Algorithm as Boss or Coworker? Randomized Field Experiment on Algorithmic Control and Collaboration in Gig Platform

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Abstract

Without a doubt, the heavy use of artificial intelligence (AI) will be involved in the future of work. Pertinent to the deployment of AI in organizations, algorithmic control is the managerial use of intelligent algorithms as a means to align individual worker behaviors with organizational objectives. While algorithmic control may facilitate efficient management of workers, it also leads to intrusive and unilateral exertion of controls over workers, also known as "algorithm as boss" phenomenon. In this study, we attempt to understand the outcomes and tradeoffs that different configurations between the AI and gig workers would produce, by conducting a randomized field experiment with one of the largest delivery rider labor unions in Asia. Overall, our study suggests that providing collaborative algorithmic control not only increases gig workers' utility in terms of monetary rewards but also enhances their intrinsic rewards, which has the potential to benefit the gig platform as well.

Keywords: algorithmic control, future of work, gig economy, autonomy paradox

Introduction

Without a doubt, the heavy use of artificial intelligence (AI) will be involved in the future of work. Today, over one third of global companies are using AI in their businesses and an additional 42% are exploring ways to adopt AI (Index, 2022). Organizations are increasingly making the transition from human management to algorithmic management, to which learning algorithm executes workflow coordination and process control that used to be performed by human managers (Möhlmann et al., 2021). For instance, AI-based scheduling systems are used to predict consumer demands and assign retail workers to meet real-time demands (Gal et al., 2020). Furthermore, AI applications are widely used in human resource management, from the use of voice analytics in recruitment process to detect emotions in interviews (Jarrahi et al., 2021), to the use of people analytics in the evaluation of workers' performances (Gal et al., 2020; Pignot, 2023). Across various work processes, AI is not only redefining and transforming how people perform tasks but are increasingly becoming managers that directly enact control over human workers. As the reliance of AI in organizations continues to proliferate, it is not only important for IS scholars to understand 'whether AI will take over human work?' but uncover insights for the question of 'whether it is good for AI to take over human management*?'* (Faraj et al., 2018).

Pertinent to the deployment of AI in organizations, *algorithmic control* refers to the managerial use of intelligent algorithms and advanced digital technology to align individual worker behaviors with organizational objectives. As a specific function of algorithmic management, Algorithmic control is a new form of leadership that significantly alters the way to which worker efforts are coordinated and controlled (Benlian et al., 2022; Cram & Wiener, 2020; Kellogg et al., 2020; Verelst et al., 2022). On the one hand, algorithmic control provides substantial benefits to firms by providing instantaneous prediction through insights gleaned from detailed data collected from various aspects of work (Bucher et al., 2021; Faraj et al., 2018; Jarrahi et al., 2021; Kellogg et al., 2020). With increased computational power, algorithmic control is expected to be more objective, mathematically accurate, and less prone to errors compared to human managers (Muldoon & Raekstad, 2022). On the other hand, IS research have identified the dark sides of algorithmic control (Benlian et al., 2022; Bucher et al., 2021; Duggan et al., 2020; Li et al., 2022; Möhlmann & Henfridsson, 2019; Pregenzer et al., 2021; Rosenblat & Stark, 2016; Wiener et al., 2021). With little or no human involvement, algorithmic control bears the serious risk of dehumanizing workers through constant surveillance and not offering algorithmic transparency towards why certain organizational decisions are made (Möhlmann & Henfridsson, 2019). Furthermore, the automation of work processes limits opportunities for workers to communicate with their managers (Benlian et al., 2022), undermining workers' autonomy, which consequently weakens the relationship between employee and employer (Muldoon & Raekstad, 2022; Oldham & Hackman, 2010). Building an "iron cage" that is tighter than human managers, algorithmic control may be perceived as the "boss from hell" (Duggan et al., 2020; Faraj et al., 2018).

One of the most prominent industries that rely heavily on AI techniques in managing the tasks of human workers is the gig economy. Platforms like Uber, Lyft, Upwork and Fiverr are utilizing AI in the matching and dispatching of service providers to clients (Möhlmann et al., 2021). While workers are granted the freedom to decide when to work, they are under the close supervision of the platform when they do come onto the platform (Möhlmann et al., 2021). Such a work environment can generate strong tensions between workers and the platform's algorithms (Pregenzer et al., 2021). For instance, Uber drivers are assigned to specific tasks, payment rate, and delivery route generated by the algorithm and are punished accordingly if they fail to comply with the platform policies and rules; When drivers reject three consecutive trip requests, the app would switch off for a certain period of time and not allow them to work (Möhlmann et al., 2021; Muldoon & Raekstad, 2022). In several of these gig platforms, workers perceive the platform's algorithms as a manager (Curchod et al., 2020) and may resist against it actively using workarounds, striking, and even leaving the platform (Choudhury et al., 2020; Deng et al., 2016; Faraj et al., 2018). Such worker responses are detrimental to gig platforms, as low worker retention rate has been a key challenge (Hall & Krueger, 2018).

While algorithmic control may facilitate the efficient management of workers, it leads to asymmetric power relationships between workers and platforms because it is designed by managers who, instead of delivering direct controls, now embed value choices in the algorithm's control configurations (Muldoon & Raekstad, 2022; Newlands, 2021; Shapiro, 2018). (Jain et al., 2021) calls for a deeper understanding of the *algorithm as boss* phenomenon, specifically towards knowledge on how algorithmic control can be designed to support workers. Recently, a number of researchers have adopted sociotechnical perspective to suggest an alternative role of the algorithm as a mediator between workers and platforms (Benlian et al., 2022; Bucher et al., 2021; Jarrahi et al., 2021; Wiener et al., 2021). That is, algorithmic control that allows for bidirectional decision-making process between algorithm and workers reduce intrusiveness to benefit gig workers (Jain et al., 2021; Schuetz & Venkatesh, 2020). Collaboration between humans and algorithms in various stages of development and deployment have been identified as an effective way to create synergies between algorithm's computational power and humans' domain knowledge (Lebovitz et al., 2021; Lou & Wu, 2021; van den Broek et al., 2021). Nevertheless, little is understood about the impact of collaborative decision-making between algorithm and workers in the context of gig economy.

In view of these knowledge deficiencies, we explore varying configurations of the relationship between workers and algorithm in the gig economy. The gig economy is a unique context where algorithms are programmed to manage and allocate human workers in the most efficient way, while workers on the platform want to maximize their individual utility (e.g., profit maximization). At times, the objectives of the algorithm and workers may not be fully aligned. Our study sets forth to understand the outcomes and tradeoffs that different configurations between the AI and gig workers would produce. In addition to the baseline condition where algorithm exerts unilateral control over humans (i.e., traditional algorithmic control), we examine two new ways that human workers can be involved in decision-making process: collaborative algorithmic control and full-human decision-making. In collaborative algorithmic control, workers are partially involved in the decision-making process, choosing tasks among the choices provided by the algorithm. Thus, both platforms and workers have the possibility of pursuing their own utility. In full-human decision-making, human workers retain the full autonomy in choosing which tasks to perform but may not benefit from the computational power that algorithm may provide. Considering different impacts that each configuration between algorithm and workers may have on workers' and platform's utilities, we answer the following two research questions:

RQ 1: How does increasing gig workers' roles in decision-making affect gig workers' utility?

RQ 2: How does increasing gig workers' roles in decision-making affect gig platform's utility?

To answer our research questions, conducted a randomized field experiment with one of the largest delivery services in Asia. Our partner is a food delivery app with the highest market share (i.e., 60%) and the largest monthly active users (MAU) in the country. We randomly assigned 130 gig workers into three conditions: traditional algorithmic control where the AI dictates and assigns the tasks for workers, collaborative algorithmic control where workers get to choose their tasks from an AI-recommended list) and no algorithmic control (no interference from AI) and conducted individual-level analyses on delivery time and profit per distance travelled. Additionally, we surveyed workers to measure the impact of different forms of algorithmic control on workers' perceived autonomy and competence. Our findings indicate that while workers in collaborative algorithmic control took longer to complete delivery than those in traditional algorithmic control condition, and they earned higher profit. Interestingly, results show that workers under collaborative algorithmic control have higher perceived competence and autonomy than those working under traditional algorithmic control or without algorithmic control. Overall, our study suggests that providing collaborative algorithmic control not only increases gig workers' utility in terms of monetary rewards but also enhances their intrinsic motivation, which has the potential to benefit the gig platform as well.

Our study offers some theoretical and practical implications. First, through our randomized field experiment, we are among the first to provide causal answers to the question of how workers and platforms are affected by different types of algorithmic control, which has been of interest for prior studies on algorithmic control. Second, our study also contributes to the literature on human-AI collaboration by extending the understanding of collaborative decision-making process between workers and algorithms to blue-collar jobs. Third, our findings shed lights into resolving the autonomy paradox in gig economy, where gig platforms promote themselves as providing more autonomy while its unilateral and intrusive algorithmic control restricts workers' autonomy. Lastly, our study highlights the importance of allowing gig economy workers to be part of the decision-making process in performing the tasks.

Theoretical Background

Gig Economy

Defined as digital, on-demand platforms that enable flexible work arrangements, gig economy has witnessed a significant growth in the past years (Burtch et al., 2018; Greenwood et al., 2017; Huang et al., 2020). Gig platforms offer a unique organizational model where a small number of managers coordinate millions of disaggregated workers and clients (Gulati & Kletter, 2005). In such two-sided gig platforms, the long-term business success depends on establishing a strong network effect, in which the platform's value to one side increases with the size of the other side (Eisenmann et al., 2006; Parker et al., 2016; Rochet & Tirole, 2003; Zhu & Iansiti, 2019). Thus, rather than directly providing products or services, gig platforms seek to efficiently coordinate supply and demand of labor.

Many researchers have examined gig economy in two-fold. First, studies have focused on the relationship between platform and consumers (i.e., demand side), such as consumer behaviors (Edelman & Luca, 2014), pricing strategies (Chen & Horton, 2016), and market designs for efficient matching of workers and customers (Hong et al., 2016). Second, the supplier side of the labor has been studied. A number of researchers have examined gig platforms' attempts to maximize the value created by workers' labor and minimize any associated costs by focusing on worker coordination (Kellogg et al., 2020; Li et al., 2021; Schwellnus et al., 2019). However, while gig platforms' efforts to facilitate efficient coordination may optimize firm revenue, they may not be as beneficial to gig workers; For instance, adopting algorithmic control to facilitate coordination efficiency may deprive workers of autonomy and demotivate workers (Kellogg et al., 2020; Möhlmann et al., 2021; Newlands, 2021).

Considering important roles that gig workers play in establishing a strong network effect, several scholars have taken an organizational approach to understand how gig platforms could empower gig workers (Deng et al., 2016; Mas & Pallais, 2017; Möhlmann et al., 2021). Empowerment leads to worker retention and derives affective commitment, leading to managerial effectiveness (Galletta et al., 2011; Spreitzer, 1995). In gig platforms, where low worker retention rate has been a key challenge, understanding workers' extrinsic and intrinsic motivational factors that lead to empowerment is of utmost importance (Behl et al., 2022; Hall & Krueger, 2018). As one of the first antecedents in empowerment, *monetary rewards* (i.e., profit) constitute as a major extrinsic motivational factor for gig workers (Behl et al., 2022; Deng et al., 2016; Galletta et al., 2011). Because gig works are smaller and more temporary than traditional employment, the per-work payment tends to be low, which is detrimental to many gig workers who work in gig platforms for a living (Allon et al., 2023). This aligns with prior studies' notion that monetary reward is a primary extrinsic reward for low-skill employees (Huang et al., 2020; Kalleberg & Griffin, 1978). Furthermore, autonomy and competence are the intrinsic motivational factors that motivate workers to join gig platforms (Allon et al., 2023; Byrne & Pecchenino, 2019; Deng et al., 2016; Healy et al., 2017). As a sense of having a choice in initiating and regulating actions, *autonomy* is the key motivating factor that gig workers seek to achieve by working in gig platforms (Friedman, 1996; Healy et al., 2017). Compared to traditional firms, gig platforms project an image of giving workers unprecedented freedom to choose their work schedule; As such, high degree of autonomy is expected by many gig workers, who wish to choose "where they want, when they want" (Muldoon & Raekstad, 2022; Weber et al., 2022). Lastly, *competence* reflects "an individual's belief in his or her capability to perform work role activities with skill," and is a powerful measure of worker empowerment (Spreitzer, 1995).

It is worthwhile to note that gig workers identify themselves as self-interested freelancers independent from the gig platforms (Möhlmann et al., 2021); While gig platforms aim to maximize platform-level coordination efficiency, workers are rather myopic and seek to maximize their individual utility (i.e., monetary rewards, autonomy, competence) by choosing gig work that would benefit themselves (Allon et al., 2023; Byrne & Pecchenino, 2019). As workers who are not empowered tend to leave the workplace (Galletta et al., 2011; Spreitzer, 1995), adopting appropriate control mechanisms that could balance workers and platforms' utilities is an important challenge for gig platforms.

Algorithmic Control

The introduction of algorithm has unfolded an important avenue of research on whether and how algorithms could control workers with minimal involvement of human managers. Algorithmic control, defined as "managerial use of intelligent algorithms and advanced digital technology as a means to align individual worker behaviors with organizational objectives," has significantly altered the way coordination and control are delivered to workers (Cram & Wiener, 2020; Kellogg et al., 2020). In gig platforms, where a small number of employers coordinate millions of disaggregated workers and consumers, algorithmic techniques of controlling gig workers have been widely explored (Jarrahi et al., 2021). There are certain benefits of adopting algorithmic control; Combined with high computational power and large availability of fine-grained data, algorithmic control allows gig platforms to monitor workers' performance, provide real-time feedback, and even punish workers (Benlian et al., 2022; Kellogg et al., 2020; Möhlmann et al., 2021; Wiener et al., 2021). However, while algorithms may provide a comprehensive, instantaneous and accurate control over workers without any human errors, it may not be benefitting workers as much. Indeed, algorithms exert intrusive and unidirectional power over workers, building a tight "iron cage" where algorithms behave like "bosses" (Faraj et al., 2018). To counteract the uncontrolled power of algorithms, workers show implicit and explicit resistance by adopting gaming strategies, striking, and even switching to another platform (Bucher et al., 2021; Faraj et al., 2018; Möhlmann et al., 2021; Tassinari & Maccarrone, 2020).

Along with identifying affordances of algorithmic control and its impacts on gig companies and workers, scholars have recently adopted sociotechnical perspective to develop comprehensive understanding of the tension around algorithmic control in gig platforms (Faraj et al., 2018; Jarrahi et al., 2021; Muldoon & Raekstad, 2022). In this perspective, adoption of algorithms is viewed as a distinctive organizational choice for augmenting the existing capacities of managers (Muldoon & Raekstad, 2022). The relationship between workers and gig platforms becomes asymmetric when algorithm takes over the role of middle managers because, unlike human managers who tolerate some maneuvers and actively communicate with workers, algorithms deliver controls in a strict and unilateral manner, managing every behavior of workers and giving little or no room for tolerance or negotiation (Möhlmann et al., 2021; Muldoon & Raekstad, 2022). Algorithmic control thus carries a risk of limiting workers' capacity to maximize their utility, such as autonomy, leading to a paradoxical situation where workers who enter gig platforms with a hope of gaining greater autonomy are deprived of it (Ahuja et al., 2007; Deng et al., 2016; Möhlmann et al., 2021; Wood et al., 2019).

Human-AI Collaboration

While prior studies have viewed algorithm and gig workers as controller-controlee relationship, we attempt to view algorithm as a mediator by exploring potential human-AI collaboration in gig context. Addressing the concerns of existing algorithmic control that significantly limits workers' autonomy, several scholars have called for collaborative architectures of algorithmic control that allows bidirectional decision-making process in gig platforms (Jain et al., 2021; Schuetz & Venkatesh, 2020). Human-AI collaboration is a novel way of combining "human and artificial intelligence to collectively achieve superior results than each could have done in separation" (Dellermann et al., 2021). The importance of including humans "in the loop" has been emphasized in prior studies of the IS literature as a way to create symbiotic relationship between algorithms and humans in development and deployment of algorithms (Fügener et al., 2022; Lebovitz et al., 2021; Lou & Wu, 2021; van den Broek et al., 2021).

While an algorithm is capable of deriving patterns from a large set of data and of automating work processes (Sturm et al., 2021), humans also play an essential role in the decision-making process (Dellermann et al., 2021). For instance, van den Broek et al. (2021) highlights the value of human domain knowledge when constructing training data and building a model. Lebovitz et al. (2021) also finds that human experts' know-how helps managers better understand the risks and benefits of using AI tools. In an experimental study by Fügener et al. (2022), algorithms and humans working together has outperformed algorithm or humans working alone because humans can recognize the complementarities between the two agents. Overall, researchers on human-AI collaboration emphasize humans' role in various stages of decision-making process.

Nevertheless, little is understood about the impact of collaborative relationship between algorithm and workers in the context of task allocation in gig platforms. Gig platform creates a unique triad relationship between platform managers who design algorithm, algorithm that executes the controls, and workers who work under the algorithm's control. Unlike in traditional work environment where algorithm is designed to assist its users (i.e., assisting doctors make diagnosis and HR managers select best job candidates), algorithm in gig platform is designed to control its users. Therefore, whether allowing workers to collaboratively make decisions with algorithm would be beneficial (and if so, to whom it would benefit) is a key question that needs to be answered.

Facilitating collaborative interaction between gig workers and algorithms by increasing gig workers' role in decision making may have varying impact on workers. On the one hand, the collaborative decision-making between control algorithms and human workers may give workers more decisional power, leading to increased autonomy and competence (Deng et al., 2016). As utility maximizers, gig workers would choose works that grant them greater financial rewards (Byrne & Pecchenino, 2019; Healy et al., 2017). By satisfying both intrinsic and extrinsic motivational factors, the collaborative interaction with algorithm would help gig workers maximize their individual utility. On the other hand, increasing humans' role in decision making may harm gig workers who would not be able to fully benefit from algorithm's superior computational power. Unlike human workers, algorithm has access to a broader set of information about other workers and clients, as well as greater capacity to derive the optimal result. Therefore, while gig workers may be internally motivated, they may not be able to choose higher paying works.

The impact of collaborative relationship between algorithms and gig workers is also not clear for gig platforms. Designed to maximize the total efficiency (i.e., delivery time of entire workers), algorithmic control ensures that gig platforms maximize their utility. Thus, reducing the level of efficiency by allowing workers to interfere with the algorithmic control may hinder gig platforms from achieving their organizational goal. It is also possible, however, for gig platforms to benefit from collaborative algorithmic control, considering that gig platforms face a serious problem of low worker retention due to their strict algorithmic control mechanisms (Hall & Krueger, 2018). By increasing workers' role in decision making process, collaborative algorithmic control may satisfy workers' intrinsic and extrinsic motivations, encouraging them to remain in the gig platform and bringing benefits to platforms in the long term.

While building a collaborative algorithmic control in gig platforms has been suggested by prior studies (Benlian et al., 2022; Bucher et al., 2021; Jarrahi et al., 2021; Wiener et al., 2021), there has not been an empirical attempt to examine the impact of incorporating human autonomy in workers' interaction with algorithm on both gig workers and gig platforms. Thus, we attempt to contribute to human-AI contribution by providing a comprehensive understanding of how algorithm should interact with gig workers to benefit both gig platforms and workers.

Research Method

Study Design

To examine the impact of collaborative algorithmic controls on gig workers and platform utility, we partnered with one of the largest delivery rider labor unions in Asia. This focal labor union is the oldest delivery rider labor union and has members across all regions in the country where the experiment has been conducted. We recruited union members who work for the food delivery app with the highest market share (i.e., 60%) and are monthly active users (MAU) in the experiment site. The food delivery app (hereinafter referred to as "app") has adopted an Artificial Intelligence (AI)-based order dispatch system, which according to the app managers, is designed to optimize delivery time for each order; In order to dispatch orders that minimize delivery time for workers, the algorithmic control takes into account several factors including the distance between the worker and the restaurant, the distance between the restaurant and the delivery location, as well as the current delivery order being handled by the worker. The app provides workers with information about expected delivery time, expected food preparation time, fixed fee (i.e., fee that workers would receive for the delivery), distance, restaurant name, and restaurant location. After an order has been dispatched, the app offers GPS navigation routes for both getting to the restaurant and delivering the food. Simultaneously, the app shows the worker's location and expected delivery time to the customer in real time. Once the delivery is completed, the app displays the total fee and completion status for each order to the worker.

Our field experiment was conducted over four weekdays in late August 2022. We have chosen to launch our experiment in late August because it does not coincide with either the monsoon season or the summer vacation period. To reduce the regional differences, our experiment was conducted in a single state. The population of this state is approximately 1 million, thus ensuring a sufficient number of delivery orders. To eliminate the effects of different transportation methods such as cars, e-scooters, or bicycles, we limited our focus to delivery workers who only ride motorcycles. Lastly, to prevent Hawthorne effect (i.e., observation bias), we selected workers that are newly registered to our focal gig platform.

The field experiment was performed as follows. First, we randomly assigned 130 workers to one of three groups: 1) traditional algorithmic control ("AI group") 2) collaborative algorithmic control ("AI-Human group"), or 3) full-human decision-making with no algorithm involved ("Human group"). The AI group serves as the baseline group. In the AI group, workers must follow the AI's recommendation, representing perfect algorithmic control. In contrast, workers in the AI-Human group could either make their own choices or follow recommendations from the AI. Lastly, in Human group, workers made their own choice for every order. The three different conditions are illustrated in Figure 1. Next, based on their assigned groups (i.e., AI, AI-Human, Human), workers delivered orders during the experiment period. During the experiment, the delivery app collected data on order dispatch status, delivery time, distance travel, delivery fees, and delivery completion status for each order. Lastly, on the last day of the experiment, workers participated in an online survey. Upon completion of the survey, a small amount of participation fee was provided.

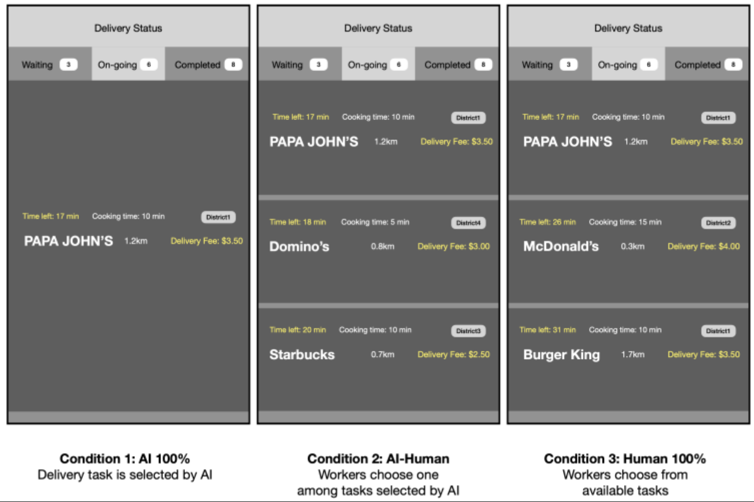

Figure 1. Experiment Manipulations

Data Collection

Our information of the 130 workers (47 in AI group, 51 in AI-Human group, and 32 in Human group), include their gender, age, tenure, income, working hours, previous AI acceptance rate, and region, which is solicited through a survey. Age is reported as a number. Gender is a dummy variable that indicates 1 if the worker is male and 0 if female. Tenure represents the length of time worked as a delivery worker, reported as year. Income indicates the total income earned in the month prior to the start of the study, and has four categories (i.e., less than $1,000, $1,000 - $2,000, $2,000 - $3,000, and more than $3,000). Working hours is reported by average daily working hours in the past month prior to the start of the study.[1]The previous AI acceptance rate is represented as a percentage. It is calculated by the frequency of orders following AI recommendation divided by total orders in the past month prior to the start of the study. This information is automatically calculated by the app and represented by the worker. In the survey, we guided workers to check their AI acceptance rate, working hours, and income from the app before filling out the survey form. The region is defined as the main delivery area in the month before the study started and is divided into six regional categories (at the county level) within the same state. Table 1 represents a detailed description of our dataset, indicating that 95% of workers are male and the average age is 37 years old. On average, workers have 2.6 years of delivery experience and work more than 8 hours per day. In addition, the majority of workers (70%) earned more than 2,000 USD per month. We observed that the AI acceptance rate prior to the study was less than 50%, indicating that our participants were not biased toward workers who relied solely on AI. These findings are consistent with previous reports that suggest the majority of delivery workers are around 40 years old and male (Gridwise, 2020; Zippia, 2022). For this reason, we believe that our worker samples are representative in terms of demographics. Table 2 displays the comparison of means for the different covariates across the three groups. Except for two income ranges, we find that *t*-test results are not statistically significant for the variables (i.e., gender, age, tenure, working hours, previous AI acceptance rate, and region) relative to the baseline case (i.e., AI group). We later conducted matching to balance income levels between Human and AI-Human groups.

	Mean	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Age	37.913	1.00								
(2) Female (%)	1.739	0.03	1.00							
(3) Tenure	2.652	-0.01	0.08	1.00						
(4) % of income range less than $1,000	9.565	0.01	-0.04	0.02	1.00					

[1] We included income range and working hour as a proxy for our two dependent variables: profit per travel distance and delivery time. We do not have data of workers' previous profit per travel and delivery time, as these workers are new to the platform.

(5) % of income range $1,000 - $2,000	16.522	-0.13	-0.06	-0.01	-0.14	1.00				
(6) % of income range $2,000 - $3,000	23.478	-0.03	0.08	-0.07	-0.18	-0.25	1.00			
(7) % of income range more than $3,000	50.435	0.12	0.00	0.05	-0.33	-0.45	-0.56	1.00		
(8) Working hours	8.478	0.21	-0.03	-0.04	-0.21	-0.32	-0.16	0.50	1.00	
(9) AI acceptance rate (%)	46.174	0.09	0.08	-0.24	0.02	0.06	0.12	-0.16	0.08	1.00

Table 1. Summary Statistics and Correlation Table

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. The region has six regional categories (county-level). Randomization check results of region dummy variables are omitted for the interest of space.

Variable	Group Average			P-value of t-statistics		
	(1)	(2)	(3)	(1) – (2)	(1) – (3)	(2) – (3)
	AI	Human	AI-Human	AI - Human	AI – AI-Human	Human – AI-Human
(1) Age	38.00	37.78	37.91	0.22	0.09	-0.13
(2) Female (%)	0.00	3.70	2.33	-3.70	-2.33	1.38
(3) Tenure	2.42	2.63	2.91	-0.21	-0.48	-0.28
(4) % of income range less than $1,000	13.33	11.11	4.65	2.22	8.68	6.46
(5) % of income range $1,000 - $2,000	15.56	7.41	23.26	8.15	-7.70	-15.85*
(6) % of income range $2,000 - $3,000	20.00	18.52	30.23	1.48	-10.23	-11.71
(7) % of income range more than $3,000	51.11	62.96	41.86	-11.85	9.25	21.10*
(8) Working hours	8.11	9.04	8.51	-0.93	-0.40	0.53
(9) AI acceptance rate (%)	43.40	49.63	46.91	-6.23	-3.51	2.72

Table 2. Randomization check by group

Notes: * p < 0.1, ** p < 0.05, *** p < 0.01. The region has six regional categories (county-level). Randomization check results of region dummy variables are omitted for the interest of space.

Empirical Strategy

Our main empirical analyses aim to estimate the effect of collaborative algorithmic control on the workers and gig platforms' utilities. For the worker's utility, we measure profit per travel distance (in USD), where the net profit is determined by subtracting the total travel expenses (i.e., fuel costs) from the total profit. Since the AI's optimization objective is to minimize the delivery time for each order, we define the gig platform's utility as the delivery time per order (in minutes). We adopt an order level as the unit of analysis, with the AI group serving as the baseline. Specifically, we estimate the following specification:

$$y_{ij} = \beta_0 + \beta_1 AI\_Human_i + \beta_2 Human_i + \alpha_i + \lambda_j + \gamma_j + \varepsilon_{ij} \quad (1)$$

The subscripts i and j represent each worker and order unit, respectively. Our dependent variable, denoted by y_{ij}, represents the log-transformed profit per travel distance of worker i for order j, and the log-transformed delivery time of worker i for order j. As dependent variables are continuous variables, we employ Ordinary Least Square (OLS) in our estimation. $\alpha_i$is a vector of control variables, and ε_{it} comprises of idiosyncratic error terms. The set of controls α_i includes gender, age, tenure, working hours, and previous AI acceptance rate. In addition, we directly address concerns on potential confounders by including region-level fixed effects (λ_j) and the day-level-fixed effects (γ_j) in our analyses; The former controls for the time-invariant differences across regions and the latter controls for potential extraneous events happening on different days.

Experiment Results

Main Results

Table 3 summarizes our main results. Regarding delivery time, the coefficients for the AI-Human group and Human group in Column (1) are both positive and significant, meaning that workers in both groups significantly take longer to complete delivery compared to those in the AI group. Considering that delivery time reflects platform's objective of coordination efficiency, our results indicate that adopting traditional algorithmic control is significantly beneficial for the platform's utility. As for profit per travel distance, Column (2) indicates significant and positive coefficient for AI-Human group; That is, collaboration between AI and workers lead to increased profit, increasing worker's individual utility. Interestingly, however, when decision is made solely by humans (i.e., Human group), workers' profit per travel distance significantly decreases. This negative impact may be due to the absence of AI's computational power. The results for the second analysis thus indicate that workers' utility (i.e., monetary gain) is maximized when workers are allowed to make collaborative decision with AI, but not when AI is entirely unavailable.

Dependent Variable	ln(Delivery Time)	ln(Profit per Travel Distance)
	(1)	(2)
AI-Human	0.0590** (0.0242)	0.0362** (0.0143)
Human	0.0739** (0.0336)	-0.0607*** (0.0191)
Controls	Yes	Yes
Day-fixed effects	Yes	Yes
Location-fixed effects	Yes	Yes
Observations	4,245	4,245
R-Squared	0.021	0.064

Table 3. Effect of AI Usage on Delivery Time and Profit per Travel Distance

*** p < 0.01; ** p <0.05; * p<0.1. Baseline group ins AI group. Controls include age, gender, tenure, income, working hours, and AI acceptance rate. Robust standard errors are in parentheses.

For clearer comparison between traditional and collaborative algorithmic controls, we excluded Human group and directly compared workers under AI and AI-Human conditions. The results are shown in Table 4, with AI group as the baseline group. Here, the coefficient of AI-Human for delivery time in Column (1) are consistent with our previous findings; Compared to workers in AI group, those in AI-Human group take significantly longer delivery time but earn higher profit per travel distance. Overall, our findings confirm that collaborative algorithmic control significantly increases workers' individual utility rather than platform's utility.

Dependent Variable	ln(Delivery Time)	ln(Profit per Travel Distance)
	(1)	(2)
AI-Human	0.0605** (0.0245)	0.0295** (0.0144)
Controls	Yes	Yes
Day-fixed effects	Yes	Yes
Location-fixed effects	Yes	Yes
Observations	3,306	3,306
R-squared	0.007	0.028

Table 4. Effect of AI Usage on Delivery Time and Profit per Travel Distance Without Human Group

*** p < 0.01; ** p <0.05; * p<0.1. Baseline group ins AI group. Controls include age, gender, tenure, income, working hours, and AI acceptance rate. Robust standard errors are in parentheses.

Robustness Checks

To validate our findings, we conducted a series of robustness checks. First, to account for the possibility that the results are sensitive to our choice of dependent variables, we replicated our estimations using alternative dependent variables: changes in time taken per travel distance (i.e., companies' utility) and profit per order (i.e., workers' utility). Results in Columns (1) and (2) of Table 6 demonstrate that the results are consistent with our main findings, which thus confirm that our main findings are influenced by our choice of dependent variables.

Dependent Variable	ln(Time Taken per Travel Distance)	ln (Profit per Order)
	(1)	(2)
AI-Human	0.0808*** (0.0302)	0.0151** (0.00737)
Human	0.131*** (0.0411)	-0.116*** (0.00895)
Controls	Yes	Yes
Day-fixed effects	Yes	Yes
Location-fixed effects	Yes	Yes
Observations	4,245	4,245
R-squared	0.017	0.102

Table 6. Effect of AI Usage on Delivery Time and Profit per Travel Distance Using Alternative Dependent Variables

*** p < 0.01; ** p <0.05; * p<0.1. Baseline group ins AI group. Controls include age, gender, tenure, income, working hours, and AI acceptance rate. Robust standard errors are in parentheses.

Second, we account for the possibility that our results may have been driven by workers who use other delivery apps (i.e., multi-homing). That is, workers who use multiple delivery apps prior to the study may be more experienced in working under traditional algorithmic control and the impact of increasing human decision making may thus be stronger. To rule out this possibility, we repeated our main analysis after excluding workers who used other food delivery apps in the pre-treatment period (i.e., one month prior to the experiment).[2] Our results in Columns (1) and (2) of Table 7 present findings consistent to our main results. Thus, even after removing workers who used multiple food delivery apps in the pre-treatment period, the positive impact of collaborative algorithmic control on workers' utility remains robust.

Dependent Variable	ln(Delivery Time)	ln(Profit per Travel Distance)
	(1)	(2)
AI-Human	0.0575** (0.0252)	0.0464*** (0.0148)
Human	0.0886** (0.0384)	-0.0492** (0.0217)
Controls	Yes	Yes
Day-fixed effects	Yes	Yes
Location-fixed effects	Yes	Yes
Observations	3,736	3,736
R-squared	0.017	0.043

Table 7. Effect of AI Usage on Delivery Time and Profit per Travel Distance Consider Rider use Only Focal Delivery App

*** p < 0.01; ** p <0.05; * p<0.1. Baseline group ins AI group. Controls include age, gender, tenure, income, working hours, and AI acceptance rate. Robust standard errors are in parentheses.

[2] N=509 observations. Of the total observations, 11.2% users used multiple food delivery apps in the pre-treatment period.

Third, we tested another potential explanation that our results may have been driven by the young age group, who may be more open to new technologies and prefer interactions with AI. Indeed, according to the survey with 11,004 adults in the US, 75% of young people under 30 years old have daily interaction with AI and more likely to trust AI (Kennedy et al., 2023). Therefore, the young age group may be more likely to prefer having algorithms to support their decision-making (i.e., AI group and AI-Human group) to not having algorithms at all (i.e., Human group), thereby driving the bulk of the estimated results. To check this possibility, we conducted our main estimation after removing young workers under the age of 30. As shown in Table 8, the results remain consistent, further confirming the robustness of our main findings.

Dependent Variable	ln(Delivery Time)	ln(Profit per Travel Distance)
	(1)	(2)
AI-Human	0.0591** (0.0255)	0.0424*** (0.0150)
Human	0.0761** (0.0345)	-0.0553*** (0.0196)
Controls	Yes	Yes
Day-fixed effects	Yes	Yes
Location-fixed effects	Yes	Yes
Observations	3,948	3,948
R-squared	0.018	0.049

Table 8. Effect of AI Usage on Delivery Time and Profit per Travel Distance Without Young-age demographics

*** p < 0.01; ** p <0.05; * p<0.1. Baseline group ins AI group. Controls include age, gender, tenure, income, working hours, and AI acceptance rate. Robust standard errors are in parentheses.

Finally, we conducted another robustness check to examine whether the observed results are sensitive to the effects of outliers, particularly from workers with an extremely high AI acceptance rate in the pre-treatment period (i.e., one month before the experiment). To this end, we identified and removed workers whose previous AI acceptance rate was three standard deviations above the average AI acceptance rate and replicated our main findings. As represented in Table 9, the results without workers with extremely high AI acceptance rate yielded similar results to our main findings, showing that our results are not driven by the outlier group.

Dependent Variable	ln(Delivery Time)	ln(Profit per Travel Distance)
	(1)	(2)
AI-Human	0.0566** (0.0242)	0.0363** (0.0143)
Human	0.0792** (0.0336)	-0.0608*** (0.0192)
Controls	Yes	Yes
Day-fixed effects	Yes	Yes
Location-fixed effects	Yes	Yes
Observations	4,215	4,215
R-squared	0.018	0.045

Table 9. Effect of AI Usage on Delivery Time and Profit per Travel Distance Without Outlier

*** p < 0.01; ** p <0.05; * p<0.1. Baseline group ins AI group. Controls include age, gender, tenure, income, working hours, and AI acceptance rate. Robust standard errors are in parentheses.

Additional Analysis

One of the key motivations of our study is to identify a significant impact of collaborative algorithmic control on gig workers' utility. Our main estimation and subsequent robustness checks provide empirical evidence that collaboration between gig workers and algorithms has a positive impact on workers' profit, which is regarded as the extrinsic motivational factor for joining and working in the gig platforms (Behl et al., 2022; Deng et al., 2016; Galletta et al., 2011). In this section, we attempt to take one step further to explore the impact of collaborative algorithmic control on gig workers' intrinsic rewards (i.e., autonomy and competence). We carried out an additional survey investigating workers' perceptions towards their work after working under different algorithmic control conditions (i.e., AI, AI-Human, and Human groups). To do so, we asked workers two survey questions asking (1) whether they possess skills necessary for delivery job and (2) whether they can make work decisions on their own. Formal definitions and survey questions are described in Table 10.

We conducted an additional survey on the last day of the experiment by sending out an online survey link to workers who had completed their last order. Out of the 130 experiment participants, we received 118 valid responses. Each participant responded to the survey questions based on their experience under different conditions (i.e., AI, AI-Human, and Human groups). Our findings, presented in Table 11, reveal that workers in the AI-Human group (i.e., collaborative algorithmic control) perceived the highest degree of both competence and autonomy. Compared to the AI group, workers in the AI-Human group reported higher levels of both competence and autonomy, which indicates that workers who collaborate with algorithms are more intrinsically motivated than those who work under traditional algorithmic control. Considering that empowered workers are more likely to remain in the platform (Galletta et al., 2011; Spreitzer, 1995), the positive impact of collaborative algorithmic control on workers' intrinsic motivations is beneficial for gig platforms as well. Interestingly, although workers in the Human group had the greatest freedom to choose their work, those in the AI-Human group perceived a significantly higher level of autonomy. This result suggests that simply providing options for workers to choose, regardless of whether those options are selected by algorithms or not, can help increase workers' sense of autonomy.

Measure	Definition	Question
Competence	Individual's belief in his or her capability to perform activities with skill.	I have the delivery skills necessary for my delivery job (1-5)
Autonomy	Individual's sense of having a choice in initiating and regulating actions.	I can decide on my own how to go about doing my delivery work (1-5)

Table 10. Variable Definition and Survey Question

Variable	Group Mean			Mean Difference		
	(1)	(2)	(3)	(1) – (2)	(1) – (3)	(2) – (3)
	AI	Human	AI-Human	AI - Human	AI – AI-Human	Human – AI-Human
Mean of Competence	3.913	4.000	4.227	-0.087	-0.314**	-0.227
Mean of Autonomy	3.957	3.821	4.386	0.135	-0.430**	-0.565**

Table 11. Competence and Autonomy Difference Between Three Groups

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. One-tailed t-test statistics are presented.

Discussion and Implications

Algorithmic control is a key strategy for gig platforms where a small number of managers coordinate the work of millions of employees around the world. Whereas previous research has viewed algorithmic control as an inflexible exercise of power over workers, our study adopts socioeconomic perspective that views algorithm as a mediator between workers and managers and examines its role as a collaborative mediator, rather than a strict controller. To understand the impact of this approach on workers' job performance and perception, we conducted a field experiment with one of the largest delivery rider labor unions in Asia. Our findings indicate that gig workers under traditional algorithmic control took shorter amount of time for delivery than those under collaborative algorithmic control or no algorithmic control. Furthermore, workers under collaborative algorithmic control earned the highest amount of profit. Our follow-up survey offers insights into how different algorithmic controls affect workers' perception towards their jobs. We find that workers who make collaborative decision with algorithms reported higher degrees of job competence and autonomy, which are the core values that workers seek to attain from gig companies (Deng et al., 2016; Healy et al., 2017).

Our study has several important theoretical implications. First, by conducting a field experiment, we provide empirical evidence of the impact of collaborative algorithmic control in gig platforms. While prior studies have called for the role of algorithms in balancing power between workers and managers in the gig economy, the question of how workers and platforms are affected by different types of algorithmic control has not been empirically answered. Through our field experiment, we found that collaborative relationship between gig workers and algorithms, rather than unidirectional exertion of power over workers, leads to higher profits for workers and better job perspectives. Our main findings indicate that collaborative algorithmic control increases workers' utility, as workers under collaborative algorithmic control took 5.9% longer to complete a delivery but earned 3.62% higher profit per travel distance. Interestingly, our finding that workers without algorithmic control not only took 7.39% longer time to complete the delivery but also earned 6.07% lower profit suggests that providing algorithmic control is still better than not providing algorithmic control at all. Additionally, our follow-up survey revealed that workers under collaborative algorithmic control perceived a higher level of autonomy and competence than those in other conditions, which is beneficial to both workers and platforms. To the best of our knowledge, this study is one of the first to empirically examine the benefits of adopting a socioeconomic perspective in the gig economy.

Second, our study contributes to the literature on human-AI collaboration by extending the understanding of collaborative relationship between workers and algorithms to blue-collar jobs. Previous research on human-AI collaboration has largely focused on the collaboration between algorithms and high-skill workers, such as medical doctors and IC chip designers (Lebovitz et al., 2021; Zhang et al., 2021). However, as mentioned earlier, the collaboration between algorithms and blue-collar workers may be substantially different because workers work under algorithm's control, rather than designing or deploying the algorithm. Our research recognizes this critical difference by examining the impact of collaborative algorithmic control on two sets of dependent variables: profit per travel distance and delivery time. While profit per time distance reflects gig workers' utility (i.e., extrinsic motivation), delivery time reflects gig platform's utility (i.e., coordination efficiency). By identifying that human-AI collaboration in gig platform has a different impact on workers and platforms, our paper holds significant implications for the human-AI collaboration literature and future of work, especially as algorithms are increasingly introduced to collaborate with workers in a wider range of industries and skill levels.

Third, our findings shed lights into unraveling the autonomy paradox in gig economy (Möhlmann et al., 2021). While gig platforms promote themselves as providing more autonomy to workers and freedom to choose "where they want, when they want," they create a serious autonomy paradox where algorithms deliver controls in a strict and unilateral manner, managing every behavior of workers and giving little or no room for tolerance or negotiation (Muldoon & Raekstad, 2022). Algorithmic control thus carries a risk of limiting workers' capacity to maximize their utility, leading to a paradoxical situation where workers who enter gig platforms with a hope of gaining autonomy are deprived of it. Our study findings suggest that a collaborative relationship between workers and algorithms can be a possible solution to this paradox. Involving workers in the decision-making process leads to higher levels of perceived autonomy and competence among workers, as our follow-up survey revealed. Not only is this beneficial for the workers, but it can also benefit gig platforms by preventing worker turnover. Furthermore, we found that workers under collaborative algorithmic control perceived higher autonomy than workers under no algorithmic control (i.e., Human group), which indicates that adopting algorithms is better than not adopting it at all.

Our findings from this study offer practical implications to gig industry as well. For instance, our comparison between traditional, unilateral algorithmic control and collaborative algorithmic control highlights important factors that should be considered during the algorithm design phase. Specifically, the study shows that allowing gig workers to join decision-making process can lead to higher levels of perceived autonomy and competence, which in turn can contribute to worker retention and overall job satisfaction.

Thus, gig platforms should prioritize the development of collaborative algorithmic control systems that incorporate worker input and feedback, rather than relying solely on rigid, unilateral algorithms.

Limitation and Future Research Direction

While our study provides valuable insights into the benefits of collaborative algorithmic control in gig platforms, there are some limitations that offer opportunities for future research. First, our experiment covers only a short period of time, which may not be enough to understand long-term effect adopting different types of algorithmic control. Examples of the long-term effects may include learning effect, in which workers learn how the algorithm operates and manipulate it to maximize their utility, or behave like "borgs," as suggested by Fügener et al. (2021). Second, our research focuses on collaborative decision-making in delivery task selection, there are many other ways algorithms can be used to manage gig workers, such as monitoring or rating. For instance, collaborative decision-making could include workers having more autonomy to decide which route to take to deliver food or have more input in the rating system. Future research could explore whether the positive effects of collaborative algorithmic control apply to other forms of algorithmic management. Lastly, while we examined workers' autonomy and competence, which are important indicators of job satisfaction and retention, our scope of research does not include workers' decisions to remain in the gig platform or switch to another platform. Thus, future studies may explore whether the positive impact of collaborative algorithmic control identified in this study could enhance worker retention, which is the ultimate goal of gig platforms.

Overall, our study presents comprehensive and empirical evidence for an emerging perspective on algorithmic management that views algorithm as a mediator, rather than a controller, between workers and managers, and identified positive impact of collaborative algorithmic control in workers' profit maximization and perspective towards work, both of which are critical for worker retention. As gig economy continues to grow as a major form of employment and increasingly adopts algorithm as a way to control millions of workers, this emerging understanding of the collaborative algorithmic control provides important implications for researchers, platform managers, workers. With our novel findings, we hope to extend literature on algorithmic control and future of work.

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