resistance	• How can the different triggers of workers' covert resistance interact with each other to strengthen or weaken workers' resistance intensity? • How does workers' perception of the coherence of different control instructions affect their covert resistance? • When do workers engage in positive resistance, and when do they engage in negative resistance?
Forms of covert resistance	• How does covert resistance systematically differ across different AC mechanisms? • How does covert resistance against AC differ from human-based control because of the characteristics of algorithms?
Sensemaking as enabler for covert resistance	• How do workers leverage their knowledge from algorithm sensemaking for covert resistance against AC?
Method & study context:	More quantitative studies and contexts outside of ride-hailing

Table 2. Future research directions about covert resistance against AC.

5 Discussion

This study aimed to investigate how workers can covertly resist against AC and what triggers them to engage in such resistance. Existing literature on workers' covert resistance against AC does not provide a systematic and context-independent overview of this topic. Therefore, we aggregated the previous findings to develop a theoretical framework. Based on this framework, we can derive three key insights: First, workers perform covert resistance against AC by influencing data collection and contesting control instructions. Second, working under AC can lead to several triggers for workers' covert resistance, reaching from low compatibility, opacity, and low profitability to technical issues. Third, workers engage in individual and collective sensemaking to understand how the input data affects the control instructions, enabling them to perform diverse forms of covert resistance against AC.

5.1 Theoretical Contributions

Broadly speaking, our study contributes to the IS literature on worker resistance. While previous research in IS about worker resistance mainly addresses resistance against organizational change induced by IS implementation (e.g., Lapointe & Rivard, 2005; Markus, 1983), we further expand the existing context of worker resistance in IS by addressing how workers resist organizational control through algorithms. More specifically, we provide three theoretical contributions to the existing literature on AC. First, we offer an overview of what different forms of covert resistance can be performed against AC. While previous research on AC on OLPs describes how workers perform covert resistance in specific contexts (e.g., Kinder et al., 2019; Tarafdar et al., 2022), we provide a holistic understanding of different forms of covert resistance against AC on OLPs by integrating previous findings into a theoretical framework. One approach of covert resistance is to influence data collection (i.e., input for AC). Because the collected data is used for AC to execute control instructions (i.e., output of AC), workers can actively affect the control instructions to their advantage by influencing the collected data accordingly. The other approach directly targets the control instructions, where workers try to mitigate the negative consequences of control instructions by contesting them. Comparing covert resistance to AC with covert resistance to human-based control, we conclude that workers under AC can more covertly manipulate the data they collect because AC cannot assess the necessary contextual information, making it difficult for platform providers to detect such manipulation. In this regard, workers may even manipulate data to pretend to comply with the platforms' interests, while in fact providing covert resistance to AC. This understanding helps to recognize the vulnerable aspects of AC.

Second, we provide a nuanced understanding of the triggers of workers' covert resistance against AC. Previous research describes single triggers of workers' covert resistance under AC (e.g., Rahman, 2021) or proposes some general frameworks to explain the antecedents of worker resistance under organizational control (e.g., Gill, 2019). We provide a synthesized overview of different triggers adapted to the context of AC on OLPs that may lead to covert resistance. The most frequent trigger is low compatibility between workers' personhood and the perceived algorithmic control (e.g., low autonomy, unfairness, pressure, and low privacy). In addition, the highly opaque working environment provided by AC intensifies such suffering and makes it even more difficult for workers to resist against AC compared to human-based control. We also discovered technology-related issues as another potential source for resistance which provides another distinction to human-based control. Hence, we offer important insights about workers' negative experiences with such tight control through algorithms, and that covert resistance can be seen as a workers' means to better deal with AC.

Third, our theoretical framework explains how covert resistance against AC is formed. Previous research described several sensemaking activities of workers (e.g., Bucher et al., 2021; Rahman, 2021) but overall has less emphasized the enabling role of sensemaking as a preparatory step for covert resistance. In our study, we discovered that workers are often systematically engaged in individual and collective sensemaking of AC before performing covert resistance. In particular, for covert resistance in the form of influencing data collection, workers need to develop a deep knowledge of the relationship between the data collected and the resulting control instructions in order to affect the control instructions in a way that makes them more desirable. While workers who perform covert resistance against human-based control are less involved in activities to understand the decision rationale behind each control instruction, workers under AC put a high effort into sensemaking to understand AC. Thus, sensemaking has a much more important role in covert resistance against AC compared to human-based control.

5.2 Practical Implications

With this study, we provide important practical insights for platform providers to understand the impact of using AC as well as how harmful workers' covert resistance can be. Based on our findings, workers' covert resistance mostly leads to negative consequences for the organization. Therefore, platform providers are interested in preventing workers' covert resistance. One sustainable way to promote platform longevity is to mitigate triggers for covert resistance, for example, by making AC more compatible with workers' interests. In this regard, platform providers could reconfigure AC with increased worker autonomy, fairness, and privacy. One possible way to do so is to make customers more accountable for their bad reviews by requiring them to state a particular reason for their bad reviews.

Our study also provides practical implications for policymakers. Next to the (above-described) sustainable ways to mitigate workers' covert resistance, platform providers could also choose less sustainable ways to mitigate workers' covert resistance by exploiting their more powerful position (compared to its workers), which leads to increased disadvantages for workers. For example, platform providers can make the algorithms behind AC much more complex, so it is even harder for workers to make sense of them, and therefore, they are less able to develop covert resistance. Further, platform providers can disable workers' covert resistance by adapting AC to eliminate loopholes that are exploited through workers' covert resistance and tighten the control intensity (e.g., increase surveillance). Hence, we encourage policymakers to enact regulations that prevent platform providers from using their power over workers to maintain or even increase unfair working conditions.

5.3 Limitations

Our study also comes with some limitations. First, as with any literature review, the selection process and inclusion and exclusion criteria may have impacted our findings. We applied established guidelines (Paré et al., 2015), searched in leading management, organizational, IS journals, and IS conferences, and included an extensive forward and backward search (Webster & Watson, 2002). Nevertheless, it is possible that our search did not detect all relevant papers on cover resistance against AC. Future studies could specifically include other search strategies and databases to cover additional fields of research.

Second, our conceptualization of workers' covert resistance emphasizes that covert resistance must contain an action. However, some studies also consider resistance as an attitude and would argue that, for example, cynicism is also a form of covert resistance (Pregenzer, Wieser, et al., 2021). Future studies could expand the definition of covert resistance to include more forms of covert resistance.

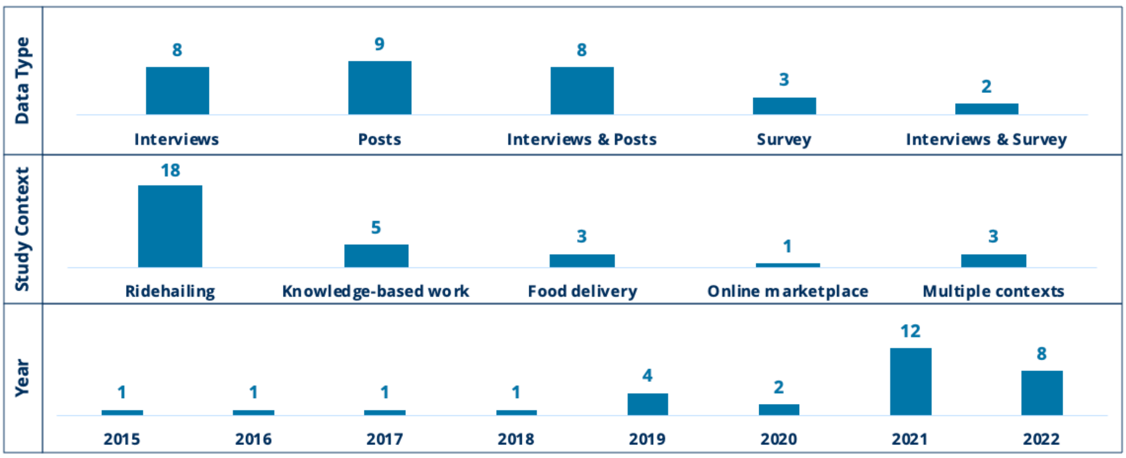
Appendix

Leading management & organizational journals (in alphabetical order)	Academy of Management Annals, Academy of Management Journal, Academy of Management Review, Administrative Science Quarterly, Journal of Management, Journal of Management Studies, Management Science, Organization Science, Organization Studies, Strategic Management Journal
Leading IS journals (in alphabetical order)	European Journal of Information Systems, Information Systems Journal, Information Systems Research, Journal of Information Technology, Journal of Management Information Systems, Journal of the Association for Information Systems, Management Information Systems Quarterly
Leading IS conferences (in alphabetical order)	European Conference on Information Systems, International Conference on Information Systems

Appendix A. Leading journals and conferences included in literature search.

Outlet type	**Outlet** (in alphabetical order; colored lines indicate IS literature)	**Articles in review sample**
Journal	Administrative Science Quarterly	2
	Chinese Journal of Communication	1
	Cultural Studies	1
	European Journal of Information Systems	1
	Industrial and Labor Relations Review	1
	Information Systems Journal	1
	International Journal of Communication	1
	International Labour Review	1
	Journal of Management Information Systems	1
	Journal of Management Studies	1
	Management Information Systems Quarterly	1
	Media International Australia	1
	New Media & Society	3
	New Technology, Work, and Employment	1
	Organization	1
	Organization Science	1
	South Atlantic Quarterly	1
Conference	Conference on Computer-Supported Cooperative Work And Social Computing	1
	Conference on Human Factors in Computing Systems	4
	European Conference on Information Systems	2
	International Conference on Information Systems	3

Appendix B. Distribution of journals and conferences in review sample.



Appendix C. Descriptives of review sample.

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